ASSESSING THE IMPACT OF CURRENT TRADE DISPUTE ON THE ECONOMIES OF CHINA AND THE U.S.

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AUGUST 16, 2019

ACKNOWLEDGEMENT

The author is deeply grateful to all those who have provided the help, guidance and support. First and foremost, the author would like to thank her supervisor Professor Stephen Buckland for offering valuable advice throughout the writing of this thesis. Thanks also to the University of St Andrews, for providing her professional mathematical statistics and data mining knowledge and resources. Last but not least, the author wants to express her gratitude to her family for supporting her financially in completing the MSc programme.

Declaration

The author, Linyue Li, hereby certify that this thesis, which is approximately 14997 words in length, has been written by her, and that it is the record of work carried out by herself and that it has not been submitted in any previous application for a degree. The project was conducted by her under the supervision of Prof Stephen Buckland from May 2019 to August 2019 at the University of St Andrews. The dissertation is to fulfil the requirement of the degree of Master of Science in Applied Statistics and Data Mining.

ABSTRACT

The U.S. utilised the vast trade deficit of goods as a pretext to evoke bilateral trade friction between China and the U.S. Therefore, the U.S. introduced a train of measures to control China in the trade areas. China promptly fought back, leading to U.S-China trade disputes between escalating into a war. Through the history of trade frictions of the major countries since the 1990s, the essence of current China-U.S. trade disputes reflects the global strategic competition between the U.S. and China in the economic field. The economic impacts causing by the current trade dispute are worth studying. Previous economic research has analysed potential influences that may be brought by China-U.S. trade disputes based on the economic impacts causing by other trade wars. However, studies of current trade disputes have not been treated much in detail, especially using statistical methods.

The present study aimed to explore the impacts of the current trade dispute on the economies by examining the future development pattern of different indicators, including imports and export s between the two countries, GDP, CPI and unemployment rate in both countries. The study utilised different time series models, containing exponential smoothing, ARIMA and neural networks, to forecast the indicators. The findings indicated that there are substrantial economic impacts on imports and exports between the two countries as well as some effects may occur in other indicators if the current trade war continues. These findings provide a robust evidence base for future research on the trade disputes between China and the U.S.

LIST OF ABBREVIATIONS

ACF – Autocorrelation Function.

AIC – Akaike Information Criterion.

ANN – Artificial Neural Network.

AR – Autoregressive Model.

ARMA – Autoregressive Moving Average Model.

ARIMA – Autoregressive Integrated Moving Average Model.

BIC – Bayesian Information Criterion.

CPI – Consumer Price Index.

ETS – Exponential Space State Smoothing Model.

GDP – Gross Domestic Product.

GNP – Gross National Product.

iid - independent and identically distributed.

LSTM – Long Short-term Memory.

MA – Moving Average.

MAE – Mean Absolute Error.

MAPE – Mean Absolute Percentage Error.

MASE – Mean Absolute Scaled Error.

NNAR – Neural Network Autoregressive Model.

PACF – Partial Autocorrelation Function.

RMSE – Root Mean Square Error.

RNN – Recurrent Neural Network.

VAR – Vector Autoregression Model.

WTO – World Trade Organisation.

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CHAPTER 1 – INTRODUCTION

1.1 GENERAL

U.S.-China trade disputes, also known as trade war or trade frictions, are significant issues in the economic relationship between China and the U.S. Trade disputes mainly occur in two aspects: One is the export sector of China has comparative advantages; The other is that China has no advantages in the field of imports and technology. The former is competitive, while the latter is that the market does not fully function. They both have different effects on the economic welfare and long-term development of the two countries, but the same point is that they must have a certain impact on the economies of the two countries and even of the world. Therefore, this paper makes a statistical analysis of the economic impact of trade disputes on China and the United States. The potential readership is the examiner of this dissertation and anyone interested in the impacts of China-U.S. trade dispute

Chapter 1 provides background information about the trade dispute between China and the U.S and connects it to the purpose of this study. This chapter also details the research approach as well as the data and software used in the paper.

Chapter 2 reviews publications and journal articles that are relevant to the study. The first part introduces different time series models and their applications, followed by the review of existing discussion on economic impacts causing by the trade war.

Chapter 3 outlines all the methodology that was used in the paper, mainly of different models, such as exponential smoothing models, ARIMA models and neural networks. This chapter also introduces dynamic regression models that combine the idea of time series models and regression models, which is used in the research as well.

Chapter 4 explores the datasets by looking at the basic statistics of each variable and plotting them to compare. The data contents and source are also explicitly detailed. This chapter also analyses the trend and seasonality in the time series data and corrects them for fitting the model in Chapter 5.

Chapter 5 summarises the results for the different models that were applied to different indicators. The prediction was drawn from the model with the optimal model.

Chapter 6 contains discussions of the findings in Chapter 5 and relates the results to relative economic significance. This chapter separately discusses the economic impacts for now and what trade war may bring to both countries in the future if the war does not stop.

Chapter 7 summarises the key findings from this study and restate the purpose of the work. This chapter also discusses the limitations and applicability of the study and provides suggestions for further study of the topic.

1.2 BACKGROUND

After the establishment of diplomatic relations and the signing of bilateral trade agreements between the U.S. and China in 1979, the development of trade between U.S. and China has become much more rapid, but constant friction exists, particularly since the election of Trump as the president of the U.S. in 2016. On the grounds of the enormous deficit in U.S.-China trade in goods, the U.S. adopted some actions against China, provoking the trade frictions between the U.S. and China (Wang, 2019).

In March 2018, Trump signed a memorandum declaring that it will impose tariffs on goods of 60 billion dollars imported from China. This is also a sign of the beginning of U.S.-China trade disputes (Associated Press, 2018). China quickly announced counter-measures on the next day to impose tariffs on 3 billion dollars imports from the U.S. In May 2018, the U.S. representatives came to China to conduct the first round of negotiations with the Chinese side in the economic and trade field. Several days later, the Chinese representatives visited the U.S. to conduct the second round of negotiations with the U.S., issuing *Joint Statement of U.S.-China Economic and Trade Consultation*. Also, both countries decide to stop increasing tariffs to each other to avoid escalating trade conflicts. U.S.-China economic relation seems to have shifted from a friction to a long-term negotiation (Wang, 2019).

In June 2018, Trump ignored the consensus that had been formed between the two countries and permitted to the imposition of tariffs on about 50 billion dollars Chinese goods. In reaction, China claimed that if the U.S. adheres to these actions, China will have to adopt necessary measures to counter the system and any trade agreements reached with the two countries in the previous negotiations will no longer be valid. In July, the U.S. officially imposed a 25% tariff on 34 billion dollars Chinese goods on the first list. As a strike back, China also adopted similar taxation measures to impose taxation on the U.S. At this point, the friction was formally upgraded to a trade war (Wang, 2019). On 10th May, 2019, the U.S. imposed a tariff on 200 billion dollars of Chinese exports to the U.S. officially increased from 10% to 25%. As a counter-measure, China legally imposes tariffs on goods imported from the U.S. of about 60 billion dollars at different rates. In this regard, the U.S.-China trade dispute has become much fiercer (Wong and Koty, 2019). The U.S.-China trade war developing to the present situation has not only seriously affected the economies of both sides, but also created a heavy blow to the world economy.

1.3 RESEARCH APPROACH

The research approach mainly contains two parts. First is to forecast the imports and exports from the beginning of trade dispute up to now using the historical data before the start of the trade friction and then compare the prediction with the actual value. Second is to forecast the value of other economic indicators for some future years with imports and exports as factors describing trade dispute. The univariate time series approaches used to forecast includes ETS, ARIMA and NNAR. The datasets used in the study to measure the economy contain trade between the U.S with China as well as GDP, CPI and unemployment rate of both countries, which are all from the government website of each country. R Studio 3.5.2 is the primary software used in the research while Microsoft Office Excel is also used to place the outputs.

1.4 PURPOSE

The objective of this dissertation is to evaluate the economic impacts that may be brought by the recent China-U.S. trade war using statistical methods. The central concept is exploring and forecasting the future trend of economic indicators based on historical data. The results of the study can be used for reference to those who would like to analyse this topic in the field of economy further. The research aims first to compare the actual and predicted values of trade after the start of the trade dispute and then conduct more prediction of other indicators on account of the effects of the trade war.

CHAPTER 2 - LITERATURE REVIEW

2.1 TIME SERIES MODELS AND FORECASTING

According to Box, Jenkins and Reinsel (2008), time series, also known as dynamic sequence, is a sequence of data in which the values of the same statistical index are arranged in chronological order. Most of the economic data is given in time series (Brown, 1962; Cheng and Zhao, 2000; Quilis, 2018). Depending on the time of observation, the time series data can be yearly, quarterly, monthly or other forms. The primary purpose of time series analysis is to predict the future values based on the existing historical data. Using time series observations to forecast the value at a future time can offer help to economic planning, industrial processing, inventory control etc. (Holt et al., 1963; Harrison, 1965).

One of the most well-known forecasting methods is called exponential smoothing. Actually, this method is the basis of many most successful forecasting methods, of which each method has the similarity that the predicted values are the combinations of weighted historical observations. Exponential smoothing methods indicate that as time closes to present, the weights of observations exponentially increase (Hyndman et al., 2008; Kolahi and Khazaei, 2017). In 1944, Brown first put forward the idea of exponential smoothing and applied it to track the speed of submarine shooting (Brown and Meyer, 1961). Additionally, in 1957, Holt studies exponential smoothing method for U.S. Office Research, which shows different trend and seasonal components compared with Brown's work (Gelper, Fried and Croux, 2010). Later on, Winters (1960) offered an empirical analysis for Holt's seasonal method. Meanwhile, Muth (1960) brought in two statistical models for theoretical exponential smoothing, which is relevant to the forecasting. The success of exponential smoothing models has led many scholars (Ansley and Kohn, 1985; Hannan and Deistler 1988; Carlin, Polson and Stoffer, 1992) to seek models that produce the same predictions, of which many are state space models. ETS has excellent flexibility in the specification of parameter structures.

Another forecasting method is the ARIMA model, which is the combination of AR and MA models (Liu et al., 2016). In 1927, Yule first presented a model to predict sunspot, which is the foundation of AR models. Later in 1931, MA model also put forward by Yule (Box, Jenkins and Reinsel, 2008). Then in 1970, Box and Jenkins proposed ARMA and ARIMA model to predict the patterns of future values from historical observations. Since then, ARIMA models were used to forecast time series data in different areas. Babu and Reddy (2012) presented an ARIMA model to forecast global temperature. Moreover, Ariyo, Adewumi and Ayo (2014) used ARIMA model to predict short-term stock price and get satisfactory results. Furthermore, Qonita, Pertiwi and Widiyaningtyas (2017) predicted exchange rate using the ARIMA model. Nevertheless, ARIMA has the restriction of many assumptions, including linearity and stationarity. In 2003, Zhang suggested that non-linear patterns cannot be predicted well by the ARIMA model. Also, ARIMA models have difficulty in capturing seasonality with limited sample observations.

In order to overcome the drawbacks of ARIMA models, some academics (Wijaya, Kom and Napitupulu, 2010; Liu, Liao and Ding, 2018) try to use typical machine learning process (e.g. ANN) to solve time series problems. Plus, RNN was put forward to forecast time series data in that the assumption of the typical machine learning process is the data is iid, which does not conform to the property of time series data (Zhang and Man, 1998). Nonetheless, as time goes on, RNN will lose the ability to absorb information, i.e. gradient vanishing (Gers and Schmidhuber, 2001). In 1997, LSTM was first proposed by Hochreiter and Schmidhuber (1997) to overcome gradient vanishing problem, which performs quite well in recognising the patterns in dynamic sequence data. In many different areas, LSTM is used to research time series problems. For instance, Wang et al. (2017) predicted water quality using LSTM. Besides, Liu, Liao and Ding (2018) studied stock price volatility and got high accuracy.

For the current trade dispute between China and the U.S., many economic models are introduced to evaluate the impacts. Irwin (1998) designed a general equilibrium model to calculate the loss of GNP in the U.S. by changing the law. Based on this, Ossa put forward a multi-industry general equilibrium model of trade and a quantitative trade model in 2014 and 2016 respectively. In this dissertation, time series models are used to assess the impacts of trade conflict by forecasting future values of economic indicators.

2.2 ECONOMIC IMPACTS ON LOCAL AND GLOBAL TRADE

For a long time, global tariff wars and its impacts have always been an issue generating heated discussion, which has been manifested in numerous economic publications. Bouet and Laborde (2017) broadly reviewed the impacts of potential US-China trade disputes derived from some changes of U.S. trade policies before the current US-China trade disputes (symbol of the start: Trump signs a memorandum on 22nd March 2018). The results of their work indicate that trade conflicts could ruin global trade relations and damage the developing and emerging countries without bringing any benefits for the U.S.

Conybeare (1987) referred to the trade war as a ‘category of intense international conflict’, of which countries retaliate and bargain over the economic targets of relevant departments by restricting the free movements of goods, services and capitals. In general cases, all trading partners may lose their economic advantages in the trade war, thus forming a prisoner’s dilemma (Baumol and Blinder, 1985). Under these circumstances, only bilateral cooperation is valuable, but non-cooperative countries would be dominant (Baumol and Blinder, 1985). However, if each country refuses to implement a cooperative strategy, the global trade system will be catastrophic (Irwin, 1998). A typical case is the Chicken War between the European Economic Community and the U.S.

Nevertheless, in the exchange economy, 'Johnson cases', the trade war between large and small countries, can usually happen (Brander and Spencer, 1985; Kennan and Riezman, 1988). In 1953, 'Johnson cases' was first presented by Johnson that the small countries would probably be severely affected while the great power would gain benefits in light of the optimal tariff theory. In the history of trade wars, exemplifications are the trade conflicts between France and Italy from 1886 to 1898 and between Russia and Germany from 1893 to 1894 etc.

Broadly speaking, global trade conflicts may pose threats to the relevant countries and even the economy of the whole world. In normal conditions, the economy of the two countries will be damaged compared with free trade. Although in the 'Johnson cases', the great power may increase its GDP (gross domestic product), the small countries and the world will lose.

For recent US-China trade disputes, there are generally three possible economic variations of trade restrictions. Primarily, since the price of imported goods increases, domestic goods may replace imported goods (Rosyadi and Widodo, 2018). Secondly, trade diversion will happen when the price of products imported from one country increases, whereas which from other areas remains the same (Dong and Walley, 2012; Bouet and Laborde, 2017). Last but not least, when domestic trade conditions change in order to improve the domestic industries, the exterior effect of trade conditions will appear (Johnson 1953; Ossa, 2011).

Authors	Measurement	United States	China	Australia	European Union	Japan	World
Dong and Whalley (2012)	Equivalent variation in income	60 billion$	-19 billion$		-1 billion$	-5 billion$	4 billion$
Bouet and Laborde (2017)	Equivalent variation in income	-0.3%	-1.0%			0.1%	
Bollen and Rojas-Romagosa (2018)	Real GDP	-0.3%	-1.2%		0.4%	0.4%	-0.1%
Li, He and Lin (2018)	Real GDP	0.3%	-1.0%		-0.001%	0.003%	-0.04%
Rosyadi and Widodo (2018)	Real GDP	-1.22%	-5.4%	1.18%	0.85%	1.52%	

FIGURE 2.1 PREVIOUS ANALYSIS OF ECONOMIC MEASUREMENTS ON US-CHINA TRADE DISPUTES IN BILATERAL RESTRICTIONS

Figure 2.1 lists the findings of some authors analysing the trade battle of US-China under bilateral protections. The extent of the impact is different, but some similarities can be drawn. First of all, the economy of the U.S. rarely dominates due to the negative effects of retaliation of China and the rest of the world. On the other hand, China, usually as the one that loses the most among all the countries, may probably benefit more when negotiating the new trade agreements. Also, trade diversion leads to global losses now and then, which results in net gains in Japan, Australia and Europe.

2.3 SUMMARY

Since the U.S.-China disputes have not ended currently, the analysis of this case is still valuable to follow up and further discuss to see what would happen in the future. After synthesizing the review, times series models, ETS, ARIMA and NNAR are selected to be used in the study to investigate GDP, CPI, unemployment rate as well as the imports and exports. Also, different from these studies, this thesis is going to mainly analyse the imports and exports only between China and the United States to eliminate the impacts of other influencing factors.

CHAPTER 3 - METHODOLOGY

3.1 GENERAL

This chapter presents the basic methods that support the study. In section 3.2, the benchmark methods of forecasting are introduced as well as the data transformations, residual diagnostics and accuracy evaluation. Section 3.3 details the exponential smoothing models, especially the ETS model that was used in the research. Section 3.4 explains the ARIMA model, one of the most popular time series models. Section 3.5 gives a brief introduction to neural network models for forecasting time series data. Finally, Section 3.6 describes a model that combines a regression model with time series model, which was used to assess the economic impacts with the effect of the trade war in the study.

3.2 TOOLBOX

3.2.1 Simple Forecasting Methods

Using a benchmark to forecast is the most basic approach in forecasting, but sometimes useful. There are generally four methods. First is the average method, which makes all the fitted values equal to the average of historical data. The equation can be expressed as $\hat{y}_{T+h|T} = \bar{y} = (y_1 + \ldots + y_T)/T$, where $\hat{y}_{T+h|T}$ represents the predicted value of $y_{T+h|T}$. Second is the naïve method, also known as random walk forecasts that set all the future values the same as the last observation, which performs quite well in financial and economic time series. The equation can be shown as $\hat{y}_{T+h|T} = y_T$. Based on the naïve method, for dramatically seasonal data, seasonal naïve method can be used. In the equation: $\hat{y}_{T+h|T} = y_{T+h-m(k+1)}$, the predicted value equals to the value of observation of the last seasonal period. The fourth method is the drift method, which allows fluctuations over time and assumes the amount of change per unit time, i.e. drift, is equal to the average amount of change in historical data.

Occasionally, the most straightforward methods may be the best predictors, but in more cases, they are used as benchmarks rather than being used directly. In other words, any prediction method proposed will be compared with benchmark methods to ensure the new ones are better. Otherwise, the new method is not worth being considered. In this study, seasonal naïve method is used as a benchmark method.

3.2.2 Mathematical Transformations

Transformations can be useful if the range of data values changes and the fluctuations in the data become larger or smaller. For instance, logarithmic transformations are often efficient. The equation of transformation can be recorded as $w_t = \log(y_t)$. Logarithmic transformations are easy to interpret: the change in the logarithm is the relative change in the original value. Assuming a base 10 logarithmic transformation, adding 1 to the logarithm is equivalent to multiplying the original value by 10. Another trait of the logarithmic transformations is the ability to limit the predicted value to a positive number. In this study, logarithmic transformations are used on imports and exports.

There are some other transformations can be used, such as square and cube root transformations, which are also called power transformations in that they can be represented in the form of $w_t = y_t^p$.

3.2.3 Residual Diagnostics

The residual in the time series model can be understood as the value remaining after fitting the model. For most time series models, the residual is equal to the difference between the observed and predicted values.

The residuals are of great use in examining whether the model adequately captures the information in the data. The residuals produced by a suitable prediction method have the following features, and the prediction methods that do not satisfy these features should be improved accordingly:

- The mean of the residuals should be 0.
- The residuals should be uncorrelated.
- The residuals should be normally distributed.
- The variance of the residuals should be constant.

3.2.4 Evaluating Forecast Accuracy

There are several ways to evaluate the accuracy of the fitted model based on forecast errors using the test dataset. RMSE is the standard deviation of the residuals, i.e. prediction errors, which measures how concentrated the data is around the best fitted line. MAE is the average of absolute value of differences between the predicted and actual values, which indicates how big of an error can be expected from the forecast on average. They are based on scale-dependent errors. The equations are $mean(|e_t|)$ and $\sqrt{mean(e_t^2)}$ respectively. The disadvantage of these measures is that they are dependent on scale and cannot be used to compare time series with different units. MAPE is on the basis of percentage errors, whose equation is $p_t = 100e_t/y_t$. The equation will then be $mean(|p_t|)$. The advantage of this measurement method is unit-free and can be used to compare the prediction performance between different datasets, but it also has the disadvantage that it penalises more heavily on the negative errors more than the positive errors. In this study, RMSE and MAE are mainly used to choose the best model and MAPE also help evaluate the accuracy with the following interpretation (Lewis, 1982):

- MAPE<10: Highly accurate forecasting.
- 10<MAPE<20: Good forecasting.
- 20<MAPE<50: Reasonable forecasting.
- MAPE>50: Inaccurate forecasting.

3.3 EXPONENTIAL SMOOTHING

3.3.1 Simple Exponential Smoothing

The simplest method of exponential smoothing is called SES, which is useful for predicting data without significant trends or seasonality. The principle of SES is that the predicted values are computed using a weighted average, where the weight exponentially drops as the observations come from the distant past, i.e. the earliest observation value is given the smallest weight: $\hat{y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha)y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \alpha(1-\alpha)^3 y_{T-3} + \cdots$, where α is the smoothing parameter that controls the speed at which the weight decreases.

3.3.2 Trend Methods

SES can be extended to forecast a time series with trend (Holt, 1957). In Holt's linear trend method, the equation is $\hat{y}_{t+h|t} = \ell_t + hb_t$, where ℓ_t is the level equation that equals to $\alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1})$ and b_t is the trend equation that equals to $\beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$. In these two equations, α and β^* are the smoothing parameters.

However, evidence have shown that Holt's linear trend method often produces over-forecasts, particularly for longer-term predictions. Therefore, Gardner and McKenzie (1985) added a parameter that can make the trend damped at some future points. The damped trend method has been demonstrated to be quite successful and can be said to be the most popular method when many time series require automatic prediction. In addition to the smoothing parameters α and β^*, the method also contains a damping parameter ϕ. The equation can be written as: $\hat{y}_{t+h|t} = \ell_t + (\phi + \phi^2 + \dots + \phi^h)b_t$, where $\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + \phi b_{t-1})$ and $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1}$. Note that the value of α , β^* and ϕ should be between 0 and 1.

3.3.3 Holt-Winters' Seasonal Method

Holt (1957) and Winters (1960) developed the Holt's linear method to catch seasonal factors. Holt-Winters seasonal method consists of a prediction equation and three smoothing equations, which has s_t that expressed the seasonality on the basis of ℓ_t and b_t. The corresponding smoothing parameters for the equation are α , β^* and γ respectively. Another letter m represents the seasonal frequency, which is the frequency of occurrence of seasons in one year. This method has two different seasonal components. When the seasonal variation remains approximately constant in the time series, the additive model is usually selected; and when the seasonal variation changes in proportion to the level of the time series, the multiplicative model is selected.

In the additive model, the seasonal component is represented by an absolute value on the scale of the observed sequence. Time series will be seasonally adjusted by subtracting the seasonal component, which will be around zero when added each year. The equation of Holt-Winters' additive method is $\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t-m+h_m^+}$, where $\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$, $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ and $s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$.

In the multiplicative model, the seasonal component is represented as a relative percentage. In the level equation, the time series will be seasonally adjusted by dividing the seasonal component, which will be about *m* when added each year. The equation of Holt-Winters' multiplicative method is $\hat{y}_{t+h|t} = (\ell_t + hb_t)s_{t-m+h_m^+}$, where $\ell_t = \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1})$, $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ and $s_t = \gamma \frac{y_t}{(\ell_{t-1} + b_{t-1})} + (1-\gamma)s_{t-m}$.

3.3.4 State Space Models for Exponential Smoothing

Exponential smoothing methods are not limited to the above-mentioned methods. Nine types of exponential smoothing methods can be obtained by considering different combinations of trends and seasonal components. Each method is marked by a pair of letter combinations (T, S) that represent trend and seasonality respectively. The methods and corresponding equations can be seen in Figure 3.1.

Trend	**Seasonal** N	**Seasonal** A	**Seasonal** M
N	$\hat{y}_{t+h\|t} = \ell_t$ $\ell_t = \alpha y_t + (1-\alpha)\ell_{t-1}$	$\hat{y}_{t+h\|t} = \ell_t + s_{t+h-m(k+1)}$ $\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)\ell_{t-1}$ $s_t = \gamma(y_t - \ell_{t-1}) + (1-\gamma)s_{t-m}$	$\hat{y}_{t+h\|t} = \ell_t s_{t+h-m(k+1)}$ $\ell_t = \alpha(y_t/s_{t-m}) + (1-\alpha)\ell_{t-1}$ $s_t = \gamma(y_t/\ell_{t-1}) + (1-\gamma)s_{t-m}$
A	$\hat{y}_{t+h\|t} = \ell_t + hb_t$ $\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$	$\hat{y}_{t+h\|t} = \ell_t + hb_t + s_{t+h-m(k+1)}$ $\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ $s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$	$\hat{y}_{t+h\|t} = (\ell_t + hb_t)s_{t+h-m(k+1)}$ $\ell_t = \alpha(y_t/s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ $s_t = \gamma(y_t/(\ell_{t-1} + b_{t-1})) + (1-\gamma)s_{t-m}$
A$_d$	$\hat{y}_{t+h\|t} = \ell_t + \phi_h b_t$ $\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + \phi b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1}$	$\hat{y}_{t+h\|t} = \ell_t + \phi_h b_t + s_{t+h-m(k+1)}$ $\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + \phi b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1}$ $s_t = \gamma(y_t - \ell_{t-1} - \phi b_{t-1}) + (1-\gamma)s_{t-m}$	$\hat{y}_{t+h\|t} = (\ell_t + \phi_h b_t)s_{t+h-m(k+1)}$ $\ell_t = \alpha(y_t/s_{t-m}) + (1-\alpha)(\ell_{t-1} + \phi b_{t-1})$ $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)\phi b_{t-1}$ $s_t = \gamma(y_t/(\ell_{t-1} + \phi b_{t-1})) + (1-\gamma)s_{t-m}$

Source: (Hyndman and Athanasopoulos, 2018)

FIGURE 3.1 FORMULAS FOR DIFFERENT EXPONENTIAL SMOOTHING METHODS

State Space Models for Exponential Smoothing refer to models that contain an equation of measurement that describe the observations and some equations of state that describe unobserved and time-varying states. Therefore, these models are called ‘state space models’. There are generally two types of models for each method: one with additive error and the other with multiplicative error. The forecast intervals of these two models are different. In order to distinguish models with additive errors and models with multiplicative errors, the third letter is added. Thus the exponential smoothing state space model can be written as ETS (errors, trend, seasonality). For each component, the notations can be: errors = {A(additive), M(multiplicative}, trend = {A(additive), A_d(additive damped), N(none)}, seasonality = {A(additive), M(multiplicative), N(none)}.The exponential smoothing state space models and the corresponding formulas can be found in Figure 3.2.

ADDITIVE ERROR MODELS

Trend	**Seasonal** **N**	**A**	**M**
N	$y_t = \ell_{t-1} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t$	$y_t = \ell_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$y_t = \ell_{t-1}s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t/\ell_{t-1}$
A	$y_t = \ell_{t-1} + b_{t-1} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$	$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$y_t = (\ell_{t-1} + b_{t-1})s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $b_t = b_{t-1} + \beta\varepsilon_t/s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t/(\ell_{t-1} + b_{t-1})$
A$_\mathbf{d}$	$y_t = \ell_{t-1} + \phi b_{t-1} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$	$y_t = \ell_{t-1} + \phi b_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$y_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $b_t = \phi b_{t-1} + \beta\varepsilon_t/s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t/(\ell_{t-1} + \phi b_{t-1})$

MULTIPLICATIVE ERROR MODELS

Trend	**Seasonal** **N**	**A**	**M**
N	$y_t = \ell_{t-1}(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1}(1 + \alpha\varepsilon_t)$	$y_t = (\ell_{t-1} + s_{t-m})(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1} + \alpha(\ell_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + s_{t-m})\varepsilon_t$	$y_t = \ell_{t-1}s_{t-m}(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1}(1 + \alpha\varepsilon_t)$ $s_t = s_{t-m}(1 + \gamma\varepsilon_t)$
A	$y_t = (\ell_{t-1} + b_{t-1})(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$	$y_t = (\ell_{t-1} + b_{t-1} + s_{t-m})(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$	$y_t = (\ell_{t-1} + b_{t-1})s_{t-m}(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$ $s_t = s_{t-m}(1 + \gamma\varepsilon_t)$
A$_\mathbf{d}$	$y_t = (\ell_{t-1} + \phi b_{t-1})(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + \phi b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\varepsilon_t$	$y_t = (\ell_{t-1} + \phi b_{t-1} + s_{t-m})(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$	$y_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m}(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + \phi b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\varepsilon_t$ $s_t = s_{t-m}(1 + \gamma\varepsilon_t)$

Source: (Hyndman and Athanasopoulos, 2018)

FIGURE 3.2 STATE SPACE EQUATIONS FOR ETS MODELS

3.3.5 Estimation and Model Selection

In addition to estimating parameters by minimising the sum of squared errors, another approach is to maximise the likelihood function. A likelihood function indicates the probability of a set of observations for different value of parameters. Therefore, a comparatively good model usually has a tremendous value of likelihood function. For a model with additive errors, the maximised likelihood (assuming the errors are normally distributed) gives the same parameter estimates as the minimised sum of squared errors. A model with multiplicative errors will give different results though.

A significant advantage of ETS models is that it can use information criteria can be used for model selection. For ETS models, AIC can be presented as $\text{AIC} = -2\log(L) + 2k$, where L is the likelihood function and k is the total number of parameters. In terms of ETS models, the corrected AIC can be presented as $\text{AIC}_\text{C} = \text{AIC} + \frac{k(k+1)}{T-k-1}$. Similarly, BIC can be expressed as $\text{BIC} = \text{AIC} + k[\log(T) - 2]$

3.4 ARIMA MODELS

3.4.1 Stationary and Differencing

The property of a stationary time series does not change with observation time. Therefore, a time series with a trend or seasonality is not a stationary time series. Calculating the difference between adjacent observations can make the non-stationary time series stationary, which is called differencing. Differencing can make the mean of a time series stationary by removing some of the variation characteristics in the time series, and thus eliminates the trend and seasonality of the time series. ACF plot can be used to diagnose non-stationary time series. For stationary data, the ACF will quickly drop to a level close to 0, whereas the ACF of a non-stationary time series will decrease more slowly and gradually. Sometimes the data after differencing is still not stationary, so it would be necessary to difference the time series again to get stationarity, that is, second-order differencing.

3.4.2 Backshift Operator

Backshift operator L is an important tag that is used to represent the delay of the time series, i.e. $Ly_t = y_{t-1}$, which means to reverse the time back by a unit time period. When L is used twice in succession, it means that the time is reversed back by two unit periods:

$L(Ly_t) = L^2 y_t = y_{t-2}$ .The backshift operator is very convenient in describing the difference. For the first-order differencing, $y'_t = y_t - y_{t-1} = y_t - Ly_t = (1-L)y_t$. and for the second-order differencing, $y''_t = y_t - 2y_{t-1} + y_{t-2} = (1 - 2L + L^2)y_t = (1-L)^2 y_t$. As a result, the *d*th-order can be described as $(1-L)^d y_t$

3.4.3 Autoregressive Models

In multiple linear regression models, we predict the variable of interest by the linear combination of multiple predictors. In AR models, the prediction of the target variable is based on a combination of historical data of it. Therefore, a *p*-order autoregressive model can be expressed as $y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t$, where ε_t is the white noise, which is equivalent to replace the predictor variable with the multiple regression of the historical value of the target variable. It can be referred to an AR(*p*) model, i.e. the *p*-order autoregressive model.

3.4.4 Moving Average Models

Unlike using historical values of predictors, MA models use historical prediction errors to build a regression-like model. The equation is $y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$, where ε_t is the white noise. The model is called MA(*q*) model, i.e. the *q*-order moving average model. Note that each predicted value can be considered as a weighted moving average of historical prediction errors.

3.4.5 Non-seasonal ARIMA Models

When combining the AR model and the MA model with the differencing, the non-seasonal ARIMA model can be obtained, which can be expressed as

$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t$. This model is called ARIMA (*p*, *d*, *q*) model, where *p* is the autoregressive model order, *d* is the degrees of differential for time series data to be stationary, *q* is the moving average order. After selecting the value of *d*, the time series will be a stationary sequence. The parameters '*p*' and '*q*' in ARIMA (*p*, *d*, *q*) can be estimated through ACF and PACF plot. For truncate, ACF and PAFC will converge to 0. For censor, ACF and PAFC will decay exponentially instead of converging to 0.

3.4.6 Estimation and Order Selection

Once selecting the adequate *p*, *d* and *q*, the parameters of the ARIMA model will be estimated using maximum likelihood estimation when using R Studio. Maximum likelihood estimation determines the parameters by maximising the probability of the observed data appearing. For ARIMA models, the maximum likelihood estimation is very similar to the least squares estimation, which is achieved by minimising the variance.

Expect for ACF and PACF plots, information criterion can also be efficient when selecting *p* and *q*. AIC is very suitable when selecting variables for regression models and can also play a significant role in determining the order of the ARIMA model, which can be presented as $\text{AIC} = -2\log(L) + 2(p+q+k+1)$, where L is the likelihood function. In terms of ARIMA model, the corrected AIC can be presented as $\text{AICc} = \text{AIC} + \dfrac{2(p+q+k+1)(p+q+k+2)}{T-p-q-k-2}$. Similarly, BIC can be expressed as $\text{BIC} = \text{AIC} + [\log(T) - 2](p+q+k+1)$. By minimising the AIC, AICc or BIC, the optimal model can be obtained.

3.4.7 Seasonal ARIMA Models

Actually, ARIMA models can also deal with seasonal time series data, which can be expressed as ARIMA$(p,d,q)(P,D,Q)_m$, where m is the number of observations each year. The uppercase characters (P,D,Q) marks seasonal parts of the model whilst the lowercase characters (p,d,q) to mark non-seasonal parts.

3.4.8 ARIMA v.s. ETS

Although the linear ETS model is a particular case of the ARIMA models, the non-linear ETS model does not have a corresponding part in ARIMA models. Besides, there are also some ARIMA models do not contain exponential smoothing. There is also another important distinction between ARIMA and ETS models that all ETS are non-stationary whereas most of the ARIMA models are stationary. Figure 3.3 shows the relation of equivalence between ARIMA and ETS models.

ARIMA Model	**ETS Model**	**Parameters**
ARIMA(0,1,1)	ETS(A,N,N)	$\theta_1 = \alpha - 1$
ARIMA(0,2,2)	ETS(A,A,N)	$\theta_1 = \alpha + \beta - 1$ $\theta_2 = 1 - \alpha$
ARIMA(1,1,2)	ETS(A,A$_d$,N)	$\phi_1 = \phi$
ARIMA(0,1,m)(0,1,0)$_m$	ETS(A,N,A)	$\phi_1 = \phi$ $\theta_1 = \alpha + \phi\beta - 1 - \phi$ $\theta_2 = (1 - \alpha)\phi$
ARIMA(0,1,m+1)(0,1,0)$_m$	ETS(A,A,A)	
ARIMA(0,1,m+1)(0,1,0)$_m$	ETS(A,A$_d$,A)	

FIGURE 3.3 RELATION OF EQUIVALENCE BETWEEN ARIMA AND ETS MODELS

3.5 NEURAL NETWORK MODELS

A neural network model is a prediction method based on simple mathematical models. It can accept a complicated non-linear relationship between the response variable and the corresponding predictors. Neural network models can be understood as a layered 'neuron' network structure. The inputs (also known as predictors) and outputs (also known as response variables) make up the underlying layer and the top layer respectively. Also, the intermediate layers consisting of 'hidden neurons' may exist in a neural network model.

The simplest network does not contain any hidden layer in the middle, which is equivalent to a linear regression model. If adding an intermediate layer that contains hidden nodes, the neural network model will become a non-linear form. Figure 3.4 is an example that contains a neural network of four predictors. The corresponding coefficients are 'weights'. The response variable is derived from a linear combination of the predictors. In the framework of a neural network model, the size of weight is determined by minimising the cost function using a 'learning algorithm'. Each layer of a multi-layer feedforward network receives inputs from a previous layer. The output node of each layer is the input node of the following layer. Each node accepts an input and weights them linearly. The result is modified with a non-linear function before the final output.

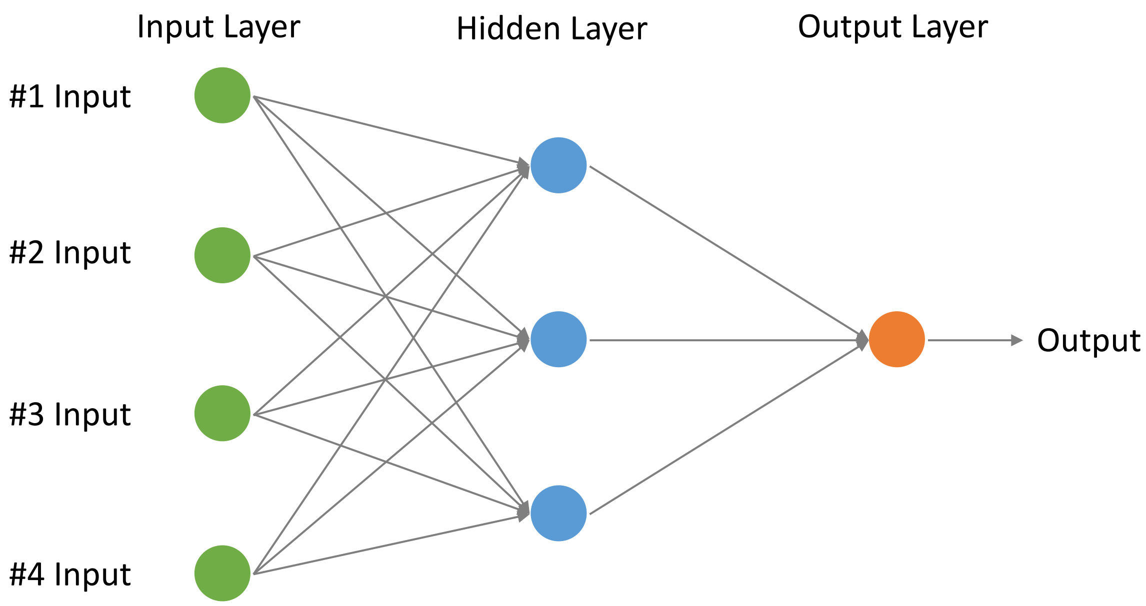

FIGURE 3.4 A NEURAL NETWORK WITH 4 INPUTS AND 1 HIDDEN LAYER WITH 3 HIDDEN NODES

For the time series, the lag value of the time series data can also be used as inputs in neural networks, which is called NNAR models. NNAR models use NNAR(p,k) to represent that there are p inputs and k hidden neurons, i.e. using hysteresis p-period observations $(y_{t-1}, y_{t-2}, \ldots, y_{t-k})$ as the inputs with k neurons in the hidden layer to predict y_t, the output, in the neural network.

For seasonal time series data, it can be considered adding the last observations of the same period of the season as the inputs. In R Studio, *nnetar()* can be used to fit the NNAR$(p,P,k)_m$ model. If the code does not specify the values for p and P, the function will automatically choose. For seasonal time series, p is selected from the best linear model obtained from seasonally adjusted data and P = 1 is the default value to show seasonality. And for the value of k, if not specified, k will be equal to (p+P+1) / 2 by default. For a non-seasonal time series, the default value according to the AIC criterion will be the best lag order of the linear AR(p) model. When using neural networks for prediction, the calculations are iterative. Such iterations will continue backwards until all required predictions are computed.

3.6 DYNAMIC REGRESSION MODELS

The impact of the relevant information generated over time on the model can be used to trim the model, so that a better time series model can be predicted. Plus, the regression model considers suffcient information about predictors, but does not use dynamic factors in the time series models. Dynamic regression models combine the two well. In R Studio, when fitting the time series model, a parameter ‘xreg’ can be specified, thereby fitting a regression model with an error term. When using the regression model with error terms for prediction, linear regression model and the time series model needs to be predicted at the same time and then the results will be combined to get the final model prediction. As for ordinary regression models, the value of the predictor should be predicted first in order to get the predicted value of the variable to be forecasted. When the future value of the predictor is known, it is easy to get the predicted value of the variable to be forecasted. However, when the future value of the predictor is unknown, the models for forecasting each predictor should be built first or future values of the predictors must be assumed.

CHAPTER 4 – DATA

4.1 GENERAL

The chapter aims to explain the specific data used in this thesis. Section 4.2 presents the source of the data and the reason for data collection. Section 4.3 follows the details of the variables in the dataset. Section 4.4 focuses on data processing before the time series analysis. Section 4.5 first shows the preliminary analysis of the trend and seasonality of the data as well as the processing of dealing with these compositions, and then explores the patterns of historical data, containing the reason that may cause the existence of unusual fluctuations.

4.2 DATA SOURCE AND COLLECTION

Generally speaking, in order to measure the economic development of a country, many economic indicators should be considered. Among all these indicators, the study chooses the four key indicators, economic growth, inflation rate, unemployment rate and balance of payments to conduct the analysis. The two variables, GDP and CPI, are used to represent economic growth and inflation rate respectively. Note that the balance of payments is consist of two variables, which are imports and exports. Also, in order to eliminate the effects of other factors, data of trade used here are only between the U.S and China. Thus, the value of imports into the U.S is equal to the value of exports from China, and vice versa.

Since the method of data collection, time range and measurement of unit differ in different databases, this paper integrates the original data collected from different government websites and databases for accuracy and fairness. Except for the *OECD iLibrary*[1] supplying most of the data, the source of other data supplement for different indicators are as below:

- GDP - U.S.: Bureau of Economic Analysis – U.S. Department of Commerce[2]
- GDP/CPI/Unemployment Rate - China: National Bureau of Statistics of China[3]
- CPI - U.S.: Bureau of Labor Statistics – U.S. Department of Labor[4]
- Unemployment Rate - U.S.: Bureau of Labor Statistics – U.S. Department of Labor
- Imports and Exports of U.S. in goods with China (i.e. Exports of China in goods with China): United States Census Bureau[5]

4.3 DATA CONTENTS

With reference to Appendix A, there are two processed datasets used directly for this study, which are all in time series, but with different frequency.

The first dataset is monthly data from January 1985 to May 2019 (the latest updated when conducting the study), which contains the balance of trade in millions of U.S. dollars with the following variables:

- The time of the observation (`year-month`).
- Imports of U.S. in goods with China (import).
- Exports of U.S. in goods with China (export).
- Balance of payments, the difference value between imports and exports (`balance of trade`).

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[1] OECD iLibrary: https://www-oecd-ilibrary-org.ezproxy.st-andrews.ac.uk/
[2] BEA Data: https://www.bea.gov/data/
[3] NBS Data: http://data.stats.gov.cn/english/index.htm
[4] BLS Data : https://www.bls.gov/
[5] U.S. Census Bureau: https://www.census.gov/foreign-trade/balance/index.html

The second dataset is yearly data from 1985 to 2018, consisting of the following variables:

- The time of the observation (year).
- GDP in the U.S. (gdp_usa), millions of U.S. dollars.
- GDP in China (gdp_china), millions of U.S. dollars.
- CPI in the U.S. (cpi_usa), annual growth rate %.
- CPI in China (cpi_china), annual growth rate %.
- Unemployment rate in the U.S. (ur_usa), % of labour force.
- Unemployment rate in China (ur_china), % of labour force.

Note that unemployment rate contains both labour force in both urban and rural area.

4.4 DATA MANIPULATION

The original data is contained in excel files. These data files were read into the statistical software R Studio for data manipulation, preliminary analysis and further exploration. In order to carry out time series analysis, the data were stored as monthly and yearly univariate time-series format data. As the beginning of U.S. - China trade dispute was on March 22 2018, the data of balance of trade before March 2018 were extracted as the dataset used as historical data to predict observations value from March 2018 to May 2019 for further analysis.

Figure 4.1 displays the time plots of imports and exports before the start of the trade dispute, which both presents increasing variation when the level of time series goes up. Before fitting the model to this dataset, a logarithmic transformation is used here. Figure 4.2 shows the plots after transformation, whose fluctuation remains constant as time goes on.

FIGURE 4.1 TIME PLOT: TRADE OF U.S. WITH CHINA FROM JAN 1985 TO FEB 2018

FIGURE 4.2 LOG-TRANSFORMED TIME PLOT: TRADE OF U.S. WITH CHINA FROM JAN 1985 TO FEB 2018

4.5 DATA EXPLORATION

4.5.1 Trade Analysis

Figure 4.3 displays the time plot of trade between China and the U.S. What can be seen in this figure is the imports seem to always been greater than exports. There has been a steady increasing trend in the imports data whereas the exports data gradually rose but tended to level off at around 10000 million dollars from 2011. The two countries signed the 'U.S.-China Comprehensive Framework for Promoting Strong, Sustainable and Balanced Growth and Economic Cooperation' to strengthen trade cooperation in May 2011 (U.S. Department of the Treasury, 2011). Thus, it can be inferred that the trade cooperation between China and the U.S. has increased the U.S. imports from China, but has little impacts on U.S. exports. By looking closely, both exports data and imports data fell sharply in 2008, which was probably caused by the financial crisis in 2008. Similarly, the pattern shows that imports data kept dropping after reaching the peak in October 2018. Although the exports data only had slight oscillation over time, but also appeared to have a sharp fall starting from March 2018. Some uncertain event seems to have occurred, which can be inferred as the impacts of the trade war.

FIGURE 4.3 TIME PLOT: U.S. TRADE WITH CHINA FROM JAN 1985 TO JUNE 2019

As mentioned above, the increasing trend existing in both imports and exports data should be removed first by differencing the data. Moreover, the imports data probably have a strong seasonality whereas the exports data may only have irregular change. The plots of differenced data are in Figure 4.4 and 4.5 for imports and exports respectively, which demonstrates no trend in both anymore.

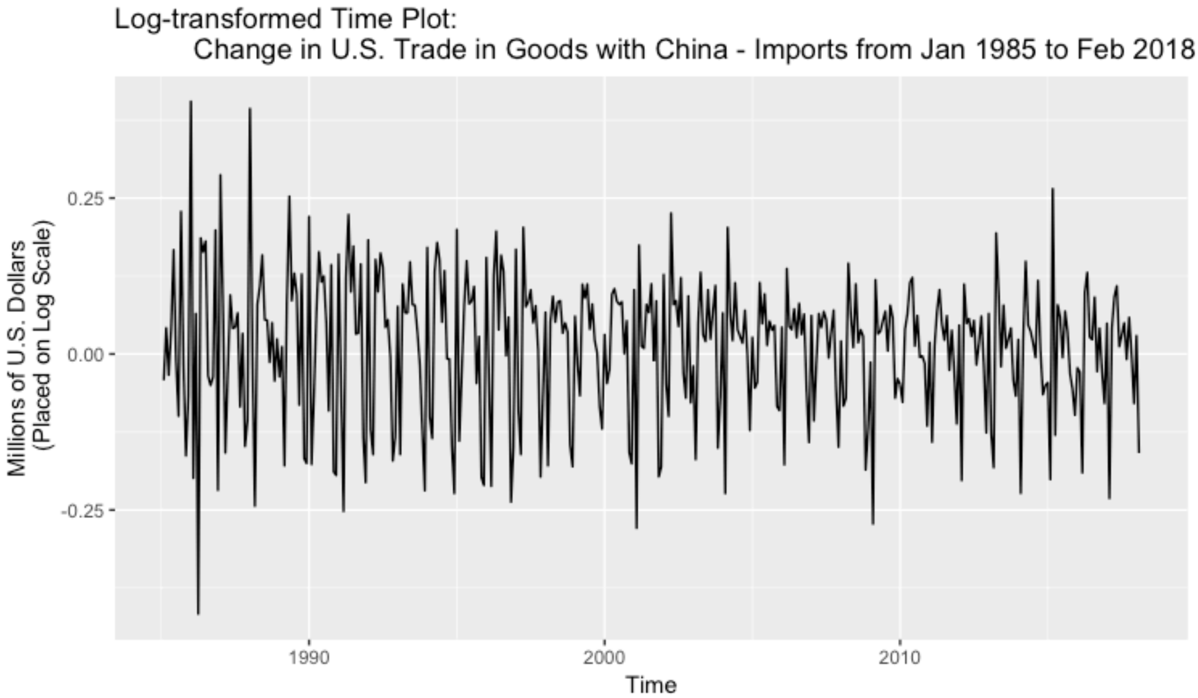

FIGURE 4.4 CHANGES IN LOG-TRANSFORMED U.S. IMPORTS WITH CHINA FROM JAN 1985 TO FEB 2018

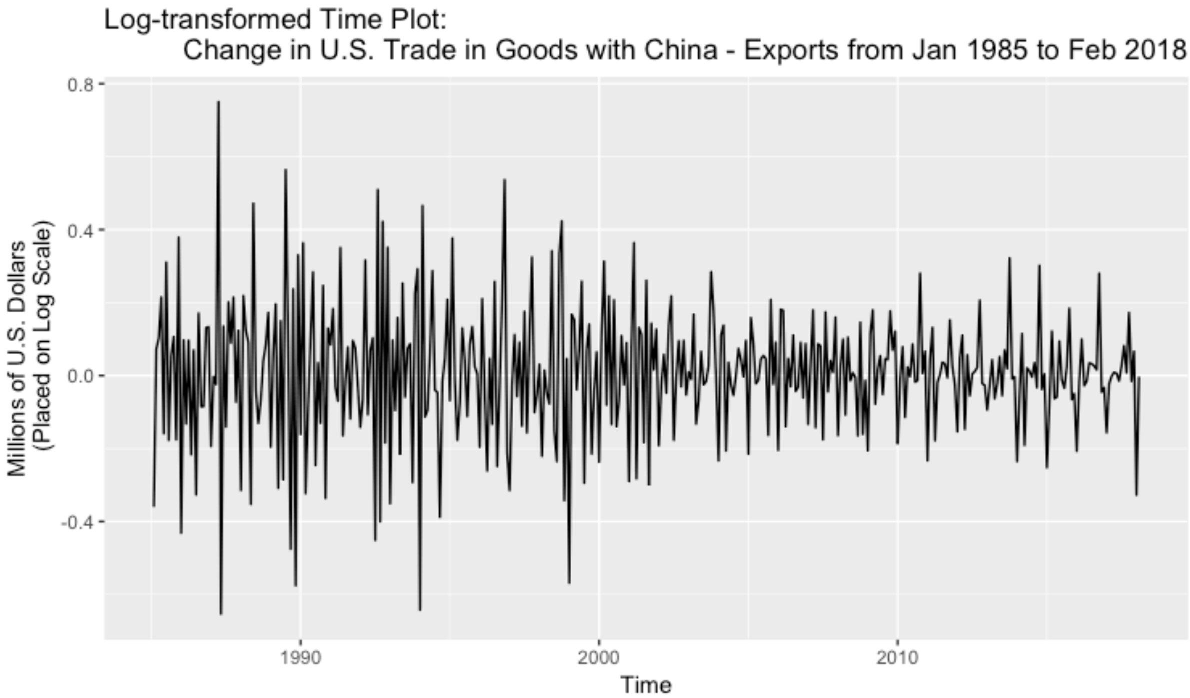

FIGURE 4.5 CHANGES IN LOG-TRANSFORMED U.S. EXPORTS WITH CHINA FROM JAN 1985 TO FEB 2018

After removing the trend, seasonal plots need to check for seasonality. In Figure 4.6, it is clear that seasonality exists in the imports data since the shape of data is the same except for a few sharp fluctuations in the early years. However, in the seasonal plot of exports data in Figure 4.7, there is basically no seasonality.

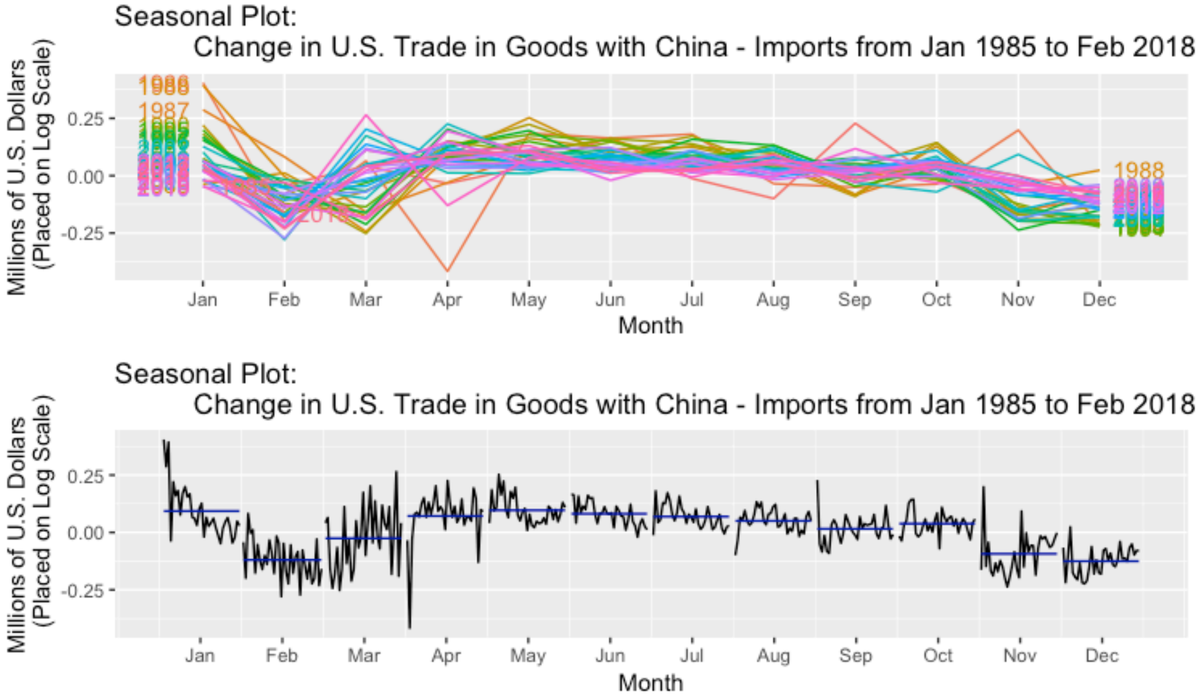

FIGURE 4.6 SEASONAL PLOT: CHANGES IN LOG-TRANSFORMED U.S. IMPORTS WITH CHINA FROM JAN 1985 TO FEB 2018

FIGURE 4.7 SEASONAL PLOT: CHANGES IN LOG-TRANSFORMED U.S. EXPORTS WITH CHINA FROM JAN 1985 TO FEB 2018

4.5.2 GDP Analysis

Figure 4.8 is a comparison of GDP in China and the U.S. From the figure, the increasing trends exist in the pattern of both countries, but there is no seasonality as GDP is a yearly indicator. However, what stands out in this figure is that GDP in China has a higher gradient than the U.S. after 2002, which may be caused by China joining the WTO in 2001 and beginning to contribute to East Asian and global consumer goods production (WTO, 2001). Additionally, GDP in the U.S. suddenly dropped in 2009. The reason behind that may be the financial crisis. It is worth mentioning that, in 2013 the GDP in both countries are almost at the same level, and subsequently, the GDP in China exceeds that in the U.S.

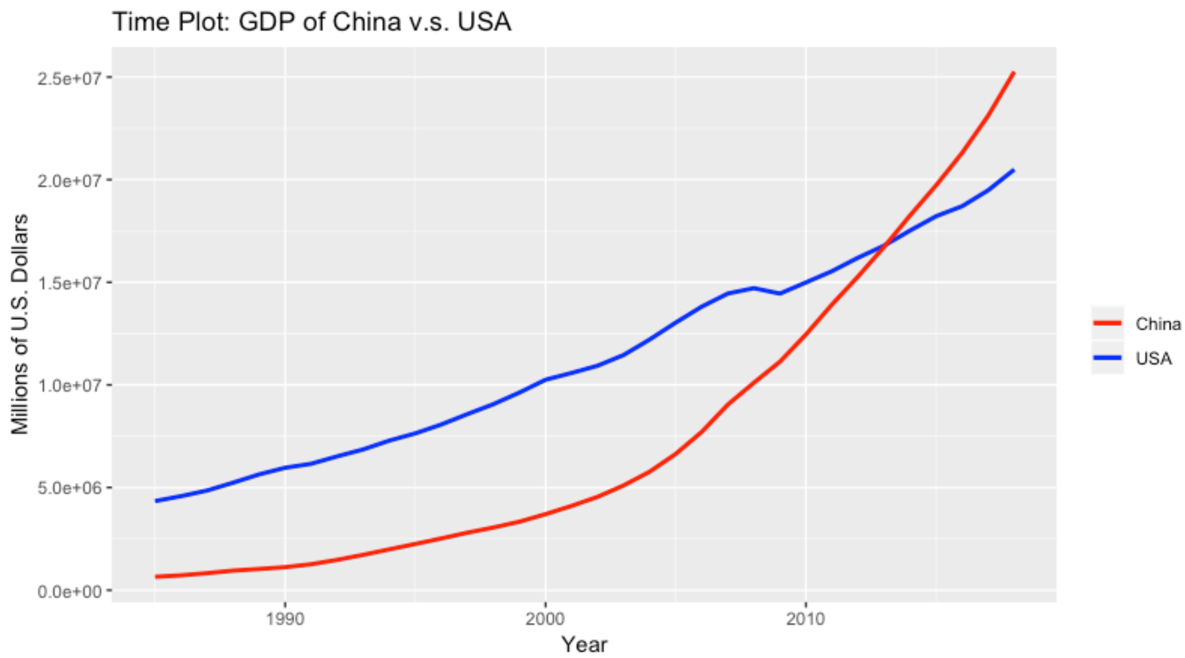

FIGURE 4.8 TIME PLOT: GDP OF CHINA V.S. USA FROM 1985 TO 2018

4.5.3 CPI Analysis

Figure 4.9 plots the pattern of CPI in China and the U.S. There is typically no clear trend and seasonality in CPI of both countries. Firstly, CPI in the U.S. fluctuates almost within 5% over time, which means that the economy is more developed, i.e. the economy in the U.S. will not have a shortage or excess demand of goods and service to affect the inflation rate. Secondly, it can be noticed that the inflation rate in China tends to fluctuate a lot, but after 1998 it tends to be steadier. In other words, it started to bound around the CPI in the U.S. It is also interesting that the CPI in China reached the peak at 24.1% in 1994, of which the causes are complicated, but mainly due to currency rising as commodity prices increase (Kojima, Nakamura and Ohyama, 2005). Apart from this, from 1998 to 2002, CPI in China experienced a few times smaller than 0, which indicates deflation. The most likely cause of this is the period of state-owned enterprise reform in China (Garnaut, Song and Fang, 2018). Additionally, both countries have a negative inflation rate in 2009, which may have been caused by the financial crisis.

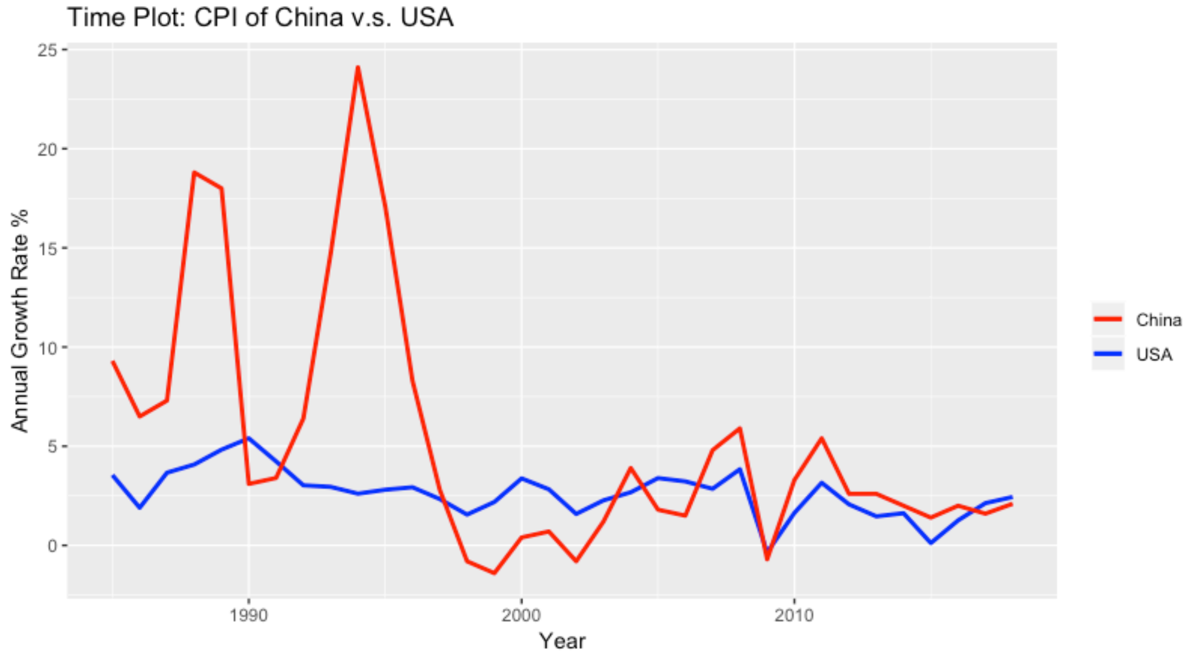

FIGURE 4.9 TIME PLOT: CPI OF CHINA V.S. USA FROM 1985 TO 2018

4.5.4 Unemployment Rate Analysis

From the time plot of unemployment rate in Figure 4.10, there is a slightly increasing trend in data of China, but it is hard to find trend in the data of the U.S. and there is no seasonality in both countries. The pattern shows that the unemployment rate of the U.S. is always greater than China; However, from the latest observations, the unemployment rate tensd to be at the same level. For the U.S., the unemployment rate reached a peak in 2009, stemming from the financial crisis. For China, from 2003, the change of unemployment rate levels off.

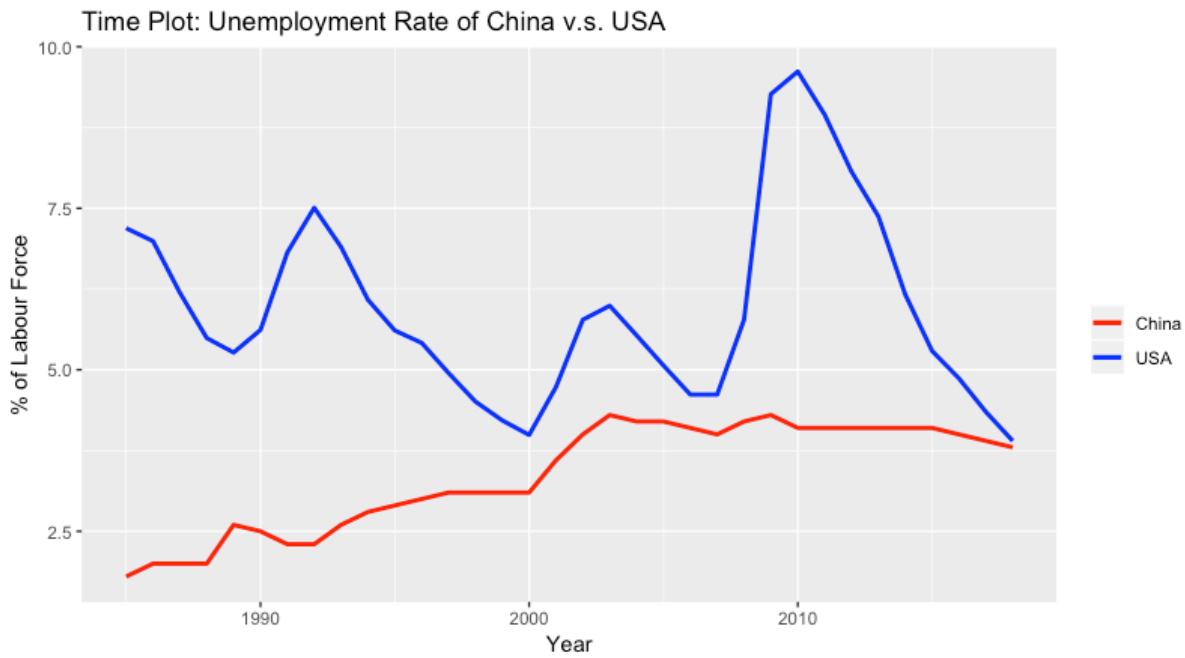

FIGURE 4.10 TIME PLOT: UNEMPLOYMENT RATE OF CHINA V.S. USA FROM 1985 TO 2018

4.5.5 Summary

Overall, it can be concluded that due to the financial crisis in 2009, some changes appeared to every indicator. From the trade plot, there is a similarity of the sharp drop in the time of both the financial crisis and current trade dispute. Thus, the changes in other indicators caused by trade disputes might be inferred from what happened to them in the period of the financial crisis. First of all, the GDP of both countries may have a slower growth rate or even decrease. Also, for CPI, the trade war may cause deflation in both countries. Last but not least, the unemployment rate may go up sharply. In the next chapter, the statistical methods are used to forecast what might happen to these indicators to see if the deduction is correct.

CHAPTER 5 - IMPLEMENTATION AND RESULTS

5.1 GENERAL

From Chapter 4, it can be summarised that U.S. Imports with China data has an increasing trend and seasonality while the exports data only has the trend. For GDP data in both countries and Unemployment Rate data in China, there is an increasing trend. For the remaining data, neither trend nor seasonality is existing.

In this chapter, the implementation of the study will be introduced clearly. In Section 5.2, monthly imports and exports from March 2018 to June 2019 will be first predicted by historical imports and exports from January 1985 to February 2018, followed by the comparison of actual data and predicted value from March 2018 to June 2019 to see if trade dispute has any impacts on the economy. In Section 5.3, monthly imports and exports of the next 18 months will be predicted by actual data from January 1985 to June 2019. After the prediction, the monthly dataset will be aggregated to yearly imports and exports and used as regressors in the prediction of other economic indicators in Section 5.4.

5.2 U.S.-CHINA IMPORTS AND EXPORTS WITH EFFECTS OF TRADE DISPUTE

5.2.1 U.S.-China Imports

5.2.1.1 Seasonal Naïve Method (as benchmark)

When forecasting a time series with trend, the accuracy of seasonal naïve method will be reduced. Therefore, the differenced dataset is used to fit SNM model. The predicted values forecasted by SNM are the observed values of the same month in the previous year. The residual standard deviation is the standard deviation of the residuals, i.e. the difference between observed and predicted values, which tells the goodness of model fitting. The obtained residual standard deviation in SNM is 0.1029, which seems to be quite small and can be used as the benchmark for the following comparison. The results of residuals are shown in Figure 5.1. From the time plot and histogram, the mean of the residuals is very close to 0, which represents the prediction is not bad, but the distribution of the residuals is leptokurtic compared with normal distribution. The ACF plot shows that some sample autocorrelations do not fall inside the 95% confidence intervals representing the model does not sufficiently extract information. Also, the L-jung box test gives a *p*-value smaller than 2.2e-16, which proves it. Therefore, there are probably better methods.

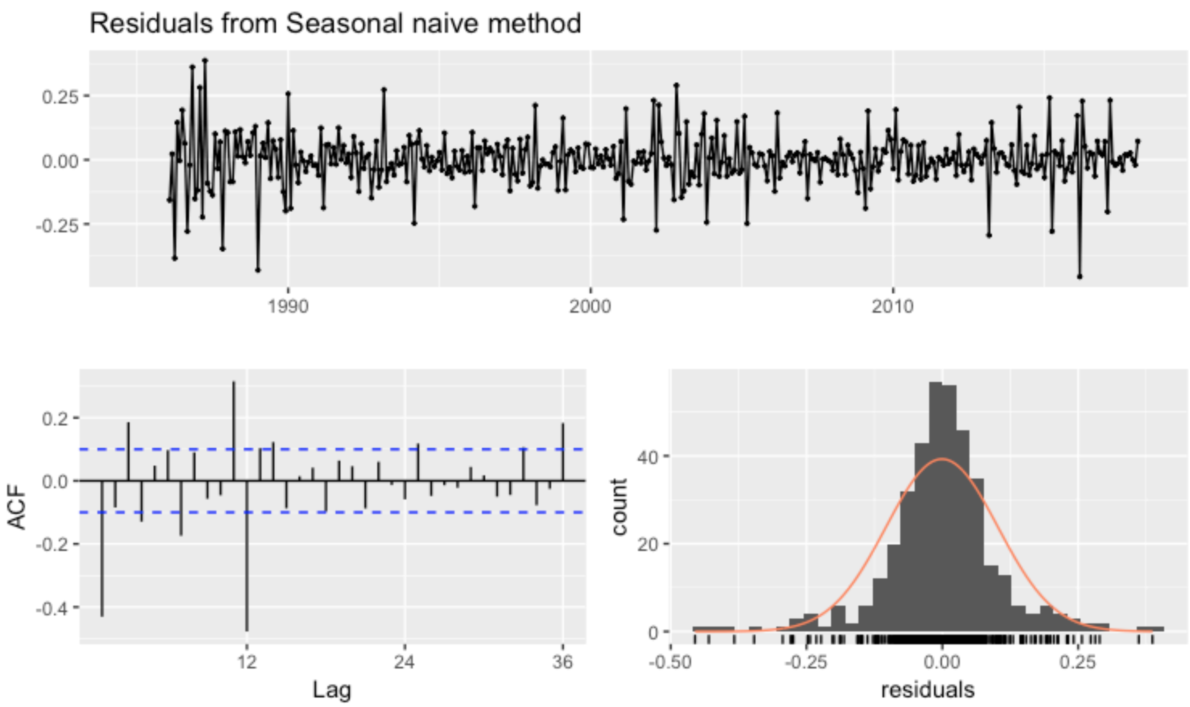

FIGURE 5.1 RESIDUALS PLOT AND ACF PLOT OF SNM ON LOG-TRANSFORMED CHANGES IN IMPORTS

5.2.1.2 ETS Model

The ETS model can directly use the original data with trend and seasonality because in R Studio, the function *ets*() will automatically decide the trend and seasonality type. The results show that the best model is ETS(A,A,A) with coefficients of alpha = 0.3983, beta = 0.0064 and gamma = 0.3089, which means an exponential smoothing model with additive trend and additive seasonality and additive errors. The residual standard deviation of ETS is 0.0748, which is smaller than SNM, so the model is better fitting than SNM literally. Figure 5.2 illustrates the residual plots and ACF plot. The histogram and time plot of residuals displays that the mean of the residuals is close to 0 and the fluctuations of residuals in historical data are irregular. Likewise, the residual histogram shows that the distribution of the residuals is slightly leptokurtic and also left-skewed. The ACF plot shows that there is still some sample autocorrelations not falling inside the 95% confidence intervals. Also, the L-jung box test gives a p-value smaller than 2.2e-16， which means there is not enough evidence to indicate that residuals are not autocorrelated. Better methods should be found continuously.

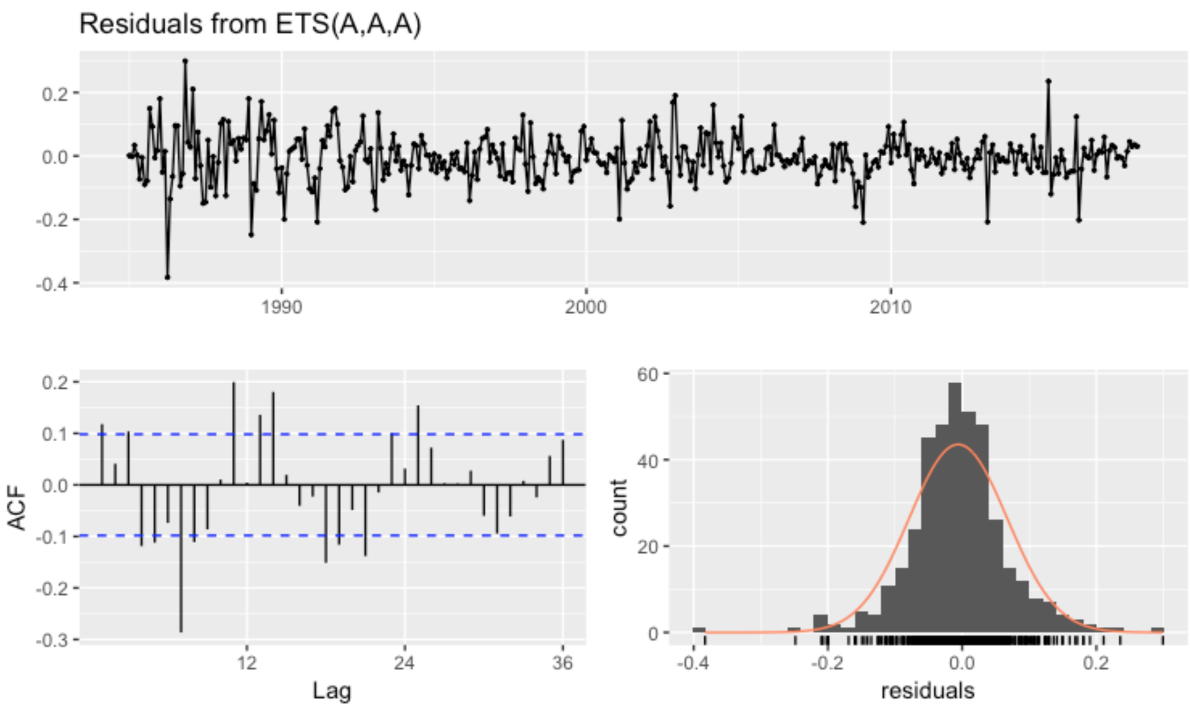

FIGURE 5.2 RESIDUALS PLOT AND ACF PLOT OF ETS ON LOG-TRANSFORMED IMPORTS

5.2.1.3 ARIMA Model

For ARIMA models, the data needs to be stationary, which means to remove the trend and seasonality. In R Studio, the function *auto.arima*() will find the best model automatically. Due to the trend and seasonality in the imports data, the specification in the function should be d = 1 and D = 1 that tells the function to take the first difference and get rid of the seasonality respectively. Additionally, *stepwise* = F and *approximation* = F should be specified to let the function try every combination of the model and use the exact AIC instead of approximate AIC. All the combinations of the ARIMA model can be found in Appendix C, of which the best is ARIMA(2,1,0)(2,1,0)[12] with the smallest AICc = -925.23. The model has terms of $p = 2$, $d = 1$, $q = 0$, $P = 2$, $D = 1$, $Q = 0$ in seasonal term 12 and the coefficients are in Figure 5.3.

	AR[1]	AR[2]	Seasonal AR[1]	Seasonal AR[2]
	-0.5190	-0.2868	-0.6871	-0.3443
s.e.	0.0499	0.0497	0.0499	0.0554

FIGURE 5.3 COEFFICIENTS OF ARIMA(2,1,0)(2,1,0)[12] ON LOG-TRANSFORMED IMPORTS

The residual standard deviation is 0.0715402, which is slightly smaller than this of ETS model, so ARIMA model is currently the best model. From the time plot and histogram of the residuals in Figure 5.4, despite the distribution of the residuals is slightly left-skewed, it generally accords with normal distribution except for one bin with higher concentration. However, the variance of residuals is still very irregular. With the ACF plot and L-jung box test, although the residuals are more random compared with SNM and ETS models, there is still no enough evidence to say the residuals are autocorrelated. Nevertheless, the model may have been quite good.

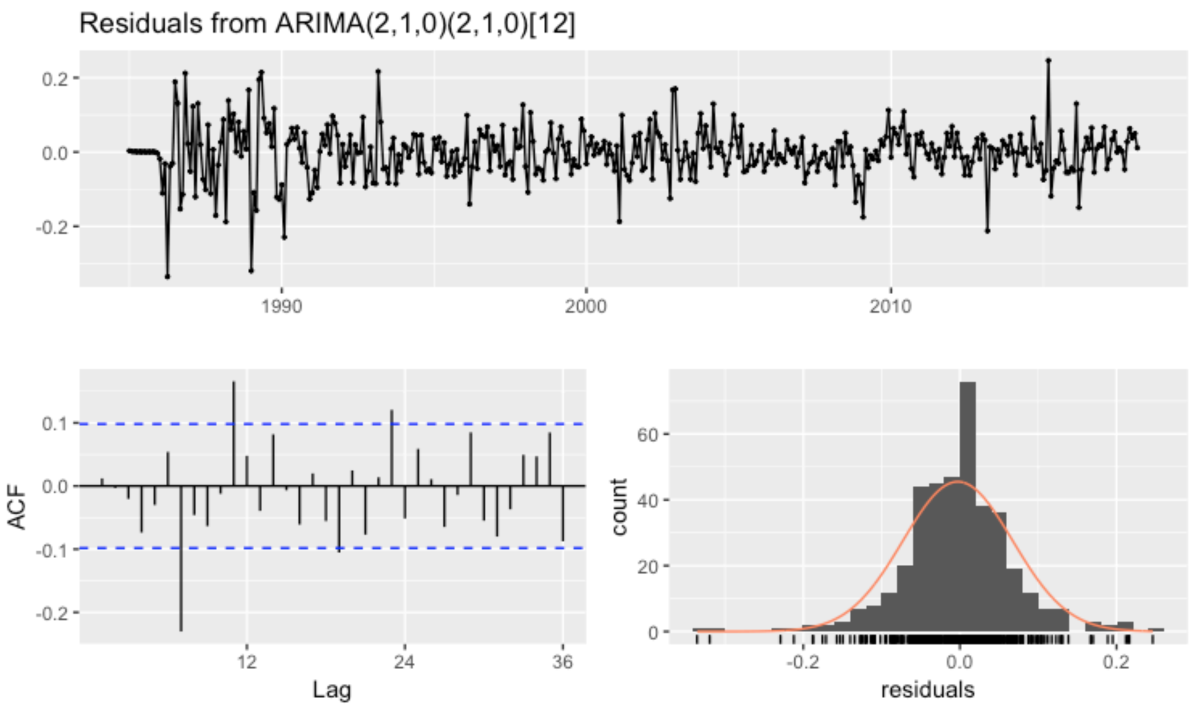

FIGURE 5.4 RESIDUALS PLOT AND ACF PLOT OF ARIMA ON LOG-TRANSFORMED IMPORTS

5.2.1.4 Neural Network

For neural network, there is no requirement for data to be stationary, thus the log-transformed data is used. In R Studio, set seed is necessary in neural network autoregression model prediction for reproducible results. The function *nnetar*() is used. The best model is NNAR(1,1,2)[12], indicating the terms are p = 1, P = 1, k = 2 and further indicates the last 1 observation is used as the predictor, seasonality exists and there are 2 hidden nodes in the hidden layer. The residual standard deviation is 0.0853112, which is quite small compared with the other three models. So far, NNAR model is the best model fitted.

5.2.1.5 Forecast

Figure 5.5 provides the accuracy of the fitted four models on test data, i.e. the actual value of imports from March 2018 to June 2019, the best model under whichever measure is the NNAR model since NNAR has the smallest RMSE and MAE among all models. Also, NNAR has the smallest MAPE = 9.681288 < 10, which means highly accurate forecasting. Thus, NNAR is chosen to be the model that will be used to forecast for yearly data in Section 5.3.

Imports	RMSE	MAE	MAPE
SNM	11757.7	10119.14	25.89406
ETS	6643.835	5508.637	14.2435
ARIMA	5680.56	4631.9	12.11285
NNAR	4800.392	3871.927	9.681288

FIGURE 5.5 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON LOG-TRANSFORMED IMPORTS

The forecast plot of imports data using NNAR(1,1,2)[12] is in Figure 5.6, where the dark blue line is the predicted imports and the medium-light blue area is the 95% confidence intervals and the lightest blue area is the 80% confidence interval. The actual value of imports lies in the red line. It can be seen that even the best fitted model does not predict the future value well, which proves that trade disputes affect the trend structure of imports. Details will be discussed in Chapter 6.

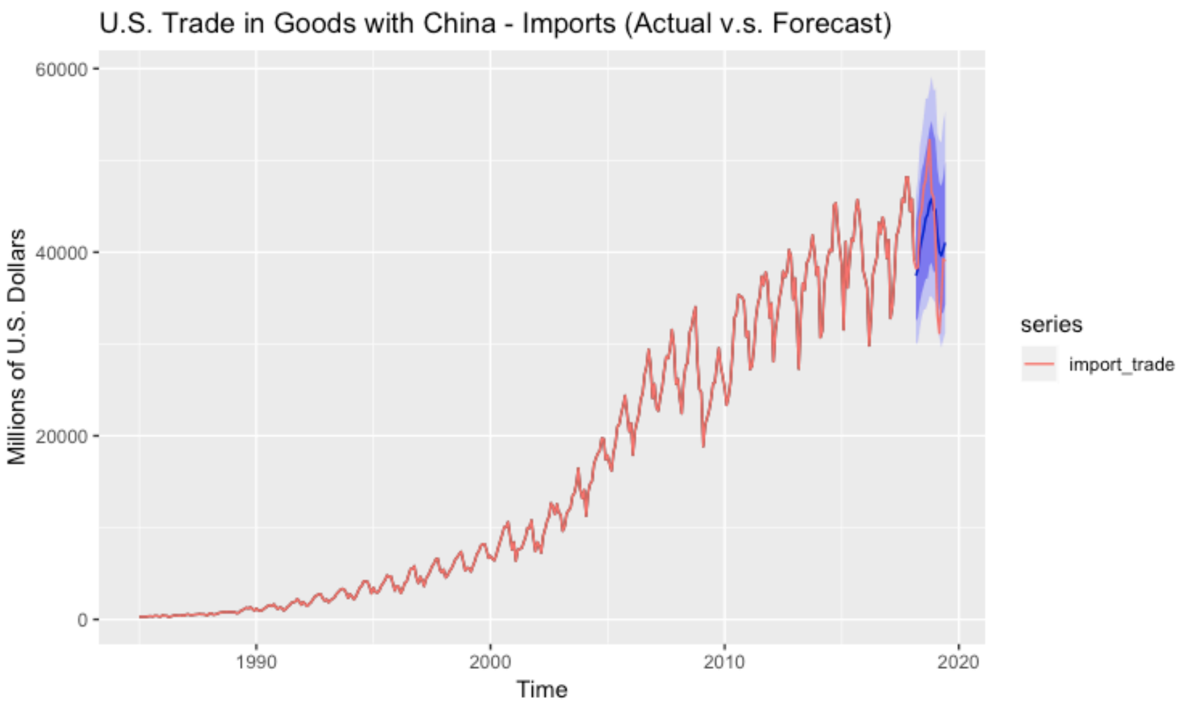

FIGURE 5.6 COMPARISON OF U.S.-CHINA IMPORTS (ACTUAL V.S. FORECAST)

5.2.2 U.S.-China Exports

5.2.2.1 Seasonal Naïve Method (as benchmark)

For U.S.-China exports data, there is also an increasing trend, thus the differenced exports data is used. The residual standard deviation is 0.2171. It still seems to be not large, but it is hard to tell since it is just the benchmark for other methods to compare. The plots of residuals are displayed in Figure 5.7. As can be seen from the figure, the mean of the residuals is close to 0, but the variance of residuals is irregular, which presents to be relatively large before 2004 and gradually small and constant after. In addition, the histogram demonstrates that the distribution of the residuals is basically leptokurtic and slightly left-skewed. The ACF plot shows that many sample autocorrelations do not fall inside the 95% confidence intervals, as well as the L-jung box test gives a *p*-value smaller than 2.2e-16, representing the residuals may not be white noise series. As a result, there should be better methods for forecasting exports data.

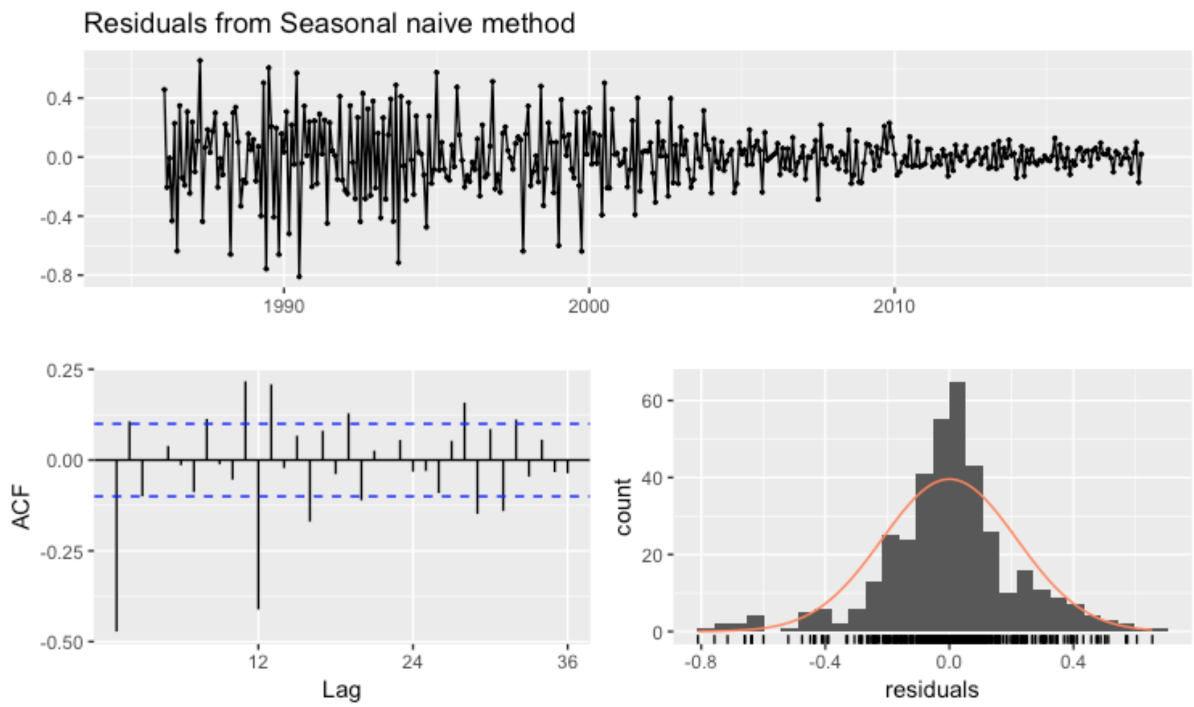

FIGURE 5.7 RESIDUALS PLOT AND ACF PLOT OF SNM ON LOG-TRANSFORMED CHANGES IN EXPORTS

5.2.2.2 ETS Model

For log-transformed exports, the best model ETS(A,A,A) with alpha = 0.4036, beta = 1e-04 and gamma = 0.0329 is given, which is also an exponential smoothing model with additive trend and additive seasonality and additive errors. The residual standard deviation is 0.1443, which is smaller than this of SNM, so the model can be considered. Figure 5.8 presents residual plots of ETS model. The model predicts well since the mean of the residuals is close to 0. And the variance of residuals is very irregular, but as time goes on, the fluctuations become smaller. Likewise, the residual histogram shows that the distribution of the residuals follows the normal distribution compared with SNM, but is slightly leptokurtic and right-skewed. The ACF plot shows that some sample autocorrelations do not fall inside the 95% confidence intervals but only exceed a little, signifying the residuals are not random but better than which in SNM. Plus, the L-jung box test gives a p-value is 6.714e-07, which verified it. Overall, this model is much better than SNM, the benchmark, which makes it can be considered in the options, but there may be better models existing.

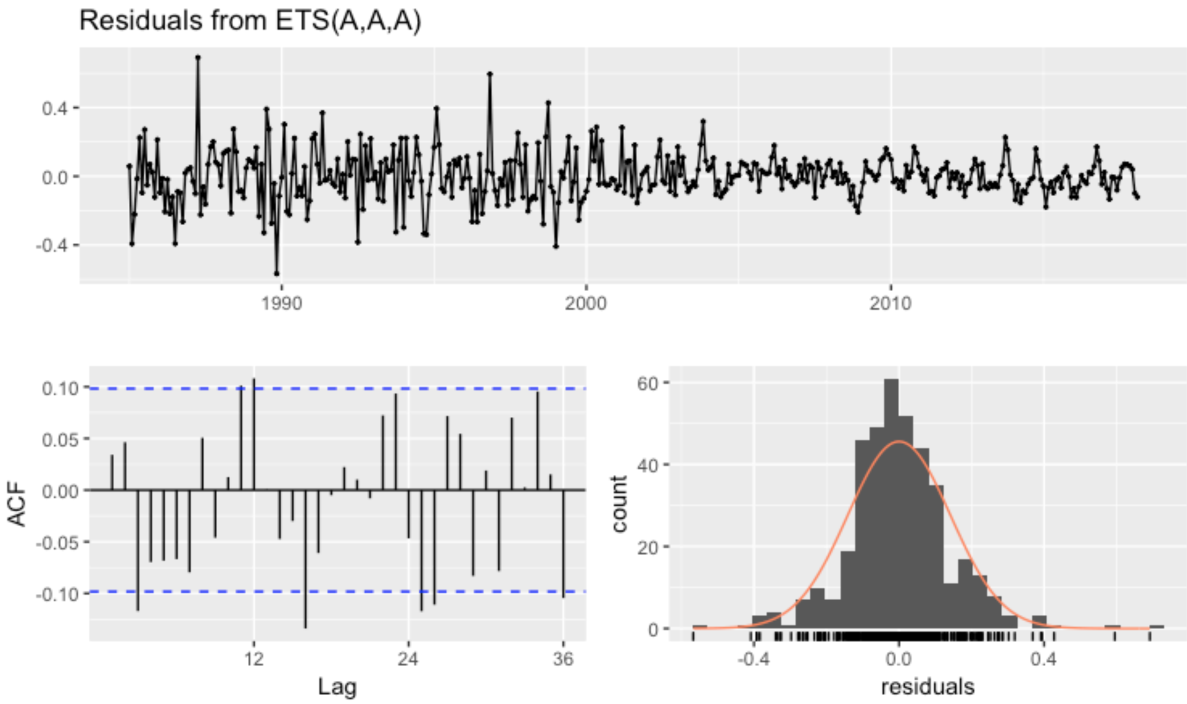

FIGURE 5.8 RESIDUALS PLOT AND ACF PLOT OF ETS ON LOG-TRANSFORMED EXPORTS

5.2.2.3 ARIMA Model

The exports data have trend but no seasonality, the specification in the function should be d = 1 that tells the function to take the first difference. The combinations of different ARIMA models can be found in Appendix C, of which the best is ARIMA(2,1,1)(2,0,0)[12] with drift with AICc = -379.6. The model demonstrates that terms are $p = 2$, $d = 1$, $q = 1$, $P = 2$, $D = 0$, $Q = 0$ in seasonal term 12 and the coefficients are in Figure 5.9.

	AR[1]	AR[2]	MA[1]	Seasonal AR[1]	Seasonal AR[2]	Drift
	0.3316	0.2618	-0.9395	0.2822	0.0941	0.0092
s.e.	0.0630	0.0601	0.0344	0.0529	0.0518	0.0018

FIGURE 5.9 COEFFICIENTS OF ARIMA(2,1,0)(2,1,0)[12] ON LOG-TRANSFORMED EXPORTS

The residual standard deviation is 0.1480878, which is larger than this of ETS model, so ETS model is still the best model since now. Figure 5.10 is the plots of residuals of the ARIMA model. The mean of the residuals is 0, the distribution of the residuals is not quite normal. The time plot of the residuals shows that the variance of residuals become smaller over time. The ACF plot shows that only a few sample autocorrelations exceed the 95% confidence intervals, signifying the information in the data has been extracted sufficiently. Also, the L-jung box test gives a p-value = 0.247, there is evidence to show that residuals are white noise. Nonetheless, the model may be worse than ETS model.

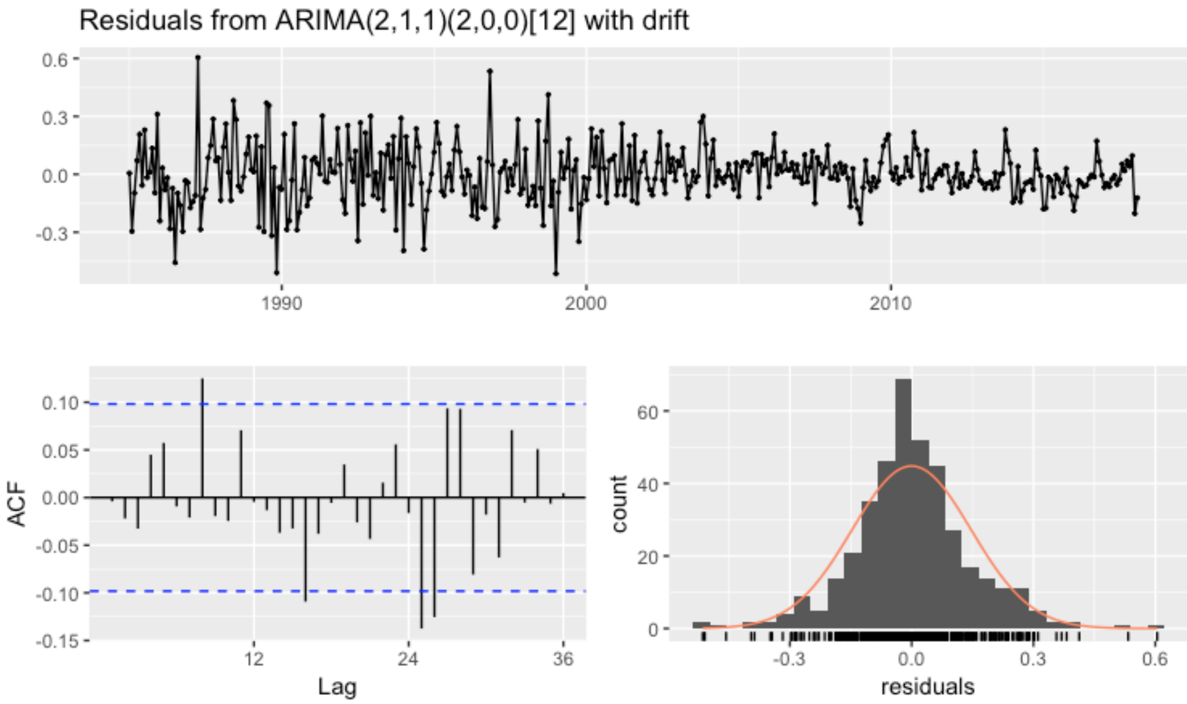

FIGURE 5.10 RESIDUALS PLOT AND ACF PLOT OF ARIMA ON LOG-TRANSFORMED EXPORTS

5.2.2.4 Neural Network

The best model given is NNAR(2,1,2)[12]. The model shows that terms are $p = 2$, $P = 1$, $k = 2$ and further indicates the last 2 observation is used as the predictors, seasonality exists and there are 2 neurons in the hidden layer. The residual standard deviation is 0.1463899, which is slightly larger than ETS model. Thus, in this study, ETS model may be the best model.

5.2.2.5 Forecast

Figure 5.11 is the error measures of different models fitting on the exports data. However, when checking on the test data, among all four models, the best model under whichever measure is the NNAR model since NNAR has the smallest RMSE and MAE. Meanwhile, NNAR has the smallest MAPE = 18.224 <20, which indicates reasonable forecasting. Thus, NNAR is chosen to be the model that will be used to forecast for yearly data in Section 5.3.

Exports	**RMSE**	**MAE**	**MAPE**
SNM	2275.069	1830.028	20.15965
ETS	2916.995	2534.352	28.60869
ARIMA	2992.87	2581.074	29.25935
NNAR	1958.823	1613.898	18.224

FIGURE 5.11 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON LOG-TRANSFORMED EXPORTS

The forecast plot of imports data using NNAR(2,1,2)[12] is in Figure 5.12, where the dark blue line is the predicted exports and the medium-light blue area is the 95% confidence intervals and the lightest blue area is the 80% confidence interval. And the actual value of exports lies in the red line. It can be seen that the predicted value fit very worse with the actual value. Details will be discussed in Chapter 6.

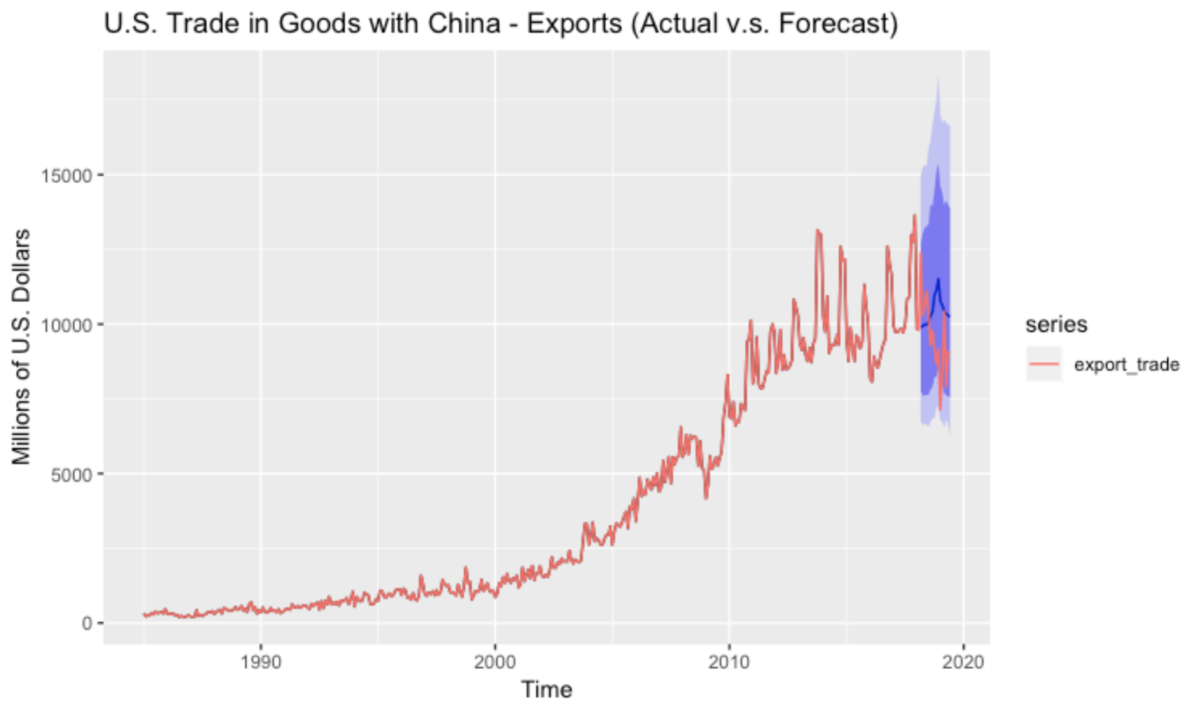

FIGURE 5.12 COMPARISON OF U.S.-CHINA EXPORTS (ACTUAL V.S. FORECAST)

5.3 FORECAST OF U.S.-CHINA IMPORTS AND EXPORTS

5.3.1 U.S.-China Imports & Exports

When forecasting the future values of imports and exports, the NNAR model was fitted on all the historical data (from January 1985 to June 2019) in case the terms in the NNAR function change. For imports data, the model is NNAR(1,1,2)[12] whereas for exports data, the model is NNAR(2,1,2)[12], which indicates more observations needs to be used in the model for exports data than imports data. After forecasting the value for next 30 months (from July 2019 to December 2021) using these models, exponentially change the predicted value back to the original form. The plots of forecasted value of imports and exports are presented in Figure 5.13 and Figure 5.14, where the darkest blue line is the mean of predicted value and the medium-light blue area is the 95% confidence intervals and the lightest blue area is the 80% confidence interval.

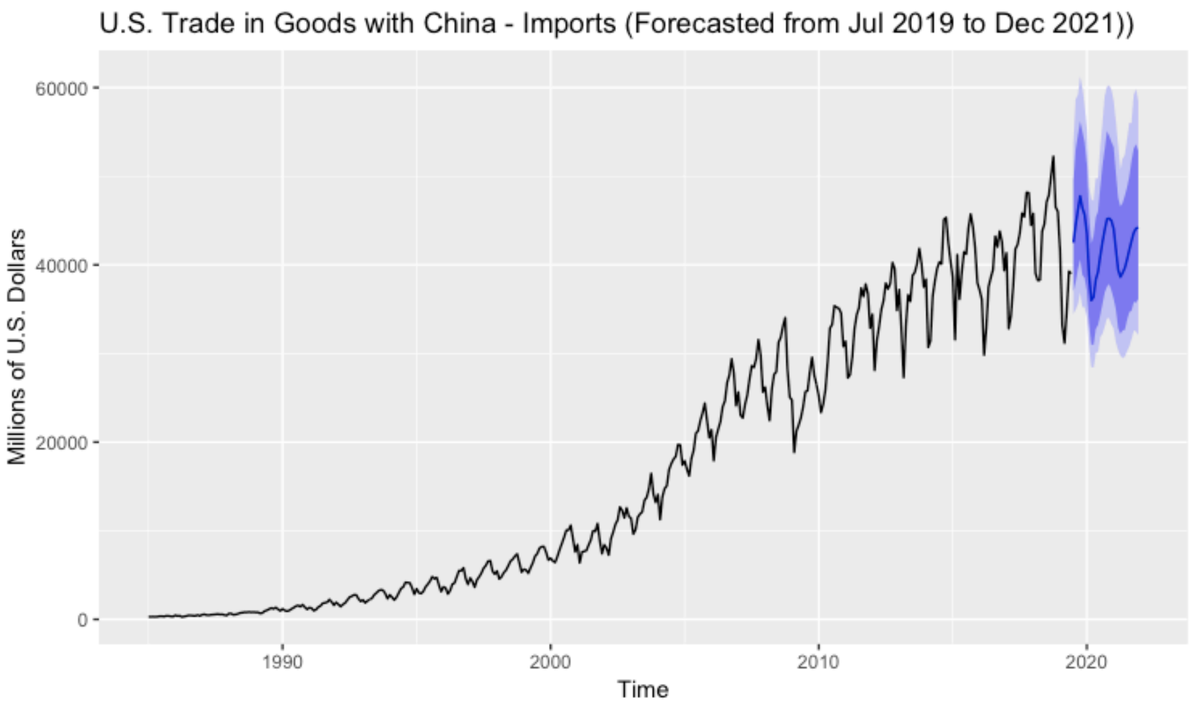

FIGURE 5.13 FORECAST OF U.S.-CHINA IMPORTS FROM JUL 2019 TO DEC 2021

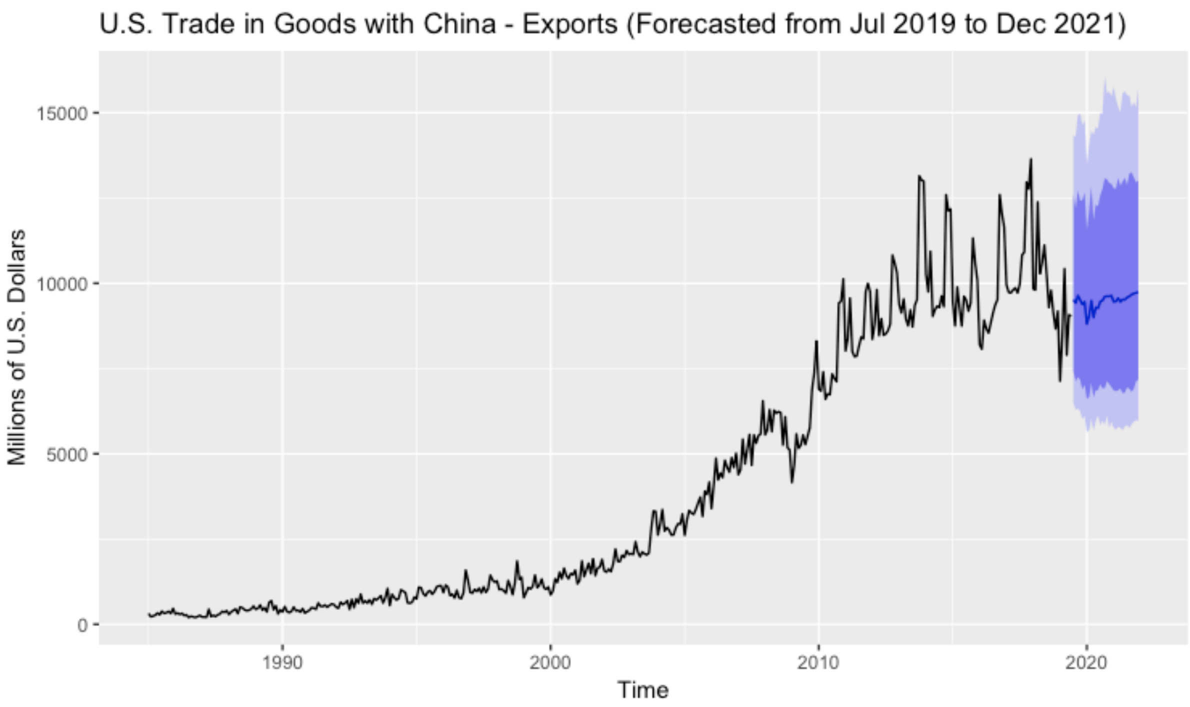

FIGURE 5.14 FORECAST OF U.S.-CHINA EXPORTS FROM JUL 2019 TO DEC 2021

5.3.2 Preparation as Regressors for Other Economic Indicators

In order to forecast the difference between the other indicators with and without the impacts of U.S.-China trade dispute, as there is no direct way to have a regressor to measure the change of trade dispute, the historical imports and exports data from January 1985 to June 2019 and predicted value from July 2019 to December 2021 are combined to be the measure of the trade war. Since the value of imports and exports from March 2018 to June 2019 have been affected by trade dispute, which has been proved in the comparison of actual and predicted value in Section 5.2, the predicted value of imports and exports from July 2019 to December 2021 that predicted from these values could also show the forecast with the impacts of trade dispute. In R Studio, 'xreg' in the function represents the regressor. Thus, the aggregation of monthly trade data to yearly needs to be done in that the other economic indicators are all yearly data. When fitting the model for other indicators, the length of regressor needs to be the same as the predictor. Therefore, the parameter 'xreg' in each model was set to be the matrix of imports and exports from 1985 to 2018. Also, the parameter 'xreg' in the forecast function was set to be the matrix of predicted imports and exports from 2019 to 2021. The detailed procedure is in Section 5.4

5.4 FORECAST OF OTHER ECONOMIC INDICATORS

5.4.1 GDP – U.S.

5.4.1.1 Dynamic ARIMA Model

GDP, as yearly data, has no seasonality, but has an increasing trend. Thus, when fitting the ARIMA model, d = 1 needs to be specified in the function *auto.arima*() to take the first difference. Moreover, a numerical matrix of external regressors of yearly imports and exports data (from 1985 to 2018) is also added as an additional parameter 'xreg'. All the combinations can be found in Appendix C, of which the best is Regression with ARIMA(2,1,0) errors with AICc = 862.96. The model demonstrates that terms are $p = 2$, $d = 1$, $q = 0$ and the coefficients are in Figure 5.15.

	AR[1]	AR[2]	Drift	Yearly Import	Yearly Export
	0.9965	-0.4174	393983.48	8.2786	-10.7484
s.e.	0.1707	0.1696	38017.02	0.8232	3.0566

FIGURE 5.15 COEFFICIENTS OF REGRESSION WITH ARIMA(2,1,0) ERRORS ON U.S. GDP

The residual standard deviation is 97877.47, which is quite large and means the model does not fit very well. From the time plot and histogram of the residuals in Figure 5.16, the mean of the residuals is close to 0, but the distribution cannot be affirmed to be normal as the number of observations is not very large. The ACF plot shows that all the sample autocorrelations fall inside the 95% confidence intervals indicating the residuals are white noise. Also, the L-jung box test gives a p-value = 0.4807, there is enough evidence to show that information is extracted sufficiently. Despite the high residual standard deviation, the model seems not bad.

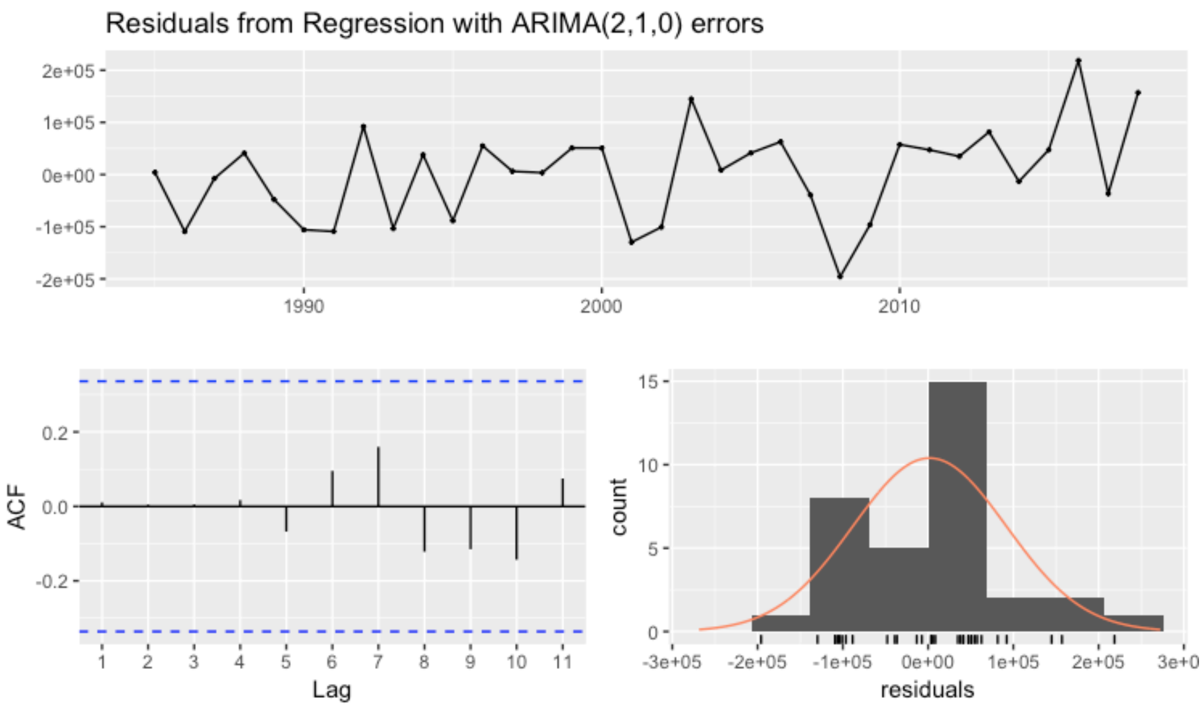

FIGURE 5.16 RESIDUALS PLOT AND ACF PLOT OF ARIMA ON U.S. GDP

5.4.1.2 Dynamic Neural Network

As before, set seed is necessary before fitting a NNAR model. Also, the regressors of imports and exports should be added using the same parameter 'xreg' as which in ARIMA model. The best model is NNAR(1,2), showing the terms are p = 1, k = 2 and further indicates the last observation is used as the predictor and the number of hidden nodes is 2. The residual standard deviation is 61335.14, which is smaller than the ARIMA model, so it may be the better model.

5.4.1.3 Forecast & Comparison

Figure 5.17 presents the accuracy of ARIMA and NNAR models. Under every measure, NNAR has a better performance than ARIMA. The MAPE of NNAR is 0.5317358 < 10, which means highly accurate forecasting. Therefore, NNAR(1,2) will be chosen to forecast. When forecasting the future values, yearly imports and exports from 2019 to 2021 should still be added as regressors in the forecast function.

U.S. GDP	RMSE	MAE	MAPE
ARIMA	88821.65	71350.91	0.7232579
NNAR	61332.4	45159.5	0.5317358

FIGURE 5.17 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON U.S. GDP

After choosing the model for forecasting the future values with the impacts of trade dispute, both ARIMA and NNAR models were fitted to the GDP in U.S. data without the imports and exports as regressors, i.e. without the effects of trade dispute. All the combination of ARIMA models can be found in Appendix C. The best ARIMA and NNAR models are ARIMA(1,1,0) with drift and NNAR(1,1), of which the error measures are in Figure 5.18. From the figure, ARIMA model has smaller RMSE and MAE and MAPE. Thus, ARIMA(1,1,0) with drift will be the model to forecast the U.S. GDP without regressors.

U.S. GDP without trade dispute	RMSE	MAE	MAPE
ARIMA	196565.1	137178.5	1.23884
NNAR	219426.4	144159	1.297575

FIGURE 5.18 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON U.S. GDP WITHOUT REGRESSORS

Figure 5.19 is the forecast of GDP in the U.S. from 2019 to 2021. The red line shows the predicted GDP without the impacts of trade dispute using ARIMA(1,1,0) with drift whereas the blue area indicates the predicted GDP with the impacts using NNAR(1,2). A more detailed discussion will be in Chapter 6.

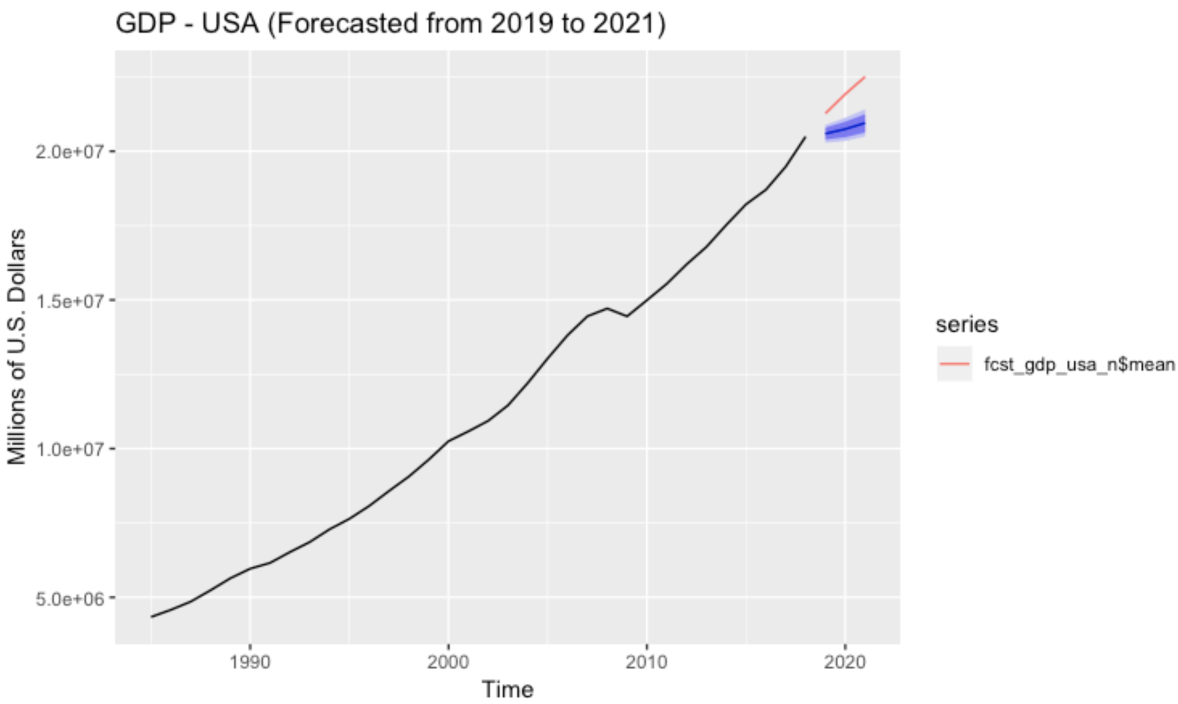

FIGURE 5.19 PLOT OF FORECAST ON U.S. GDP WITH OR WITHOUT REGRESSORS

5.4.2 GDP – China

5.4.2.1 Dynamic ARIMA Model

Same as the GDP in U.S., GDP in China is also yearly data with an increasing trend. The specification in the function should be $d = 1$ as well as the yearly imports and exports data as regressors. The combinations of ARIMA models can be found in Appendix C, of which the best is Regression with ARIMA(1,1,1) errors model with AICc = 883.95. The model indicates that terms are $p = 1$, $d = 1$, $q = 1$ and the coefficients are in Figure 5.20.

	AR[1]	MA[1]	Drift	Yearly Import	Yearly Export
	0.9854	0.4077	984004.2	1.0777	-2.3964
s.e.	0.0211	0.3505	899240	1.4913	3.495

FIGURE 5.20 COEFFICIENTS OF REGRESSION WITH ARIMA(1,1,1) ERRORS ON CHINA GDP

The residual standard deviation is 127906.2, which is also very large. From the time plot and histogram of the residuals in Figure 5.21, the mean of the residuals is close to 0, but the distribution can hardly be defined as normal distribution. The ACF plot shows that all the sample autocorrelations fall inside the 95% confidence intervals as well as the L-jung box test gives a p-value = 0.08744, indicating less autoregressive in residuals. Despite the high residual standard deviation, the model may not be terrible.

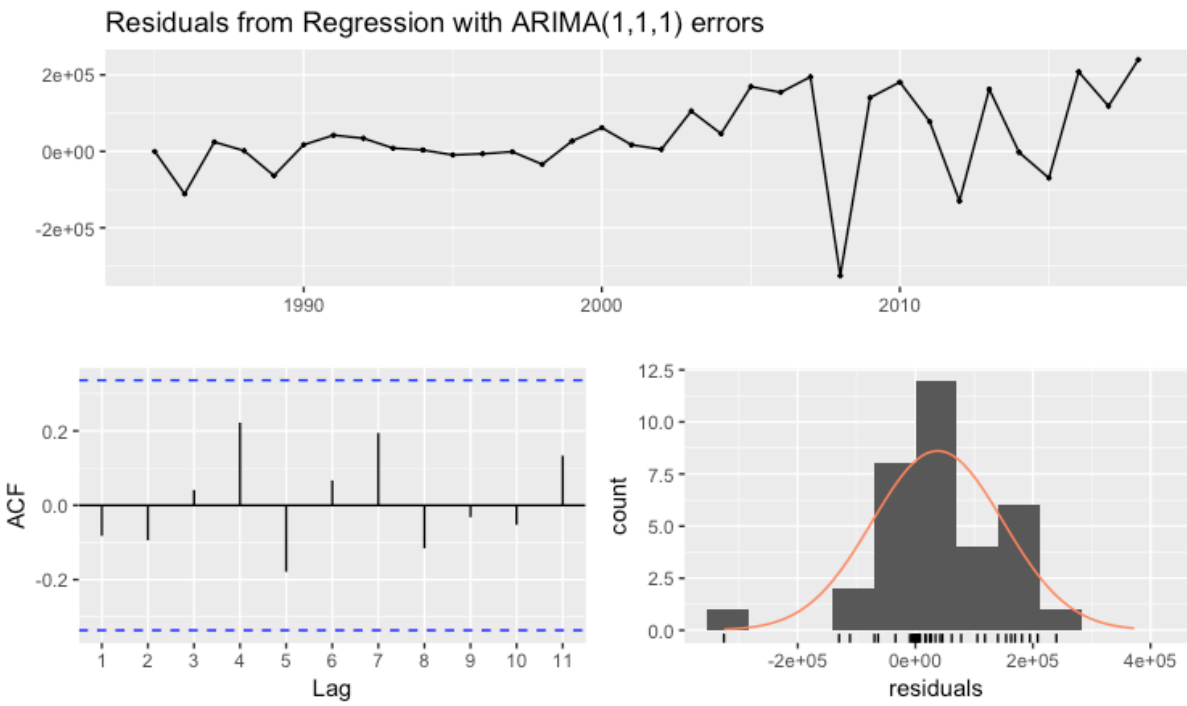

FIGURE 5.21 RESIDUALS PLOT AND ACF PLOT OF ARIMA ON CHINA GDP

5.4.2.2 Dynamic Neural Network

Also, the regressors of imports and exports should be added using the same parameter 'xreg'. The best model is NNAR(1,2), showing the terms are $p = 1$, $k = 2$ and further demonstrates the last observation is used as the predictor and the number of neurons in the hidden layer is 2. The residual standard deviation is 52839.38, which is much smaller than the ARIMA model.

5.4.2.3 Forecast & Comparison

Error measures of different models on training set are provided in Figure 5.22. Under the measure RMSE and MAE, NNAR has a better performance than ARIMA. Plus, MAPEs of both models are smaller than 10, which means both models are highly accurate models. Therefore, NNAR(1,2) will be chosen to forecast.

China GDP	RMSE	MAE	MAPE
ARIMA	116075.6	82223.14	0.1102773
NNAR	52838.25	38112.48	1.114552

FIGURE 5.22 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON CHINA GDP

Then both models were fitted to the GDP in China data without the imports and exports as regressors. All the combination of ARIMA models can be found in Appendix C. The best ARIMA and NNAR models are ARIMA(2,1,2) with drift and NNAR(1,1), of which the error measures are in Figure 5.23. From the figure, ARIMA model has smaller errors than NNAR. Thus, ARIMA(2,1,2) with drift will be the model to forecast China GDP without regressors.

China GDP without trade dispute	RMSE	MAE	MAPE
ARIMA	117082.9	81287.5	1.730513
NNAR	174000.6	119349.3	2.700539

FIGURE 5.23 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON CHINA GDP WITHOUT REGRESSORS

Figure 5.24 is the forecast of GDP in China from 2019 to 2021. The red line shows the predicted GDP without the impacts of trade dispute using ARIMA(2,1,2) with drift whereas the blue area indicates the predicted GDP with the impacts using NNAR(1,2). Further discussion will be in Chapter 6.

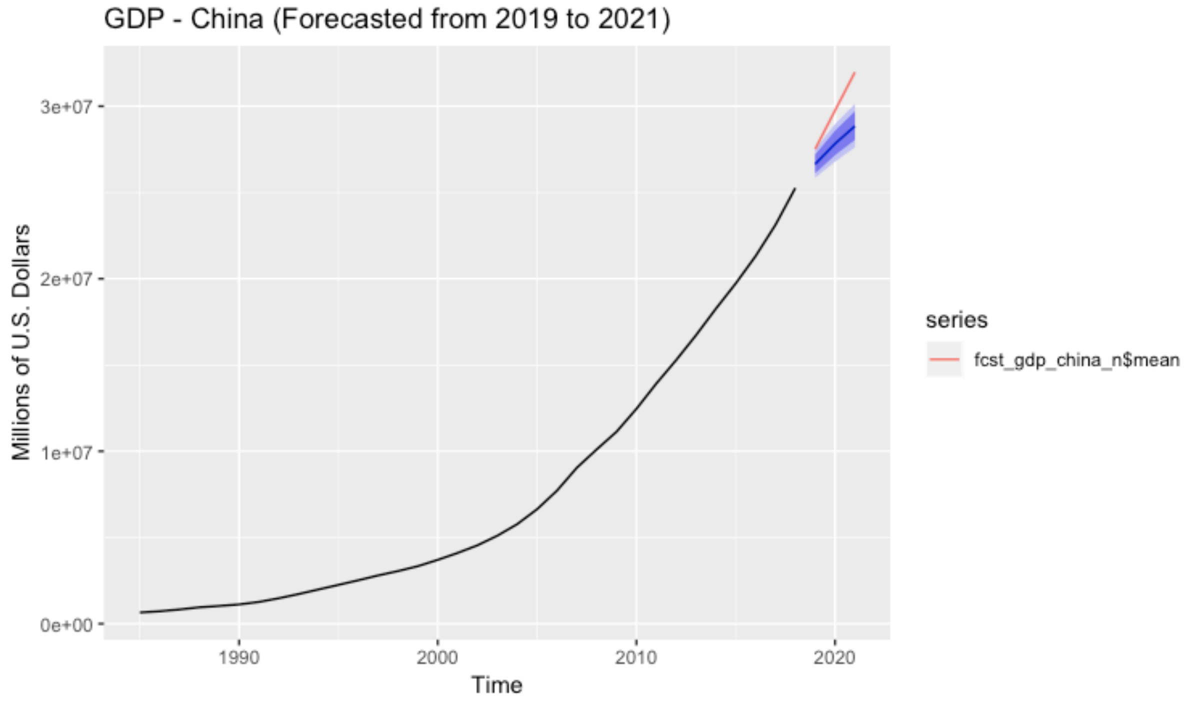

FIGURE 5.24 PLOT OF FORECAST ON CHINA GDP WITH OR WITHOUT REGRESSORS

5.4.3 CPI – U.S.

5.4.3.1 Dynamic ARIMA Model

The chosen CPI dataset uses annual growth rate as the unit of measurement. For CPI in the U.S., there is no evident trend and seasonality, thus the original data can be used with yearly imports and exports as regressors. Different combinations and AICc can be found in Appendix C, of which the best is Regression with ARIMA(0,0,1) errors model with AICc = 105.56. The model indicates that terms are $p = 0$, $d = 0$, $q = 1$ and the coefficients are in Figure 5.25, which can be inferred that the existence of imports and exports do not have many impacts on CPI in the USA.

	MA[1]	Intercept	Yearly Import	Yearly Export
	0.3560	3.2423	0	0e+00
s.e.	0.0417	0.3247	0	2e-04

FIGURE 5.25 COEFFICIENTS OF ARIMA(0,0,1) ERRORS ON U.S. CPI

The residual standard deviation is 1.015382, which is not very large but needs more comparison. Figure 5.26 presents the relevant plots of residuals, which shows the mean of the residuals is close to 0, but the distribution cannot be affirmed to be normal. The ACF plot shows that all the sample autocorrelations fall inside the 95% confidence intervals and the L-jung box test gives a *p*-value = 0.566, indicating the information of historical data is extracted well. The model has good performance overall.

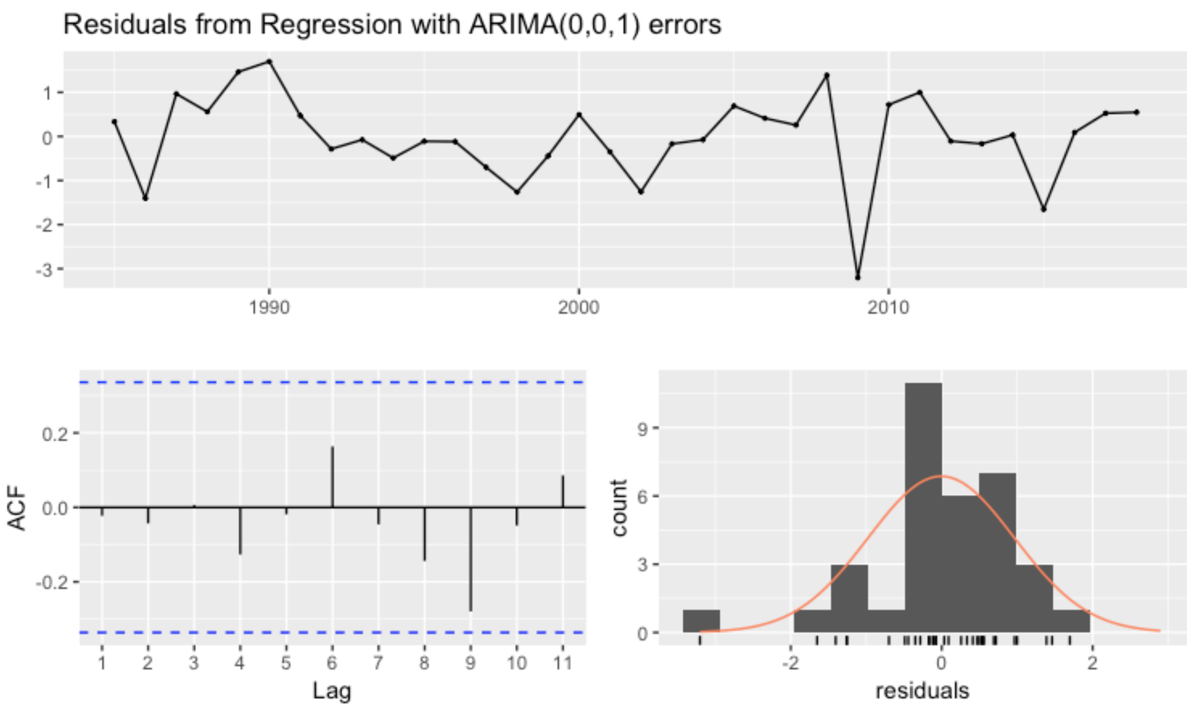

FIGURE 5.26 RESIDUALS PLOT AND ACF PLOT OF ARIMA ON U.S. CPI

5.4.3.2 Dynamic Neural Network

After setting seed, the function *nnetar*() is used here. For the regressors, yearly imports and exports should be added using the same parameter 'xreg'. The best model is NNAR(1,2), showing the terms are p = 1, k = 2 and further represents the last observation is used as the predictor and the number of hidden nodes in the hidden layer is 2. The residual standard deviation is 0.6830081, which is smaller than which in the ARIMA model.

5.4.3.3 Forecast & Comparison

In order to choose the better model, error measures of different models on training set are in Figure 5.27. Under the measure RMSE and MAE, NNAR has a better performance than ARIMA. Thus, NNAR(1,2) will be chosen to forecast. Note that actually both models do not fit quite well because both MAPEs are greater than 50, indicating the not very accurate forecasting. However, the main focus here is the comparison of impacts of trade war on CPI, the accuracy could be slightly neglected.

U.S. CPI	RMSE	MAE	MAPE
ARIMA	0.9539593	0.6913773	88.32274
NNAR	0.6829751	0.5172169	66.38162

FIGURE 5.27 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON U.S. CPI

For models without the effects of trade dispute, the best ARIMA and NNAR models are ARIMA(0,1,2) and NNAR(1,1), of which the error measures are in Figure 5.28. All the combination of ARIMA models can be found in Appendix C. From the figure, though both models have very large MAPE, ARIMA model has comparatively smaller errors than NNAR, but the difference is not large. And for RMSE and MAE, NNAR performs slightly well. Here, NNAR(1,1) is chosen to forecast.

U.S. CPI without trade dispute	RMSE	MAE	MAPE
ARIMA	1.012062	0.7433498	100.4545
NNAR	1.000271	0.7233561	101.6376

FIGURE 5.28 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON U.S. CPI WITHOUT REGRESSORS

Figure 5.29 displays the forecast of CPI in the U.S. from 2019 to 2021. The red line shows the predicted CPI without the impacts of trade dispute using NNAR(1,2) whilst the blue area indicates the predicted CPI with the impacts using NNAR(1,1). More discussion about the economic significance will be in Chapter 6.

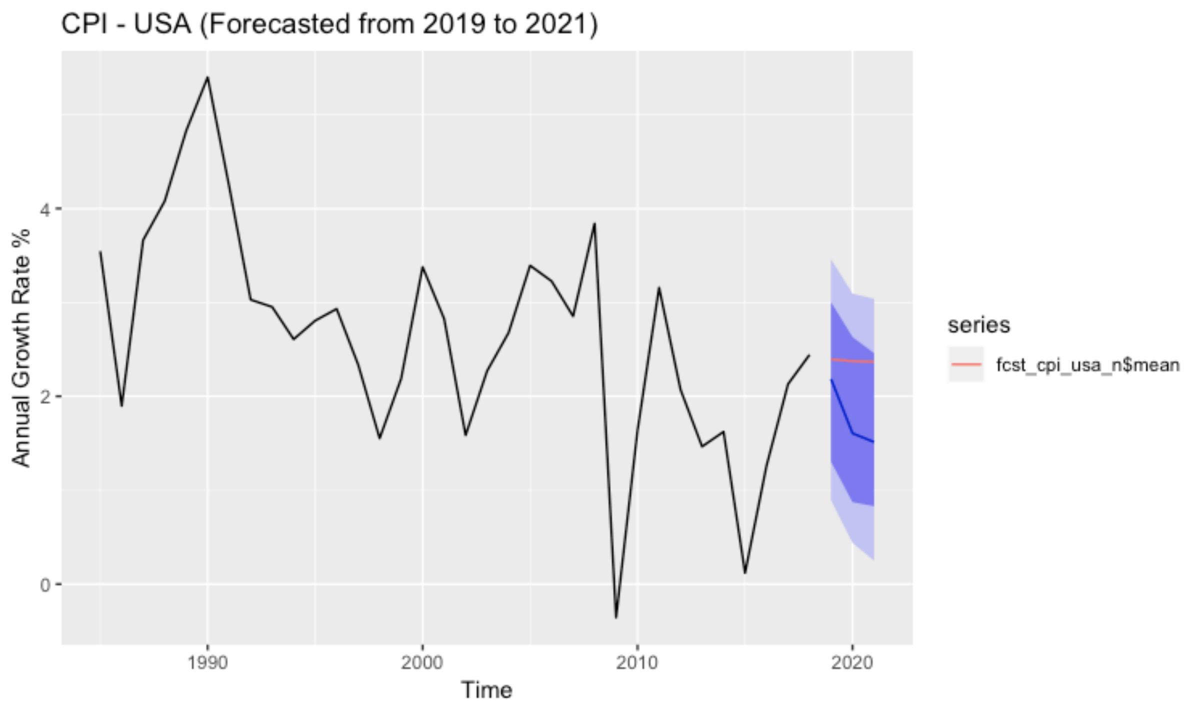

FIGURE 5.29 PLOT OF FORECAST ON U.S. CPI WITH OR WITHOUT REGRESSORS

5.4.4 CPI – China

5.4.4.1 Dynamic ARIMA Model

For CPI in China, there is also no evident trend and seasonality, thus the original data can be used as well. All the combinations of ARIMA models can be found in Appendix C, of which the best is Regression with ARIMA(0,0,1) errors model with AICc = 200.3. The model indicates that terms are $p = 0$, $d = 0$, $q = 1$ and the coefficients are in Figure 5.30, which can be inferred that similar to the U.S., the change of imports and exports do not have many impacts on CPI in China.

	MA[1]	Intercept	Yearly Import	Yearly Export
	0.8283	8.0651	0	1e-04
s.e.	0.0351	1.7321	NaN	2e-04

FIGURE 5.30 COEFFICIENTS OF ARIMA(0,0,1) ERRORS ON CHINA CPI

The residual standard deviation is 4.029888, which is not large. From the time plot and histogram of the residuals in Figure 5.31, the mean of the residuals is close to 0 and the distribution seems to be normal but cannot be affirmed since the number of observations are quite small. Furthermore. the ACF plot shows that all the autocorrelations are in the 95% confidence intervals and the L-jung box test gives a p-value = 0.2506, indicating the residuals are white noise series. Overall, the model performs quite good.

FIGURE 5.31 RESIDUALS PLOT AND ACF PLOT OF ARIMA ON CHINA CPI

5.4.4.2 Dynamic Neural Network

For neural networks, the best model is NNAR(5,4), showing the terms are p = 5, k = 4 and further indicating the last 5 observations is used as predictors and there are 4 neurons in the hidden layer. The residual standard deviation is 0.2574102, which is much smaller than which in the ARIMA model, indicating NNAR(5,4) may be the better model.

5.4.4.3 Forecast & Comparison

Accuracy of different models on training set are compared in Figure 5.32. Under every measure, NNAR has a much better performance than ARIMA, especially in MAPE, showing high accuracy. Therefore, NNAR(5,4) will be chosen to forecast.

China CPI	RMSE	MAE	MAPE
ARIMA	3.785105	2.801339	140.3367
NNAR	0.2574062	0.1751069	10.78762

FIGURE 5.32 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON CHINA CPI

For models without the imports and exports as regressors, the best ARIMA and NNAR models are ARIMA(0,1,2) and NNAR(5,3), of which the error measures are in Figure 5.33. All the combination of ARIMA models can be found in Appendix C. From the figure, for every measure, NNAR performs quite well. Here, NNAR(5,3) is chosen to forecast China CPI without regressors.

China CPI without trade dispute	RMSE	MAE	MAPE
ARIMA	3.863039	2.861922	135.8875
NNAR	0.876869	0.64863	41.13341

FIGURE 5.33 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON CHINA CPI WITHOUT REGRESSORS

Figure 5.34 is the forecast of CPI in China from 2019 to 2021. The red line shows the predicted CPI without the impacts of trade dispute using NNAR(5,3) whilst the blue area indicates the predicted CPI with the impacts using NNAR(5,4). Further discussion about the economic significance will be in Chapter 6.

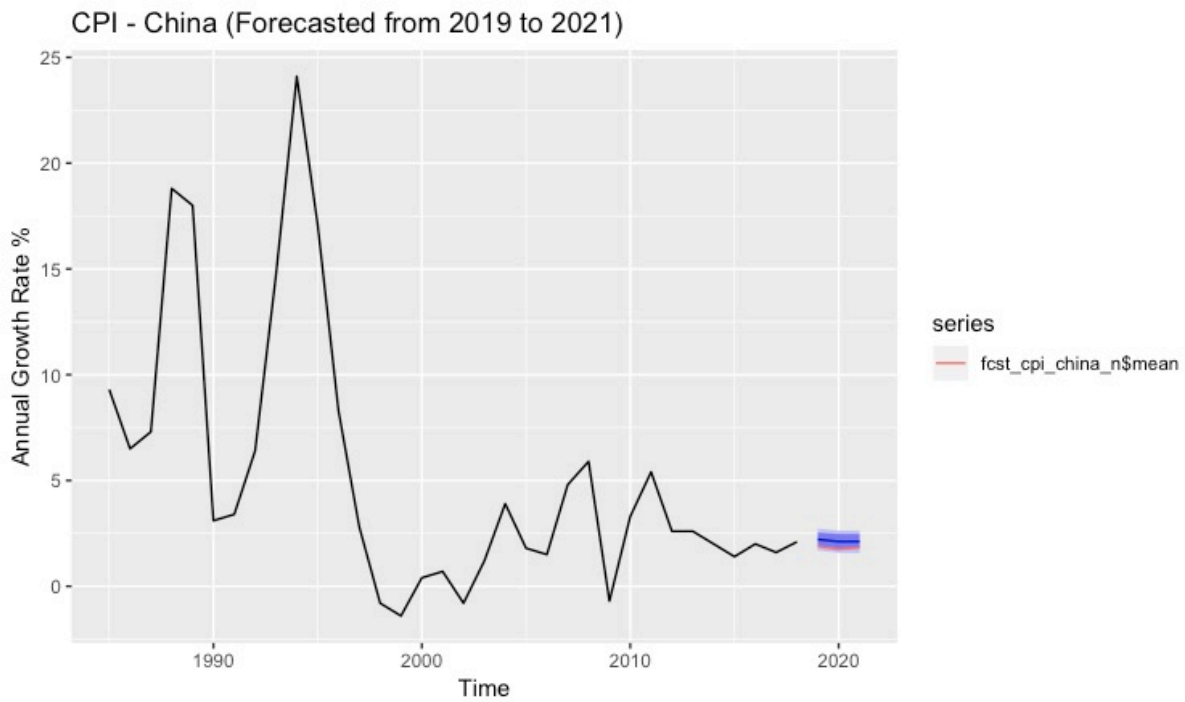

FIGURE 5.34 PLOT OF FORECAST ON CHINA CPI WITH OR WITHOUT REGRESSORS

5.4.5 Unemployment Rate – U.S.

5.4.5.1 Dynamic ARIMA Model

The unemployment rate data in the U.S. does not have trend and seasonality. Thus, using the function *auto.arima*(), the best ARIMA model is Regression with ARIMA(2,0,1) errors model with AICc = 70.94. The model indicates that terms are $p = 2$, $d = 0$, $q = 1$ and the coefficients are in Figure 5.35, which can be inferred that the change of imports and exports do not have many impacts on unemployment rate in the United States.

	AR[1]	AR[2]	MA[1]	Intercept	Yearly Import	Yearly Export
	1.4016	-0.4541	0.6842	9.7033	0	0
s.e.	0.1100	0.1352	0.1783	0.2787	NaN	NaN

FIGURE 5.35 COEFFICIENTS OF REGRESSION WITH ARIMA(2,0,1) ERRORS ON U.S. UNEMPLOYMENT RATE

The residual standard deviation is 0.5349766, which is not large, but needs more comparison. Figure 5.36 displays the plots of residuals, the distribution seems to be right-skewed and does not show good agreement with normal distribution. However, the ACF plot shows that all the sample autocorrelations fall inside the 95% confidence intervals and the L-jung box test gives a p-value = 0.3583, indicating the residuals are white noise.

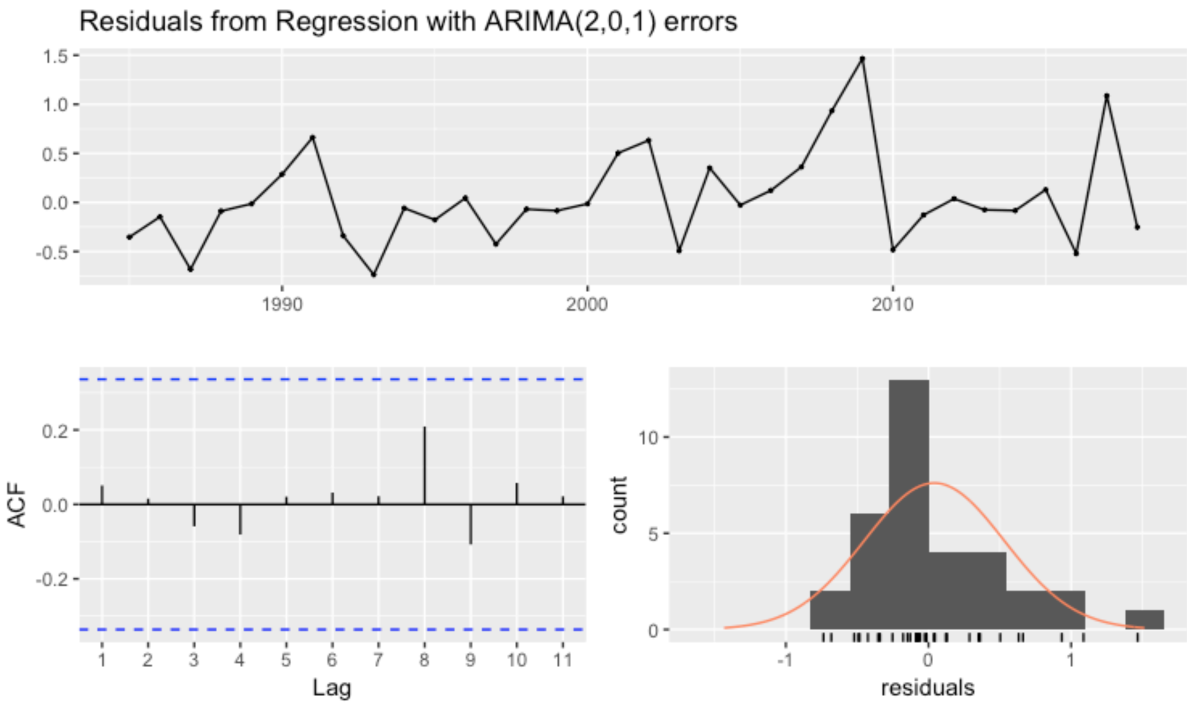

FIGURE 5.36 RESIDUALS PLOT AND ACF PLOT OF ARIMA ON U.S. UNEMPLOYMENT RATE

5.4.5.2 Dynamic Neural Network

For the regressors, yearly imports and exports should be added. The best model is NNAR(2,2), showing the terms are p = 2, k = 2 and further indicating the last 2 observations is used as predictors and there are 2 neurons in the hidden layer. The residual standard deviation is 0.2834784, which is smaller than in the ARIMA model. Thus, NNRA(2,2) could be the better model.

5.4.5.3 Forecast & Comparison

Figure 5.37 shows the accuracy of two models, from which it can be indicated that NNAR has a much better performance than ARIMA. Also, MAPE = 4.108182 < 10, showing highly accurate forecast. Therefore, NNAR(2,2) will be chosen to forecast.

U.S. Unemployment Rate	RMSE	MAE	MAPE
ARIMA	0.4854454	0.8105623	5.892881
NNAR	0.2834774	0.2275057	4.108182

FIGURE 5.37 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON U.S. UNEMPLOYMENT RATE

For models without the imports and exports as regressors, the best models are ARIMA(2,0,0) with non-zero mean and NNAR(2,2), of which the error measures are in Figure 5.38. From the figure, for every measure, NNAR performs better. Here, NNAR(2,2) is chosen to forecast unemployment rate in the U.S. without regressors.

U.S. Unemployment Rate without trade dispute	RMSE	MAE	MAPE
ARIMA	0.63207	0.4333709	7.11417
NNAR	0.5224743	0.3699153	6.279768

FIGURE 5.38 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON U.S. UNEMPLOYMENT RATE WITHOUT REGRESSORS

Figure 5.39 is the forecast of unemployment rate in China from 2019 to 2021. The red line shows the predicted unemployment rate without the impacts of trade dispute using NNAR(2,2) whilst the blue area indicates the predicted unemployment rate with the impacts using NNAR(2,2). Further discussion about the economic significance will be in Chapter 6.

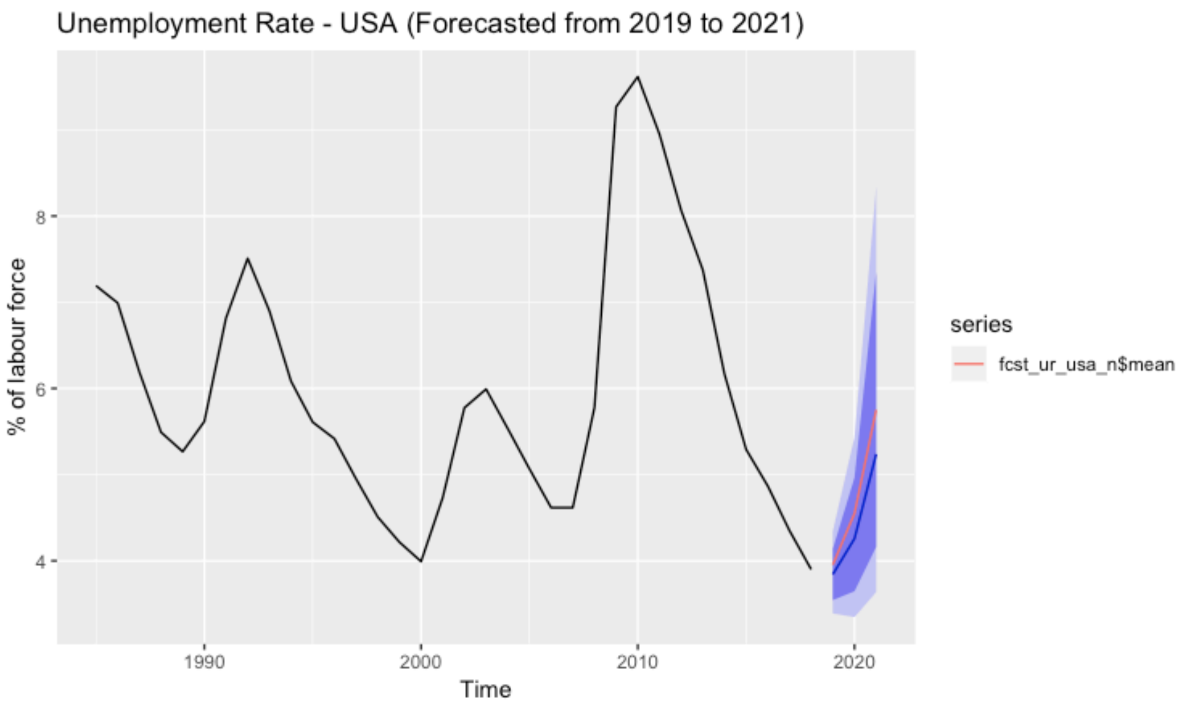

FIGURE 5.39 PLOT OF FORECAST ON U.S. UNEMPLOYMENT RATE WITH OR WITHOUT REGRESSORS

5.4.6 Unemployment Rate – China

5.4.6.1 Dynamic ARIMA Model

The China unemployment rate dataset has a trend over time. The best ARIMA model is Regression with ARIMA(0,1,0) errors model with AICc = -11.48. The model indicates that terms are $p = 0$, $d = 1$, $q = 0$ and the coefficients are in Figure 5.40, which can be inferred that the change of trade does not have many impacts on unemployment rate in China.

	Drift	Yearly Import	Yearly Export
	0.1073	0	0e+00
s.e.	NaN	0	2e-04

FIGURE 5.40 COEFFICIENTS OF REGRESSION WITH ARIMA(0,1,0) ERRORS ON CHINA UNEMPLOYMENT RATE

The residual standard deviation is 0.1848783. From the time plot and histogram of the residuals in Figure 5.41, the distribution seems to be right-skewed and is not normal distribution. The ACF plot shows that all the sample autocorrelations fall inside the 95% confidence intervals and the L-jung box test gives a p-value = 0.5683, indicating the forecast used the information from the data adequately.

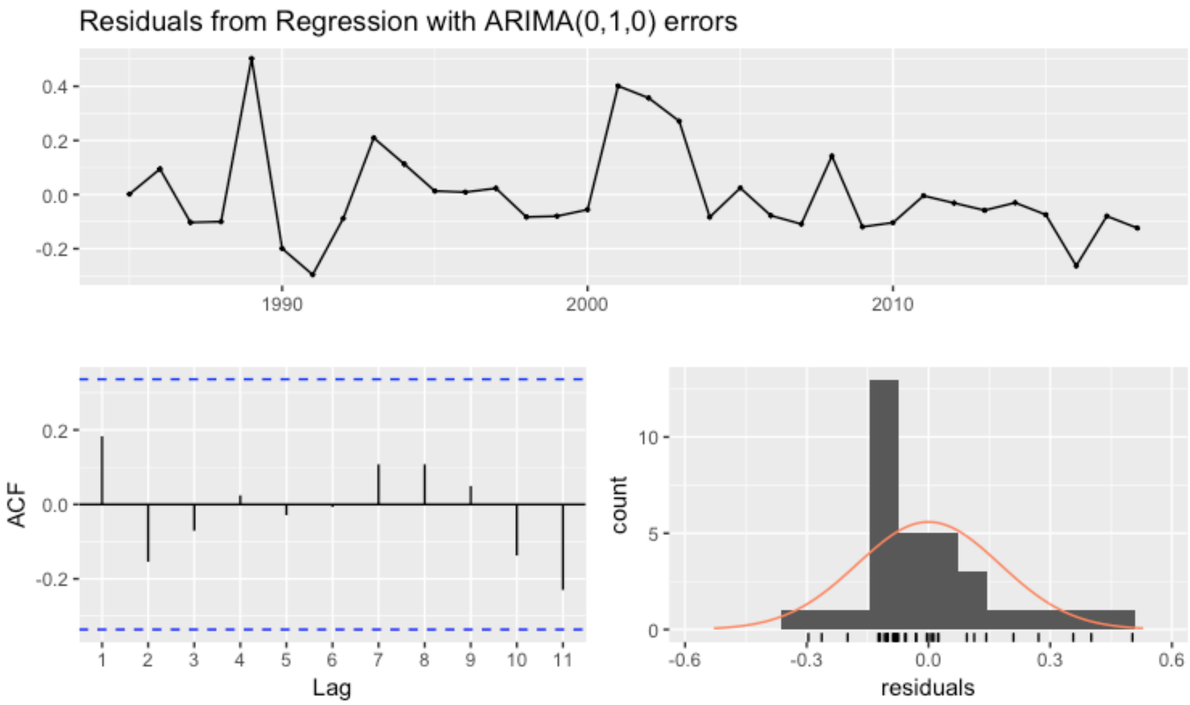

FIGURE 5.41 RESIDUALS PLOT AND ACF PLOT OF ARIMA ON CHINA UNEMPLOYMENT RATE

5.4.6.2 Dynamic Neural Network

In the function *nnetar*(), the best model is NNAR(1,2), showing the terms are $p = 1$, $k = 2$, i.e. the last observation is used as predictors and 2 neurons in the hidden layer. The residual standard deviation is 0.1078425, which is smaller than which in the ARIMA model. Thus, the NNAR model may be the better one.

5.4.6.3 Forecast & Comparison

In order to choose the better model, error measures of different models on training set are compared in Figure 5.42. Under every measure, NNAR has a better performance than ARIMA. Thus, NNAR(1,2) will be chosen to forecast.

China Unemployment Rate	RMSE	MAE	MAPE
ARIMA	0.1736537	0.1271638	4.074366
NNAR	0.1078269	0.08266885	2.83701

FIGURE 5.42 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON CHINA UNEMPLOYMENT RATE

For models without the imports and exports as regressors, the best models are ARIMA(0,1,1) and NNAR(1,1), of which the error measures are in Figure 5.43. All the combination of ARIMA models are listed in Appendix C. From the figure, for MAE and MAPE, ARIMA performs better and should be chosen to forecast unemployment rate in the China without regressors.

China Unemployment Rate without trade dispute	RMSE	MAE	MAPE
ARIMA	0.182061	0.1208995	3.877175
NNAR	0.1602561	0.125162	4.148301

FIGURE 5.43 COMPARISON OF ERROR MEASURES IN DIFFERENT MODELS ON CHINA UNEMPLOYMENT RATE WITHOUT REGRESSORS

Figure 5.44 is the forecast of unemployment rate in China from 2019 to 2021. The red line shows the predicted unemployment rate without the impacts of trade dispute using ARIMA(0,1,1) whilst the blue area indicates the predicted unemployment rate with the impacts using NNAR(1,2). Further discussion about the economic significance will be in Chapter 6.

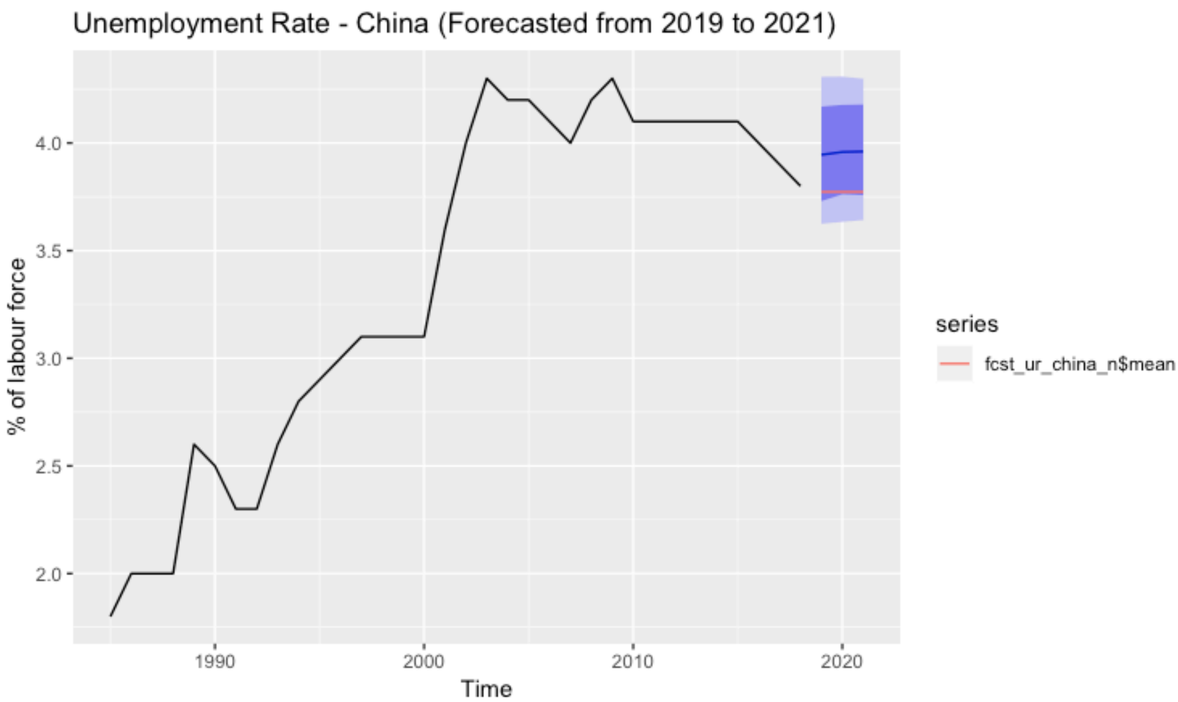

FIGURE 5.44 PLOT OF FORECAST ON CHINA UNEMPLOYMENT RATE WITH OR WITHOUT REGRESSORS

CHAPTER 6 - DISCUSSION

6.1 DISCUSSION OF CURRENT ECONOMIC IMPACTS

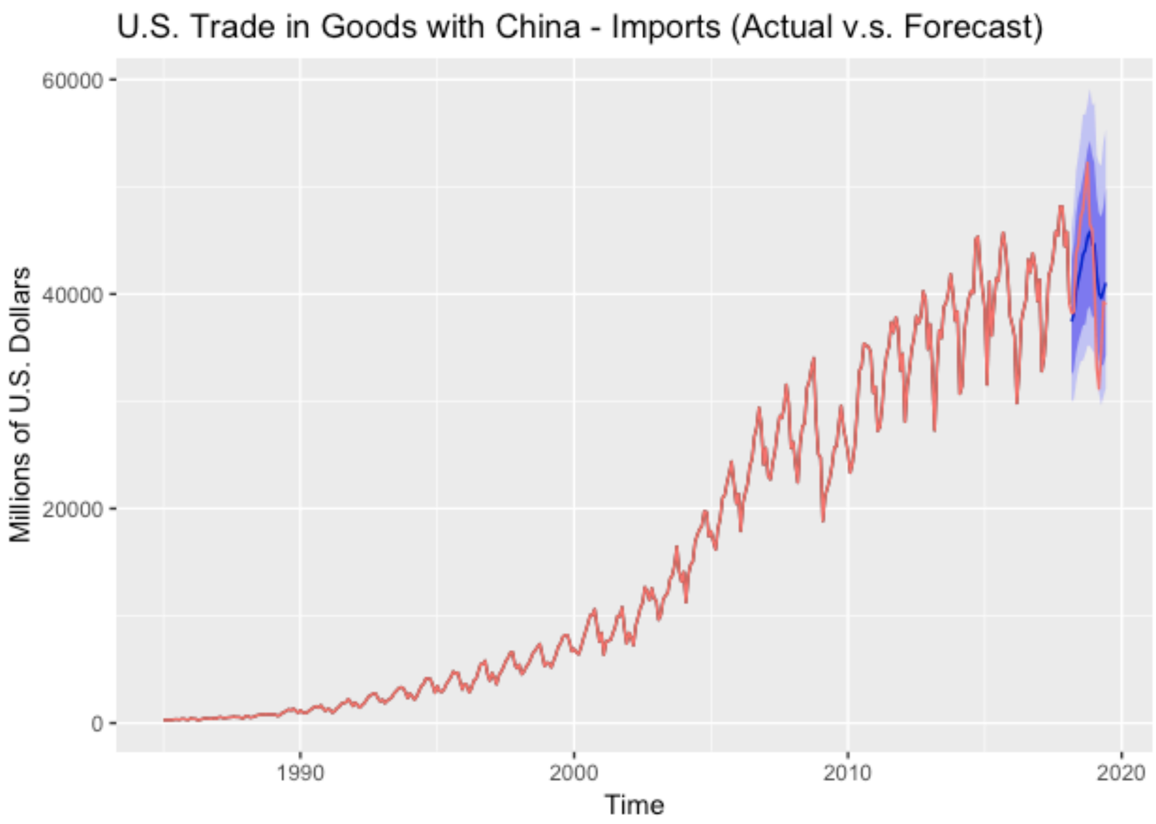

FIGURE 6.1 COMPARISON OF ACTUAL AND PREDICTED U.S. TRADE IN GOODS WITH CHINA – IMPORTS

As stated in Chapter 5, the red line is the actual values while the blue area is predicted values. According to Figure 6.1, the level of actual fluctuation appears to be higher than the predicted one, but still lies in the 80% confidence interval. Hence, it could conceivably be hypothesised that despite trade dispute has some effects on the U.S imports with China, the impact is not significant. It can thus be suggested that the quantity demand of the products produced from China may not have a significant effect from the trade war, i.e. elasticity of import demand from the U.S. to China are relatively inelastic. Additionally, the prediction still lies in the 95% confidence interval at the peak. Nevertheless, when it reaches the minimum level, the forecast is at the lower boundary of the 80% confidence interval, and nearly falls outside. It is possible to hypothesise that even if the elasticity of import demand is inelastic, there may be some effects if the trade disputes continue.

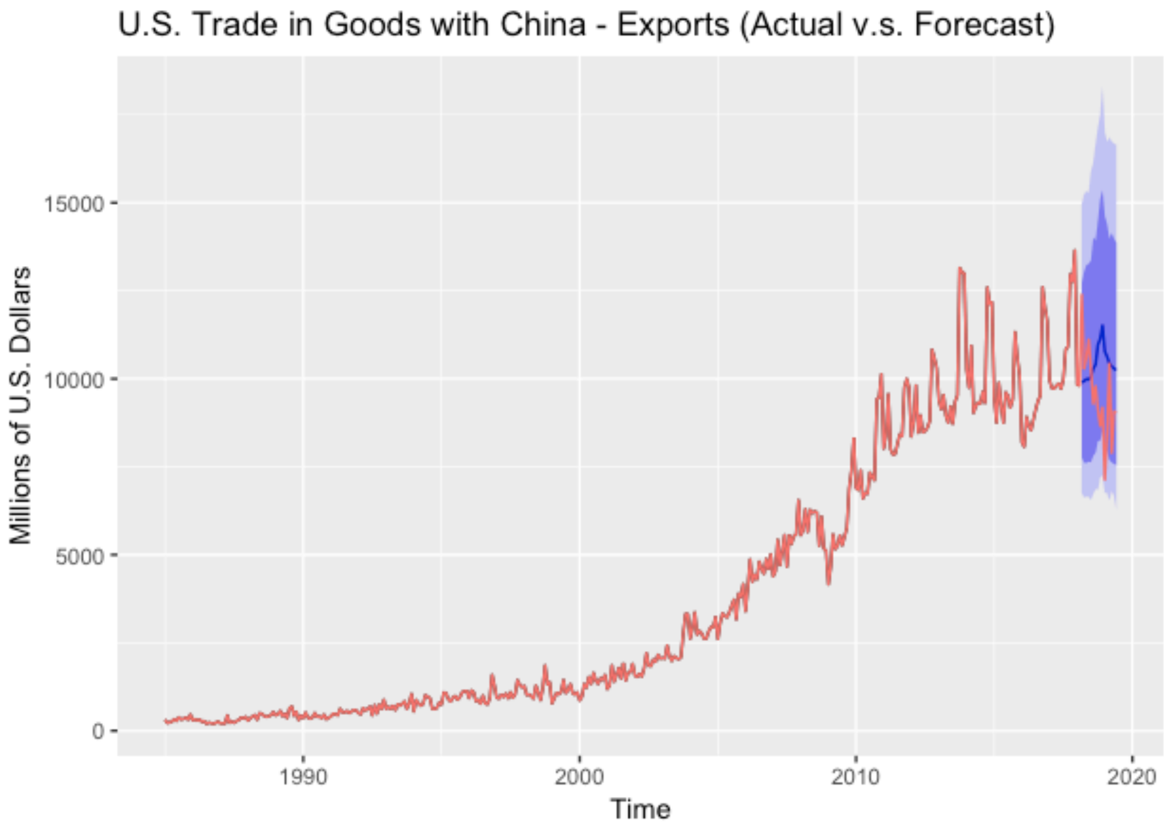

FIGURE 6.2 COMPARISON OF ACTUAL AND PREDICTED U.S. TRADE IN GOODS WITH CHINA – EXPORTS

By looking at Figure 6.2 that compares U.S. exports with China, the prediction still falls inside the 80% confidence interval, but it does not fit well with the actual values. It can be found that when the prediction is expected to experience a boom period, the actual exports drop to the lowest point. It can be implied that exports in U.S. with China are experiencing a long decreasing period. Combining with the prediction in imports, it is likely that the exports in U.S. experience a more significant effect than the imports. The reason for may have something to do with the extraordinary size of the manufacturing industry in China recently, which actually makes its competitive advantage much stronger (Li, 2018). Therefore, not only the U.S., but many countries imports products from China. Also, with the scientific and technological progress of China, an increasing number of Chinese people are keen on Chinese products. In terms of mobile phones, not only in China, but Huawei smartphones are popular all over the world (Villas-Boas and Eadicicco, 2019). Overall, it seems that the trade war between China and the U.S. may have a stronger impact on America than China.

6.2 DISCUSSION OF FUTURE ECONOMIC IMPACTS

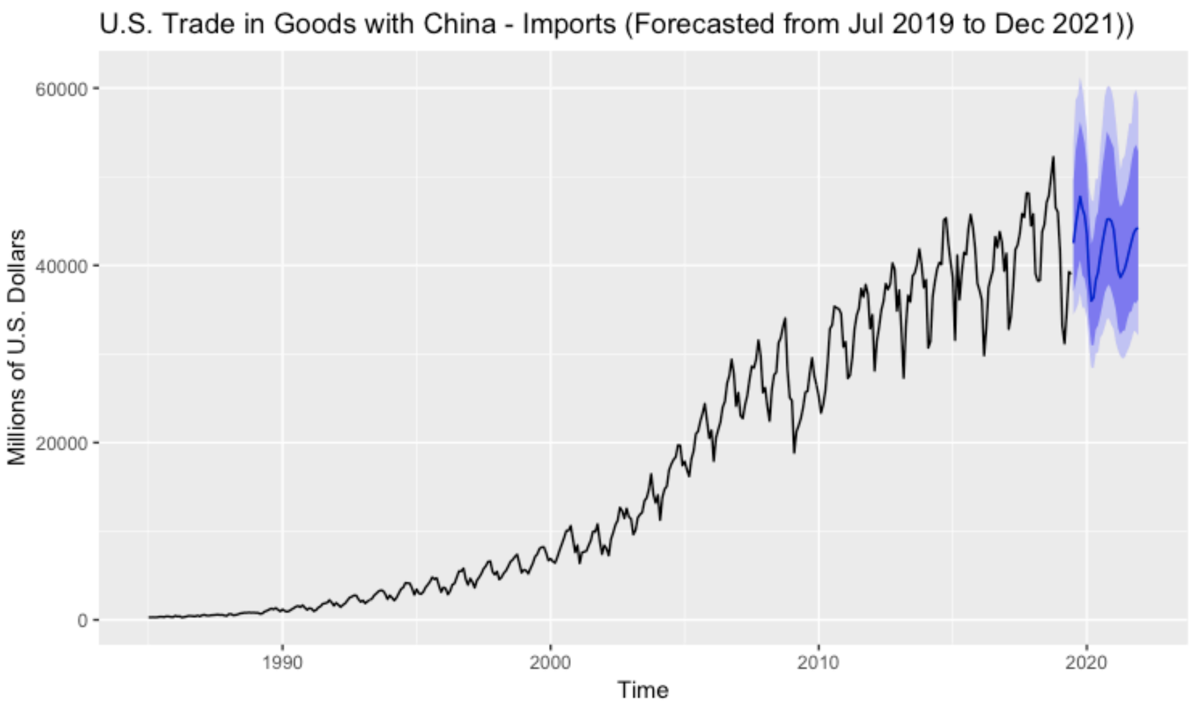

FIGURE 6.3 FORECAST OF U.S. TRADE IN GOODS WITH CHINA – IMPORTS

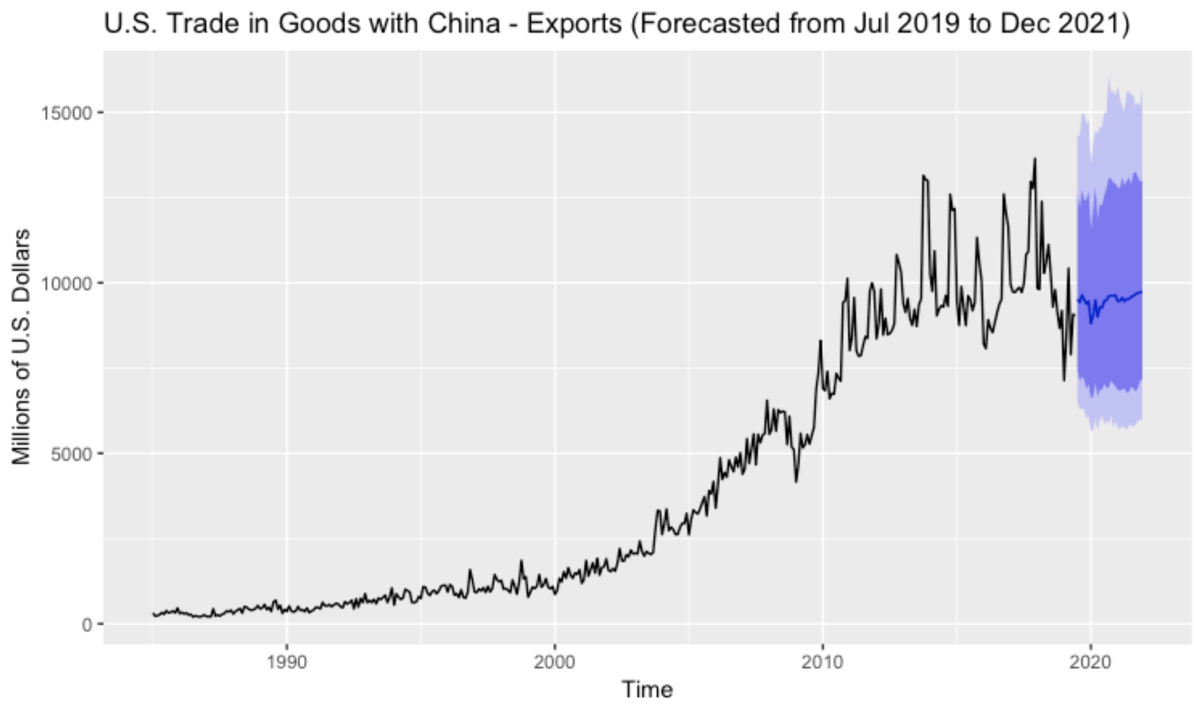

FIGURE 6.4 FORECAST OF U.S. TRADE IN GOODS WITH CHINA – EXPORTS

Figure 6.3 and Figure 6.4 are the predictions of U.S. imports and exports with China for the next 30 months. From Figure 6.3, the patterns show similar variations as in previous time. By looking at the 80% confidence interval of prediction, there is also a slight increase similar to the historical trend. It could be implied that the behaviour of U.S. imports may not be significantly affected by trade disputes.

However, when looking at Figure 6.4, the forecast presents a substantially steady state of just under 10000 million dollars, which is much lower than the exports in the previous time. This unexpected result indicates the exports may suffer from heavy losses. Compared with the prediction of the imports, the trade disputes may pose more threats to U.S. exports with China than imports. Two main reasons may cause this. Primarily, as mentioned before, Chinese people are now starting demand more on domestic products instead of foreign brands (People's Daily Online, 2018). Another reason that the exports may be affected so much might be that

China imposed much tariff on the imports from the U.S, which leads to Chinese importers steering clear of the U.S. exporters and move to Europe (Pandey, 2019).

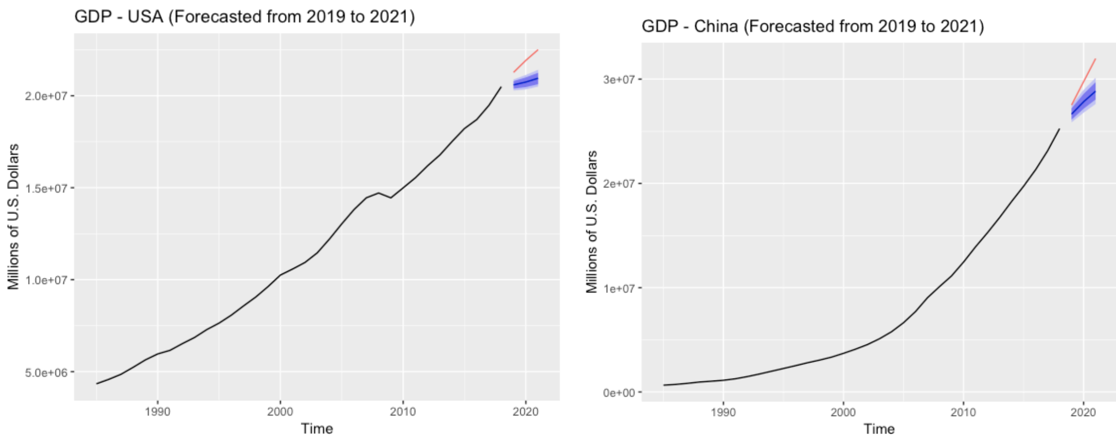

FIGURE 6.5 FORECAST OF GDP IN U.S. AND CHINA WITH AND WITHOUT IMPACTS OF TRADE DISPUTE

In Figure 6.5, the forecast of GDP, the red line represents the forecast without the effects of trade war whereas the blue area refers to the forecast with the impacts. In both countries, with the effects of trade frictions, GDP appears to be lower than under normal condition. This suggests that the GDP may easily be affected by the trade war, causing it to increase more slowly. What is surprising is that the GDP in the U.S. seems to suffer from a larger impact than China. This could be linked to the previous analysis of exports that demonstrates the trade war has a significant negative effect on U.S. exports with China. Since the export is a component of aggregate demand, if the export falls at a greater rate than the import, the aggregate demand will also drop and further contribute to the decrease of GDP. This could further enhance the analysis previously, which is trade war has more impacts on the U.S. compared to China.

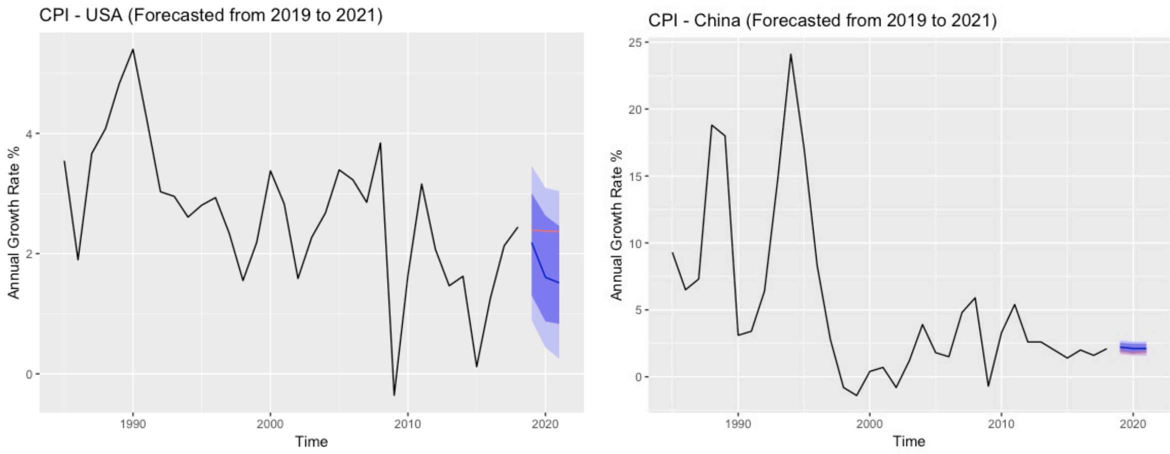

FIGURE 6.6 FORECAST OF CPI IN U.S. AND CHINA WITH AND WITHOUT IMPACTS OF TRADE DISPUTE

From Figure 6.6, the prediction of CPI in both countries without the impacts of trade disputes remains at about 2.5%. However, with the impacts of trade disputes, CPI in the U.S. appears to increase at a lower rate as time goes on. It could be inferred that the trend may keep dropping to 0 or even less than 0, causing deflation. Deflation refers to an increase of consumers' purchasing power, but the continuation could lead to an increase in debt burden, a decrease in corporate investment income and the negative consumption of consumers (Atkeson and Kehoe, 2004). Therefore, if the U.S.-China trade disputes last long, the economy of America may fall into a difficult situation of economic recession. For China, the forecast of CPI with impacts of trade war stays at the same rate over time despite slightly higher than the normal forecast, which indicates that the trade war has almost no effects on the price level of China.

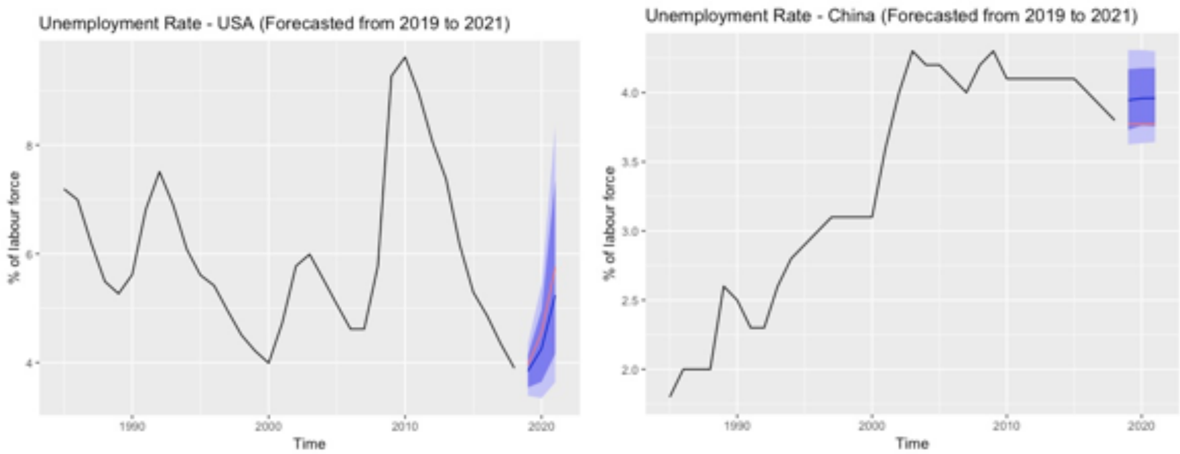

FIGURE 6.7 FORECAST OF UNEMPLOYMENT RATE IN U.S. AND CHINA WITH AND WITHOUT IMPACTS OF TRADE DISPUTE

Figure 6.7 shows the forecast for the unemployment rate in both countries. From the figure, the unemployment rate in the U.S. will increase whether or not with the impacts of trade friction. It is somewhat surprising that the prediction with impacts is lower than without the impacts, which means that trade war may bring more job opportunities to the U.S. It is hard to explain the reason for this, but the potential reason might be that since the manufacturers from China may move to other countries (as above suggested), the U.S. might need to establish its own manufacturers. Future studies on this topic are therefore recommended. For the unemployment rate in China, it can be interpreted that the unemployment rate tends to be constant over time instead of dramatically increasing or decreasing. Nevertheless, the normal prediction tends to be lower than the mean forecast with the effects of the trade war. It can therefore be implied that the effects of the trade war lead to a higher unemployment rate in China.

6.3 SUMMARY

To summarise, the discussion of all indictors demonstrates the trade disputes may have a more significant impact on the economy of the U.S. than China. First, the exports of U.S. to China may experience more barriers compared with the imports, which may lead to the trade deficit of China with the U.S. reaching a more disparity. Second, the growth rate of GDP in the U.S. could probably have a lower gradient compared with China. Third, America may experience deflation if the trade war continues whereas China may be almost unaffected. Fourth, despite the unemployment rate in the U.S. may increase at a lower level, trade dispute could not make unemployment rate decrease. There are indications that if the China-U.S. trade war continues, the U.S. economy is likely to suffer a heavy setback while China may also be affected, but much less than the United States.

CHAPTER 7 - CONCLUSION

7.1 RESEARCH PURPOSE AND FINDINGS

The primary aim of this study is to assess the economic impact of current trade friction between China and the U.S. by statistical analysis on economic indicators. The main approach is to forecast the future value of different indicators to analyse the potential impacts. The purpose of the research is first to compare the actual and predicted values of trade after the start of the trade dispute and then conduct more prediction of other indicators on account of the effects of trade war.

For the comparison in current economic impacts, it can be concluded that the imports and exports between China and the U.S. enormously affected by the trade disputes. For imports, the predicted value squeeze within the 80% confidence interval, but the drop almost falls outside. For exports, the predicted value and actual value lie very differently. For both tendencies, similarities are existing with the financial crisis in 2009. The accuracy of different models indicates that NNAR models are the best for forecasting imports and exports.

By using all the data to predict the future values in the next 30 months, the imports of the U.S. with China fluctuate as previously, but the fluctuations are smaller. However, the exports may remain at the same level and only have slight fluctuations.

In the comparison of future values of GDP of both countries, the growth rate of GDP will be slower with the impacts of trade disputes. Although NNAR models are better predicting the GDP with the impacts of trade dispute, ARIMA models perform better in GDP without the impacts.

CPI in both countries remains at the same level without the impacts of trade disputes, but a drop in the U.S. with trade disputes, which can be inferred that if the drop lasts, the deflation may occur in the U.S. since the supply is greater than purchasing power. For CPI in both countries with or without the effects of trade war, NNAR is the optimal model forecasting the future values.

For unemployment rate in both countries, NNAR is the best model either with or without the trade regressors. It is interesting that the unemployment rate in the U.S. has less growth with the impacts of trade disputes compared with the one without trade disputes, but still increase sharply for some reasons. For China, the unemployment rate will be higher with the impacts of trade friction but still remain at the same level with no large fluctuations.

To sum up, trade disputes display more impacts on the economy of the U.S., which may lead to a decrease in GDP and pull down CPI. Also, despite of lower gradient, the unemployment rate in the U.S may still be very high. On the other hand, China may not take as much risk as the U.S. despite the GDP and CPI may also decrease, but more slightly compared to the U.S. Similar to the U.S., the unemployment rate may increase but will not fluctuate a lot.

7.2 LIMITATIONS

The indicators that this study used are GDP, CPI, unemployment rate and trade. However, for GDP, we use GDP for the whole country instead of GDP per capita, which may be affected by the price and purchasing power. In addition, GDP, CPI and unemployment rate would possibly be affected by the world economy, but have less relationship with the trade war that only occurs between China and the U.S.

The time series data we used in the study for GDP, CPI and unemployment rate is yearly data. In order to control the same length with the imports and exports dataset, the time is only from 1985 to 2018. For time series analysis, the lack of observations may lead to inaccurate results. Also, for some reasons, the data of China mainly starts in 1978 or later, which will definitely affect the study.

The methodology that applied to predict the future values contains ETS, ARIMA and NNAR. There should be more time series models fitted to forecast if there is more space to analyse. Furthermore, some more neural networks, such as LSTM or hybrid models, can be applied to the study to find a more accurate model to increase the accuracy of forecasting, though it is not the focus of this paper.

7.3 APPLICATIONS OF THIS STUDY

There are generally two main applications of the research. First is to be the statistical reference for economic reports about the impacts of trade war. Second, this paper can be continued to work on to study more on these datasets over time until the end of trade dispute. Likewise, the study can be compared to the actual data as time goes on to see if the trade war really has the impacts on the economy.

7.4 RECOMMENDATIONS FOR FUTURE STUDY

The methodology applied to the study can be expanded to more neural network models. From the literature review, we can see that LSTM has a better development prospect despite of some drawbacks. However, hybrid ARIMA and neural networks may solve this problem, but more researches need to be done. Also, in the dynamic regression models, the impacts from trade to other indicators are defaulted to be one-way, but in real world, the impacts of these indicators may be two-way or more. Thus, VAR, a stochastic process model of multiple time series, can be considered to build. The study may also be expanded for more economic indicators to discuss. For instance, interest rate, stock market etc. can also be considered, which may lead to more diversified analysis.

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APPENDIX

A – DATA

A – 1 U.S. Trade in goods with China (Millions of U.S. Dollars)

year-month	import	export	balance of payment
1985-01	293.1	319.2	-26.1
1985-02	281	222.7	58.3
1985-03	293	239.5	53.5
1985-04	283.3	265.6	17.7
1985-05	295.1	329.3	-34.2
1985-06	348.7	280.9	67.8
1985-07	344.4	383.1	-38.7
1985-08	311.8	320.9	-9.1
1985-09	391.8	339.1	52.7
1985-10	385.5	377.1	8.4
1985-11	327.5	316.3	11.2
1985-12	306.5	462	-155.5
1986-01	459.5	300	159.5
1986-02	376.6	330.6	46
1986-03	401.8	289.6	112.2
1986-04	264.9	318.9	-54
1986-05	319	256.8	62.2
1986-06	375.7	275.3	100.4
1986-07	450.2	198.6	251.6

1986-08	434.7	235.6	199.1
1986-09	413.4	216.4	197
1986-10	398.5	198.8	199.7
1986-11	486	226.7	259.3
1986-12	390.7	259	131.7
1987-01	520.6	213.3	307.3
1987-02	565.3	212.7	352.6
1987-03	482.5	207.6	274.9
1987-04	468.3	439.6	28.7
1987-05	514.7	228.7	286
1987-06	536.3	261.8	274.5
1987-07	560	227.4	332.6
1987-08	598.1	278.2	319.9
1987-09	549.6	304.1	245.5
1987-10	567.9	376.9	191
1987-11	489.8	350.5	139.3
1987-12	440.5	396.5	44
1988-01	652.8	289.5	363.3
1988-02	650.6	360.3	290.3
1988-03	509.9	407.8	102.1
1988-04	551.9	446.5	105.4
1988-05	615.1	313.8	301.3
1988-06	720.8	503.2	217.6
1988-07	761.6	483.6	278

1988-08	803.9	424.4	379.5
1988-09	793.3	396.4	396.9
1988-10	834	412.9	421.1
1988-11	798.8	449.3	349.5
1988-12	818.2	533.9	284.3
1989-01	788.9	439	349.9
1989-02	798.1	464.7	333.4
1989-03	667.3	565.4	101.9
1989-04	728.5	415.3	313.2
1989-05	937.9	482.4	455.5
1989-06	1021.7	362.7	659
1989-07	1162.7	637.7	525
1989-08	1279.6	688.5	591.1
1989-09	1179.3	427.9	751.4
1989-10	1340.4	542.4	798
1989-11	1133.8	305	828.8
1989-12	951.5	424.4	527.1
1990-01	1186.1	361.2	824.9
1990-02	993.8	519.6	474.2
1990-03	931	376.1	554.9
1990-04	996.4	343.6	652.8
1990-05	1173.5	379.9	793.6
1990-06	1317.2	504.5	812.7
1990-07	1492.5	394.4	1098.1

1990-08	1568.6	408.4	1160.2
1990-09	1432.1	358.6	1073.5
1990-10	1652.1	459	1193.1
1990-11	1367.9	327.9	1040
1990-12	1126.2	373.2	753
1991-01	1321.6	406	915.6
1991-02	1253.7	487.6	766.1
1991-03	974.3	472.3	502
1991-04	1104.2	440.3	663.9
1991-05	1380.8	625.3	755.5
1991-06	1525.5	530.2	995.3
1991-07	1813.2	522.8	1290.4
1991-08	1872.4	565.2	1307.2
1991-09	1936.3	501.9	1434.4
1991-10	2236.4	552.3	1684.1
1991-11	1957.6	595.3	1362.3
1991-12	1593.2	579	1014.2
1992-01	1912.6	502.5	1410.1
1992-02	1693.7	471.1	1222.6
1992-03	1441.8	646.3	795.5
1992-04	1677.6	580.7	1096.9
1992-05	1853.9	621.7	1232.2
1992-06	2179.2	689.2	1490
1992-07	2503.8	438.8	2065

1992-08	2613	730.4	1882.6
1992-09	2760.5	489.3	2271.2
1992-10	2748.4	746.3	2002.1
1992-11	2316	620.5	1695.5
1992-12	2027	881.7	1145.3
1993-01	2187.6	620.7	1566.9
1993-02	1862.4	683.8	1178.6
1993-03	2083.2	621.6	1461.6
1993-04	2226.3	728.4	1497.9
1993-05	2376.3	586.2	1790.1
1993-06	2754.2	754.8	1999.4
1993-07	2981.1	711.6	2269.5
1993-08	3223.3	766.5	2456.8
1993-09	3338.7	836.2	2502.5
1993-10	3277.6	623.8	2653.8
1993-11	2899.6	781.8	2117.8
1993-12	2329.6	1047.5	1282.1
1994-01	2763.1	551	2212.1
1994-02	2499.2	877.9	1621.3
1994-03	2183	783.7	1399.3
1994-04	2491.6	712.7	1778.9
1994-05	2979	757.3	2221.7
1994-06	3463.3	1009.4	2453.9
1994-07	3645.4	970.4	2675

1994-08	4165.8	926.4	3239.4
1994-09	4134.4	628.5	3505.9
1994-10	4101.2	618.4	3482.8
1994-11	3534.3	648	2886.3
1994-12	2826.5	798	2028.5
1995-01	3450.6	744.9	2705.7
1995-02	3001.5	1085.5	1916
1995-03	2910.4	1070.1	1840.3
1995-04	3148.3	896.4	2251.9
1995-05	3654.9	831	2823.9
1995-06	3960.7	946.7	3014
1995-07	4311.8	985.7	3326.1
1995-08	4804.7	881.4	3923.3
1995-09	4584.1	959.6	3624.5
1995-10	4714.3	1097.4	3616.9
1995-11	3868	1124.7	2743.3
1995-12	3133.9	1130.3	2003.6
1996-01	3657.7	929.2	2728.5
1996-02	3539.6	1146.9	2392.7
1996-03	2863.7	1092.5	1771.2
1996-04	3247.9	841.3	2406.6
1996-05	3954.3	881.6	3072.7
1996-06	4111.2	771.6	3339.6
1996-07	4816.7	998.2	3818.5

1996-08	5495.7	778.3	4717.4
1996-09	5480.7	753.4	4727.3
1996-10	5812.9	927.5	4885.4
1996-11	4585.4	1586.4	2999
1996-12	3947	1285.7	2661.3
1997-01	4667.6	938.4	3729.2
1997-02	4262.4	913.3	3349.1
1997-03	3628.6	1021.6	2607
1997-04	4445	964.7	3480.3
1997-05	4795.1	1056.8	3738.3
1997-06	5213.5	920.3	4293.2
1997-07	5777.2	1097.1	4680.1
1997-08	6073.6	938	5135.6
1997-09	6561.4	1039.8	5521.6
1997-10	6606.5	1438.8	5167.7
1997-11	5425.7	1300.7	4125
1997-12	5101.1	1232.7	3868.4
1998-01	5453.2	1271.1	4182.1
1998-02	4559.6	1019.3	3540.3
1998-03	4798.1	1034.2	3763.9
1998-04	5262.9	984.9	4278
1998-05	5539.4	911.3	4628.1
1998-06	6020.2	1282.7	4737.5
1998-07	6556.2	1100.8	5455.4

1998-08	6779.9	869.9	5910
1998-09	7125.2	1214.9	5910.3
1998-10	7377.7	1855.2	5522.5
1998-11	6374.1	1317.2	5056.9
1998-12	5322.1	1379.7	3942.4
1999-01	5654	781.3	4872.7
1999-02	5563.1	923.9	4639.2
1999-03	5204	1076	4128
1999-04	5818.9	1035	4783.9
1999-05	6363.1	1113.8	5249.3
1999-06	7117.4	1442	5675.4
1999-07	7405.7	1074	6331.7
1999-08	8022.1	1151.3	6870.8
1999-09	8198.2	1325.3	6872.9
1999-10	8207.9	1069.1	7138.8
1999-11	7543.5	1025.5	6518
1999-12	6690.3	1093.9	5596.4
2000-01	6902.1	863.1	6039
2000-02	6584.4	972.7	5611.7
2000-03	6424.1	1330.5	5093.6
2000-04	7070.5	1227.5	5843
2000-05	7850.2	1526.3	6323.9
2000-06	8541.7	1335.6	7206.1
2000-07	9246.4	1642.8	7603.6

2000-08	10054	1429	8625
2000-09	10061.7	1333.3	8728.4
2000-10	10611.6	1487.3	9124.3
2000-11	9066.8	1450.4	7616.4
2000-12	7604.7	1586.7	6018
2001-01	8427.5	1187.5	7240
2001-02	6375.6	1289.8	5085.8
2001-03	7590.2	1855.8	5734.4
2001-04	7686.8	1398.9	6287.9
2001-05	7757.9	1596	6161.9
2001-06	8398.2	1786.4	6611.8
2001-07	8975.3	1487	7488.3
2001-08	10042.9	1929.7	8113.2
2001-09	9927.8	1427.8	8500
2001-10	10808.3	1647.7	9160.6
2001-11	8878.8	1674.5	7204.3
2001-12	7409.1	1901.2	5507.9
2002-01	8415.4	1569.3	6846.1
2002-02	8020.8	1529.5	6491.3
2002-03	7259	1620.5	5638.5
2002-04	9097.6	1544.5	7553.1
2002-05	9846.9	1773.9	8073
2002-06	10727.2	2205.9	8521.3
2002-07	11213.2	1848	9365.2

2002-08	12671.4	1839.8	10831.6
2002-09	12291.5	2023.7	10267.8
2002-10	11455	1962.7	9492.3
2002-11	12569.6	2160.8	10408.8
2002-12	11625	2049.1	9575.9
2003-01	11403.4976	2069.83189	9333.665682
2003-02	9629.62711	2048.67082	7580.956295
2003-03	10110.0446	2423.10471	7686.939854
2003-04	11521.8524	2121.94668	9399.905702
2003-05	11884.7015	1984.31868	9900.38281
2003-06	12127.3014	2119.62114	10007.68029
2003-07	13438.6351	2067.40558	11371.22951
2003-08	13764.867	2034.42823	11730.43878
2003-09	14747.5254	2090.9768	12656.54862
2003-10	16458.3176	2778.33646	13679.98115
2003-11	14156.948	3319.69265	10837.25531
2003-12	13192.7793	3309.60924	9883.170025
2004-01	14089.0155	2620.48979	11468.5257
2004-02	11267.1477	2928.99162	8338.156059
2004-03	13800.12	3361.9107	10438.20927
2004-04	14744.7842	2734.55386	12010.23029
2004-05	15067.1109	2835.05207	12232.05886
2004-06	16887.7626	2764.21712	14123.54547
2004-07	17562.0999	2618.79392	14943.30596

2004-08	18067.8671	2620.97081	15446.89624
2004-09	18386.9457	2823.07055	15563.87519
2004-10	19718.1575	2946.74382	16771.41366
2004-11	19678.9921	2938.17537	16740.81677
2004-12	17412.0308	3234.80283	14177.228
2005-01	17885.8406	2609.32613	15276.51448
2005-02	16937.5948	3058.08909	13879.50572
2005-03	16184.945	3336.38118	12848.56377
2005-04	18148.4582	3263.67075	14884.78741
2005-05	19053.1869	3222.90974	15830.27714
2005-06	20976.7019	3370.73081	17605.97105
2005-07	21272.6695	3559.97215	17712.69732
2005-08	22421.2923	3728.72385	18692.5685
2005-09	23294.4817	3165.81327	20128.66841
2005-10	24382.8527	3899.1515	20483.70123
2005-11	22426.1283	3807.49157	18618.63674
2005-12	20485.953	4169.7501	16316.20289
2006-01	21382.5059	3396.87015	17985.63576
2006-02	17905.3535	4072.24509	13833.10838
2006-03	20531.2583	4867.06471	15664.19362
2006-04	21459.0699	4232.4045	17226.66544
2006-05	22317.6351	4434.09005	17883.54508
2006-06	23989.6994	4302.90534	19686.79406
2006-07	24632.0108	4806.2751	19825.73566

2006-08	26713.3352	4603.26858	22110.06666
2006-09	27570.6179	4461.00988	23109.60804
2006-10	29388.6017	4885.26418	24503.33756
2006-11	27775.0792	4595.82262	23179.2566
2006-12	24109.1856	5015.78817	19093.39741
2007-01	25640.5627	4389.53462	21251.02805
2007-02	23038.8804	4532.88997	18505.99039
2007-03	22723.0442	5425.39389	17297.65035
2007-04	24241.5228	4703.95122	19537.57156
2007-05	25290.5744	5129.43674	20161.1377
2007-06	27070.9612	5561.77325	21509.18795
2007-07	28601.1708	4665.93726	23935.23356
2007-08	28424.5014	5552.79757	22871.70387
2007-09	29418.9625	5311.87091	24107.09162
2007-10	31555.4064	5532.91998	26022.48642
2007-11	29780.7188	5581.505	24199.21379
2007-12	25656.5613	6548.88118	19107.68011
2008-01	26193.0321	5556.70885	20636.32329
2008-02	24095.8865	5698.05478	18397.83168
2008-03	22440.2418	6294.35171	16145.89006
2008-04	25951.667	5651.24836	20300.41864
2008-05	27634.5324	6275.67232	21358.86013
2008-06	27930.6405	6188.16634	21742.4742
2008-07	31247.2707	6234.6357	25012.63497

2008-08	31823.6979	6201.29638	25622.40151
2008-09	33078.7306	5257.64664	27821.08399
2008-10	34032.3883	6083.40014	27948.98815
2008-11	28265.025	5180.95014	23084.07489
2008-12	25079.515	5110.7062	19968.80878
2009-01	24743.4574	4159.64976	20583.80765
2009-02	18845.4952	4661.68136	14183.81385
2009-03	21224.7135	5579.25902	15645.45449
2009-04	21920.5952	5161.44261	16759.15264
2009-05	22734.1478	5256.0181	17478.12975
2009-06	23972.7742	5548.57458	18424.19966
2009-07	25671.0844	5269.2867	20401.79771
2009-08	25798.1197	5517.97423	20280.14543
2009-09	27893.9166	5764.34879	22129.5678
2009-10	29557.7829	6879.30003	22678.48283
2009-11	27541.7208	7374.16064	20167.56014
2009-12	26470.0757	8324.9828	18145.09294
2010-01	25215.919	6898.35886	18317.56015
2010-02	23342.7775	6840.22748	16502.55003
2010-03	24292.2132	7400.77462	16891.43858
2010-04	25920.1881	6600.72543	19319.46272
2010-05	29052.4383	6755.2858	22297.15255
2010-06	32843.1	6733.71855	26109.38149
2010-07	33266.8336	7339.25603	25927.57756

2010-08	35375.2884	7209.73485	28165.55358
2010-09	35196.6989	7114.31123	28082.38763
2010-10	35083.2994	9417.28853	25666.01091
2010-11	34564.2939	9475.84497	25088.44893
2010-12	30799.5831	10125.5546	20674.02853
2011-01	31377.3537	8017.79183	23359.56191
2011-02	27244.7358	8383.31012	18861.42569
2011-03	27599.6669	9563.72828	18035.93858
2011-04	29580.2827	8000.50332	21579.77939
2011-05	32788.0716	7849.15932	24938.9123
2011-06	34374.8308	7867.00509	26507.82571
2011-07	35152.2433	8157.90119	26994.34207
2011-08	37374.1365	8421.64207	28952.49446
2011-09	36418.6429	8370.06356	28048.5793
2011-10	37824.0717	9745.55614	28078.51556
2011-11	36764.9116	9997.19559	26767.71605
2011-12	32872.2851	9747.66714	23124.61799
2012-01	34417.5404	8359.47271	26058.06771
2012-02	28105.1864	8785.66278	19319.52364
2012-03	31431.3489	9811.57653	21619.77241
2012-04	33016.2538	8468.14198	24548.11185
2012-05	34937.8299	8960.15498	25977.67495
2012-06	35949.3595	8478.11731	27471.24214
2012-07	37930.7552	8515.0955	29415.65971

2012-08	37280.6291	8613.33532	28667.29383
2012-09	37891.8231	8804.20969	29087.61337
2012-10	40257.0835	10824.4314	29432.65213
2012-11	39543.6932	10587.7855	28955.90764
2012-12	34857.5795	10308.6319	24548.94761
2013-01	37193.6588	9382.92315	27810.73566
2013-02	32742.6776	9133.3176	23609.35999
2013-03	27294.0672	9539.03134	17755.03586
2013-04	33131.9263	8953.95453	24177.97177
2013-05	36617.6236	8752.82769	27864.79596
2013-06	35885.9788	9217.62633	26668.3525
2013-07	38800.4306	8723.70815	30076.72248
2013-08	39161.2995	9352.1195	29809.18002
2013-09	40144.3925	9527.17664	30617.21587
2013-10	41845.4721	13147.7638	28697.70831
2013-11	40112.2796	13027.0826	27085.19697
2013-12	37500.2129	12988.6573	24511.55558
2014-01	38377.1996	10264.5425	28112.65702
2014-02	30700.3523	9750.69618	20949.65615
2014-03	31420.8753	10934.2761	20486.59918
2014-04	36450.2188	9031.90081	27418.31798
2014-05	38188.1358	9220.16198	28967.97379
2014-06	39607.1187	9330.21957	30276.89909
2014-07	40319.6183	9291.79106	31027.82728

2014-08	40093.8171	9625.17276	30468.64432
2014-09	45102.7754	9313.9677	35788.80771
2014-10	45335.3517	12593.3343	32742.01742
2014-11	42483.5294	12125.9305	30357.59892
2014-12	40395.9025	12175.2099	28220.6926
2015-01	38589.6967	9459.19839	29130.49834
2015-02	31563.9882	8754.58818	22809.39998
2015-03	41136.9175	9886.51916	31250.39837
2015-04	36121.3945	9279.91285	26841.48162
2015-05	39082.0299	8749.78756	30332.24234
2015-06	41453.8398	9615.75412	31838.08568
2015-07	41215.0782	9505.17356	31709.90462
2015-08	44138.0553	9183.45608	34954.59919
2015-09	45724.9512	9419.42117	36305.53008
2015-10	44309.9325	11324.8562	32985.07627
2015-11	41884.7742	10603.5927	31281.18147
2015-12	37980.9974	10091.1053	27889.8921
2016-01	37145.8351	8202.84144	28942.99363
2016-02	36081.8293	8070.08459	28011.74472
2016-03	29827.3443	8916.28601	20911.05828
2016-04	32929.2616	8672.73197	24256.52959
2016-05	37524.3469	8539.88816	28984.45871
2016-06	38556.1028	8838.79325	29717.30951
2016-07	39460.7535	9128.1434	30332.61011

2016-08	43220.1288	9370.43063	33849.69822
2016-09	42028.2178	9519.99555	32508.22228
2016-10	43798.2788	12598.5562	31199.72259
2016-11	42605.4482	12039.5008	30565.9473
2016-12	39364.4575	11648.2556	27716.20197
2017-01	41343.0832	9961.09716	31381.98599
2017-02	32804.2956	9735.78563	23068.50999
2017-03	34186.9421	9719.18645	24467.75568
2017-04	37465.6355	9805.65765	27659.97787
2017-05	41783.0586	9862.17719	31920.88144
2017-06	42289.1521	9717.40224	32571.74991
2017-07	43589.1688	9979.05796	33610.11088
2017-08	45817.7679	10828.3393	34989.42855
2017-09	45429.7197	10911.6774	34518.04232
2017-10	48167.6526	12963.4345	35204.2181
2017-11	48127.8095	12765.0211	35362.78836
2017-12	44465.6687	13644.7502	30820.91856
2018-01	45788.0406	9835.25935	35952.7812
2018-02	39067.6016	9806.09267	29261.50898
2018-03	38256.7351	12382.0863	25874.64874
2018-04	38230.01	10268.0355	27961.97455
2018-05	43797.3698	10610.8175	33186.55224
2018-06	44599.4627	11115.6234	33483.83928
2018-07	47096.0076	10261.688	36834.3196

2018-08	47863.9065	9294.3443	38569.56215
2018-09	50032.1206	9789.08107	40243.03954
2018-10	52232.992	9130.52032	43102.47172
2018-11	46525.6825	8664.89529	37860.78718
2018-12	46013.4988	9182.98185	36830.51693
2019-01	41603.8305	7134.33573	34469.49482
2019-02	33194.398	8433.55193	24760.84611
2019-03	31175.6732	10426.5342	20749.13897
2019-04	34798.9295	7896.34578	26902.58369
2019-05	39269.1088	9074.49865	30194.61019
2019-06	39002.3235	9034.70187	29967.62158

A – 2 GDP in the U.S. and China (Millions of U.S. Dollars)

Year	USA	China
1985	4338979	651783.6676
1986	4579631	723584.3794
1987	4855215	827641.0605
1988	5236438	953574.1206
1989	5641580	1032433.894
1990	5963144	1119939.472
1991	6158129	1264765.687
1992	6520327	1477496.711
1993	6858559	1722420.096
1994	7287236	1988670.752
1995	7639749	2252432.489

1996	8073122	2521266.933
1997	8577552	2801133.655
1998	9062817	3053459.216
1999	9630663	3337890.863
2000	10252347	3703733.838
2001	10581822	4104066.357
2002	10936418	4547549.215
2003	11458246	5103703.986
2004	12213730	5774277.676
2005	13036637	6639272
2006	13814609	7713671.147
2007	14451860	9041253.165
2008	14712845	10105260.65
2009	14448932	11130544.85
2010	14992052	12457429.23
2011	15542582	13919132.45
2012	16197007	15281108.14
2013	16784851	16723689.91
2014	17521747	18259747.26
2015	18219297	19726289.65
2016	18707189	21310048.18
2017	19485394	23121407.34
2018	20494100	25256694.6

A – 3 CPI in the U.S. and China (Annual Growth Rate %)

Year	USA	China
1985	3.545644	9.3
1986	1.898048	6.5
1987	3.664563	7.3
1988	4.077741	18.8
1989	4.827003	18
1990	5.397956	3.1
1991	4.234964	3.4
1992	3.02882	6.4
1993	2.951657	14.7
1994	2.607442	24.1
1995	2.80542	17.1
1996	2.931204	8.3
1997	2.33769	2.8
1998	1.552279	-0.8
1999	2.188027	-1.4
2000	3.376857	0.4
2001	2.826171	0.7
2002	1.586032	-0.8
2003	2.270095	1.2
2004	2.677237	3.9
2005	3.392747	1.8
2006	3.225944	1.5

2007	2.852673	4.8
2008	3.8391	5.9
2009	-0.3555463	-0.7
2010	1.640043	3.3
2011	3.156842	5.4
2012	2.069337	2.6
2013	1.464833	2.6
2014	1.622223	2
2015	0.1186271	1.4
2016	1.261583	2
2017	2.13011	1.6
2018	2.442583	2.1

A – 4 Unemployment Rate in the U.S. and China (% of Labour Force)

Year	USA	China
1985	7.191667	1.8
1986	6.991667	2
1987	6.191667	2
1988	5.491667	2
1989	5.266667	2.6
1990	5.616667	2.5
1991	6.816667	2.3
1992	7.508333	2.3
1993	6.9	2.6

1994	6.083333	2.8
1995	5.608333	2.9
1996	5.416667	3
1997	4.95	3.1
1998	4.508333	3.1
1999	4.216667	3.1
2000	3.991667	3.1
2001	4.733333	3.6
2002	5.775	4
2003	5.991667	4.3
2004	5.533333	4.2
2005	5.066667	4.2
2006	4.616667	4.1
2007	4.616667	4
2008	5.775	4.2
2009	9.266666	4.3
2010	9.616667	4.1
2011	8.95	4.1
2012	8.066667	4.1
2013	7.375	4.1
2014	6.166667	4.1
2015	5.291667	4.1
2016	4.866667	4
2017	4.35	3.9

2018	3.9	3.8

B – CODE

```
################################################################
# Dissertation: Aseess the impact of current trade dispute on the economies of China and the U.S.
# 180025784
# August 2019
################################################################
# setwd("/Users/apple/Desktop/MSc Dissertation/Datasets")

# Clear all variables in workspace
rm(list = ls())

# Load the packages
# install.packages("forecast")
# install.packages("fpp2")
# install.packages("Rmisc")
library(readxl)
library(forecast)
library(fpp2)
library(ggplot2)
library(Rmisc)
library(psych)
```

```
############################################################
############################################################
# 1 Comparison of predicted value & actual value
############################################################
############################################################

# Load the data from Excel
trade <- read_xlsx("BalanceofTrade.xlsx")

# Store the import/export as time-series objects
import <- ts(trade$import[1:398], frequency = 12, start = c(1985, 1))
import_trade <- ts(trade$import, frequency = 12, start = c(1985, 1))
export <- ts(trade$export[1:398], frequency = 12, start = c(1985, 1))
export_trade <- ts(trade$export, frequency = 12, start = c(1985, 1))
balance <- ts(trade$`balance of payment`, frequency = 12, start = c(1985,1))

############################################################
# Data Manipulation
############################################################
# Time plot of original data
autoplot(balance, col = "orange") +
  autolayer(import_trade) +
  autolayer(export_trade) +
  autolayer(balance) +
  ggtitle("Time Plot: U.S. Trade in Goods with China") +
```

```
  ylab("Millions of U.S. Dollars")



autoplot(import_trade) +
  ggtitle("Time Plot: U.S. Trade in Goods with China - Imports") +
  ylab("Millions of U.S. Dollars")
autoplot(export_trade) +
  ggtitle("Time Plot: U.S. Trade in Goods with China - Exports") +
  ylab("Millions of U.S. Dollars")
#*Sharp drop in 2008-2009, should be due to Great Recession
#*Also another sharp drop in 2018-2019, may be due to Trade War

# Time plot of original data (before trade war)
p1 <- autoplot(import) +
  ggtitle("Time Plot: U.S. Trade in Goods with China - Imports from Jan 1985 to Feb 2018") +
  ylab("Millions of U.S. Dollars")

p2 <- autoplot(export) +
  ggtitle("Time Plot: U.S. Trade in Goods with China - Exports from Jan 1985 to Feb 2018") +
  ylab("Millions of U.S. Dollars")

multiplot(p1, p2, cols = 1)
#*As time series goes on, the fluctuations increase

# Transform time series using natural log of the original data
```

```
log_import <- log(import)

log_import_trade <- log(import_trade)

log_export <- log(export)

log_export_trade <- log(export_trade)

#*Now the size of the fluctuations could to be roughly constant over time


###############################################################

# Preliminary analysis

###############################################################

# Basic statistics

describe(trade$import)

describe(trade$export)

describe(trade$`balance of payment`)


# Time plot

p3 <- autoplot(log_import) +

  ggtitle("Log-transformed Time Plot: U.S. Trade in Goods with China - Imports from Jan 1985
to Feb 2018") +

  ylab("Millions of U.S. Dollars

      (Placed on Log Scale)")


p4 <- autoplot(log_export) +

  ggtitle("Log-transformed Time Plot: U.S. Trade in Goods with China - Exports from Jan 1985
to Feb 2018") +

  ylab("Millions of U.S. Dollars
```

```
       (Placed on Log Scale)")

multiplot(p3, p4, cols = 1)

#*Positive trend in both import and export
#*Clear seasonal patterns in import, but hard to tell if export has one

# Investigate transformations to get rid of trend
# Take the 1st difference of the data to remove the trend
Dlog_import <- diff(log_import)
Dlog_export <- diff(log_export)

# Time plot of differenced data
autoplot(Dlog_import) +
  ggtitle("Log-transformed Time Plot:
          Change in U.S. Trade in Goods with China - Imports from Jan 1985 to Feb 2018") +
  ylab("Millions of U.S. Dollars
       (Placed on Log Scale)")
autoplot(Dlog_export) +
  ggtitle("Log-transformed Time Plot:
          Change in U.S. Trade in Goods with China - Exports from Jan 1985 to Feb 2018") +
  ylab("Millions of U.S. Dollars
       (Placed on Log Scale)")

# Series appears trend-stationary, now to investigate seasonality
```

```
p5 <- ggseasonplot(Dlog_import, year.labels = TRUE, year.labels.left = TRUE) +
  ggtitle("Seasonal Plot:
          Change in U.S. Trade in Goods with China - Imports from Jan 1985 to Feb 2018") +
  ylab("Millions of U.S. Dollars
       (Placed on Log Scale)")
p6 <- ggseasonplot(Dlog_export, year.labels = TRUE, year.labels.left = TRUE) +
  ggtitle("Seasonal Plot:
          Change in U.S. Trade in Goods with China - Exports from Jan 1985 to Feb 2018") +
  ylab("Millions of U.S. Dollars
       (Placed on Log Scale)")
#*Seasonal pattern exists except for Mar, 1990s seem negative, but 2000s seem positive
#*No seasonal pattern in export


# Another seasonal plot - subseries plot
p7 <- ggsubseriesplot(Dlog_import) +
  ggtitle("Seasonal Plot:
          Change in U.S. Trade in Goods with China - Imports from Jan 1985 to Feb 2018") +
  ylab("Millions of U.S. Dollars
       (Placed on Log Scale)")
p8 <- ggsubseriesplot(Dlog_export) +
  ggtitle("Seasonal Plot:
          Change in U.S. Trade in Goods with China - Exports from Jan 1985 to Feb 2018") +
  ylab("Millions of U.S. Dollars
       (Placed on Log Scale)")
#*Basically no seasonal pattern in export, basically flat in change in different months
```

```
#*For import, strong seasonal pattern except for Feb and Mar, basically flat in change in different months

multiplot(p5, p7)
multiplot(p6, p8)
#############################################################
# Import has trend and seasonality
# Export only has trend
# To remove the trend, we take the first difference
# The 1st differenced series still has seasonality
#
# Forecast with various methods
#############################################################
# 1 Use a benchmark to forecast (seasonal naive method as the benchmark)
# y_t = y_{t-s} + e_t
snm_import <- snaive(Dlog_import) #Residual SD = 0.1029
print(summary(snm_import))
#*Residual SD shows how well the data is fitting, the smaller the better
#*Residual SD: missing on average by roughly 0.1029 million$
checkresiduals(snm_import)
#*Residual plot shows the data looks totally random
#*ACF shows the residuals (left-over error terms), only a few autocorrelation over time, may be ideal

snm_export <- snaive(Dlog_export) #Residual SD = 0.2171
```

```
print(summary(snm_export))
#*Residual SD shows how well the data is fitting, the smaller the better
#*Residual SD: missing on average by roughly 0.2171 million$
checkresiduals(snm_export)
#*Residual plot shows the data looks totally random
#*ACF shows the residuals (left-over error terms), only a few autocorrelation over time, may be ideal

# 2 ETS method (exponential smoothing model)
ets_import <- ets(log_import) #Residual SD = sigma = 0.0748
print(summary(ets_import))
#*1st letter: error type
#*2nd letter: trend type
#*3rd letter: seasonal type
#*"N"=none, "A"=additive, "M"=multiplicative and "Z"=automatically
#AAA: additive exponential smoothing model with additive errors
checkresiduals(ets_import)
#*More autocorrelation over time, information in the data that model is not using efficiently
#*But Residual SD is smaller than snm, is the better model

ets_export <- ets(log_export) #Residual SD = sigma = 0.1443
print(summary(ets_export))
#*1st letter: error type
#*2nd letter: trend type
#*3rd letter: seasonal type
```

```
#*"N"=none, "A"=additive, "M"=multiplicative and "Z"=automatically
#AAA: additive exponential smoothing model with additive errors
checkresiduals(ets_export)
#*Alomost no autocorrelation over time
#*Residual SD is smaller than snm, is the better model


# 3 ARIMA
#*Needs to be stationary
#*Remove trend by using differenced data
#*Remove seasonality by telling the model there's seasonality
arima_import <- auto.arima(log_import, d = 1, D = 1, stepwise = FALSE, approximation = FALSE, trace = TRUE)
#*d = 1: tell the function you're free to fit ARIMA take the 1st difference of the data
#*D = 1: get rid of the seasonality
#*stepwise = F: make our model try every combination of the model
#*approximation = F: make our model more accurate using the exact AIC instead of approximate AIC
#*trace = T: print out all the models
print(summary(arima_import))
#*ARIMA(2,1,0)(2,1,0)[12]
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.005118) = 0.0715402
checkresiduals(arima_import)
#*ACF looks better, only a few lags are outside the 95% CI
```

```
arima_export <- auto.arima(log_export, d = 1, stepwise = FALSE, approximation = FALSE, trace = TRUE)
#*d = 1: tell the function you're free to fit ARIMA take the 1st difference of the data
#*stepwise = F: make our model try every combination of the model
#*approximation = F: make our model more accurate using the exact AIC instead of approximate AIC
#*trace = T: print out all the models
print(summary(arima_export))
#*ARIMA(2,1,1)(2,0,0)[12] with drift
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.02193) = 0.1480878
#*Greater than Residual SD of ets, ets should be the better model
checkresiduals(arima_export)
#*ACF also looks worse than ETS
```

```
# 4 Neural Network
set.seed(25784)
nnar_import <- nnetar(log_import)
nnar_import
#*NNAR(1,1,2)[12]
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.0001173) = 0.01083051
#*p = 1: last 1 observation is used as predictors
#*P = 1: Seasonality
#*k = 2: the number of hidden nodes (2 neurons in the hidden layer)
#*m = 12: monthly data
```

```
nnar_export <- nnetar(log_export)

nnar_export

#*NNAR(2,1,2)[12]

#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.000478) = 0.02186321

#*p = 2: last 2 observation are used as predictors

#*P = 1: Seasonality

#*k = 2: the number of hidden nodes (2 neurons in the hidden layer)

#*m = 12: monthly data


#############################################################

# Forecast

#############################################################

# 1 Import

fcst_import_snm <- forecast(snm_import, h = 16)

fcst_import_snm$mean <- exp(diffinv(fcst_import_snm$mean)[2:17])*trade$import[398]

accuracy(fcst_import_snm$mean, import_trade[399:414])

#*SNM:

#*ME      RMSE     MAE      MPE      MAPE

#*-10119.14 11757.7 10119.14 -25.89406 25.89406


fcst_import_ets <- forecast(ets_import, h = 16)

fcst_import_ets$mean <- exp(fcst_import_ets$mean)

accuracy(fcst_import_ets$mean, import_trade[399:414])

#*ETS
```

```
#*ME       RMSE     MAE     MPE       MAPE
#*-5508.637 6643.835 5508.637 -14.2435 14.2435

fcst_import_arima <- forecast(arima_import, h = 16)
fcst_import_arima$mean <- exp(fcst_import_arima$mean)
accuracy(fcst_import_arima$mean, import_trade[399:414])
#*ARIMA
#*ME        RMSE      MAE       MPE       MAPE
#*-4631.9 5680.56  4631.9    -12.11285     12.11285

fcst_import_nnar <- forecast(nnar_import, PI = TRUE, h = 16)
fcst_import_nnar$mean <- exp(fcst_import_nnar$mean)
accuracy(fcst_import_nnar$mean, import_trade[399:414])
#*NNAR
#*ME       RMSE      MAE        MPE        MAPE
#*138.4959 4800.392 3871.927 -1.291097 9.681288

#*NNAR is the best model among these four models
fcst_import_nnar$upper <- exp(fcst_import_nnar$upper)
fcst_import_nnar$lower <- exp(fcst_import_nnar$lower)
fcst_import_nnar$x <- exp(fcst_import_nnar$x)
# Plot the actual and predicted value
autoplot(fcst_import_nnar) +
  ggtitle("U.S. Trade in Goods with China - Imports (Actual v.s. Forecast)") +
  ylab("Millions of U.S. Dollars") +
```

```
  autolayer(import_trade)


# 2 Export
fcst_export_snm <- forecast(snm_export, h = 16)
fcst_export_snm$mean <- exp(diffinv(fcst_export_snm$mean)[2:17])*trade$export[398]
accuracy(fcst_export_snm$mean, export_trade[399:414])
#*SNM:
#*ME        RMSE     MAE       MPE       MAPE
#*-1109.181 2275.069 1830.028 -13.83847 20.15965


fcst_export_ets <- forecast(ets_export, h = 16)
fcst_export_ets$mean <- exp(fcst_export_ets$mean)
accuracy(fcst_export_ets$mean, export_trade[399:414])
#*ETS
#*ME        RMSE     MAE       MPE       MAPE
#*-2423.277 2916.995 2534.352 -27.71163 28.60869


fcst_export_arima <- forecast(arima_export, h = 16)
fcst_export_arima$mean <- exp(fcst_export_arima$mean)
accuracy(fcst_export_arima$mean, export_trade[399:414])
#*ARIMA
#*ME        RMSE     MAE       MPE       MAPE
#*-2317.748 2992.87 2581.074 -27.11882 29.25935


fcst_export_nnar <- forecast(nnar_export, PI = TRUE, h = 16)
```

```
fcst_export_nnar$mean <- exp(fcst_export_nnar$mean)

accuracy(fcst_export_nnar$mean, export_trade[399:414])

#*NNAR

#*ME       RMSE     MAE       MPE       MAPE

#*-1066.127 1958.823 1613.898 -13.51546 18.224


#*NNAR is the best model among these four models

fcst_export_nnar$upper <- exp(fcst_export_nnar$upper)

fcst_export_nnar$lower <- exp(fcst_export_nnar$lower)

fcst_export_nnar$x <- exp(fcst_export_nnar$x)

# Plot the actual and predicted value

autoplot(fcst_export_nnar) +

  ggtitle("U.S. Trade in Goods with China - Exports (Actual v.s. Forecast)") +

  ylab("Millions of U.S. Dollars") +

  autolayer(export_trade)


############################################################

############################################################

# 2 Forecast of monthly import/export in the following 3 years [2019-21]

############################################################

############################################################

# Building NNAR

set.seed(25784)

nnar_import_trade <- nnetar(log_import_trade)

nnar_import_trade
```

```
#*NNAR(1,1,2)[12]

#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.0001153) = 0.01073778

#*p = 1: last 1 observation is used as predictors

#*P = 1: Seasonality

#*k = 2: the number of hidden nodes (2 neurons in the hidden layer)

#*m = 12: monthly data


nnar_export_trade <- nnetar(log_export_trade)

nnar_export_trade

#*NNAR(2,1,2)[12]

#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.0004719) = 0.02172326

#*p = 2: last 2 observation is used as predictors

#*P = 1: Seasonality

#*k = 2: the number of hidden nodes (2 neurons in the hidden layer)

#*m = 12: monthly data


# Forecasting

fcst_import_trade <- forecast(nnar_import_trade, PI = TRUE, h = 30)

fcst_import_trade$mean <- exp(fcst_import_trade$mean)

fcst_import_trade$upper <- exp(fcst_import_trade$upper)

fcst_import_trade$lower <- exp(fcst_import_trade$lower)

fcst_import_trade$x <- exp(fcst_import_trade$x)

autoplot(fcst_import_trade) +

  ggtitle("U.S. Trade in Goods with China - Imports (Forecasted from Jul 2019 to Dec 2021))")

+
```

```
  ylab("Millions of U.S. Dollars")

fcst_export_trade <- forecast(nnar_export_trade, PI = TRUE, h = 30)
fcst_export_trade$mean <- exp(fcst_export_trade$mean)
fcst_export_trade$upper <- exp(fcst_export_trade$upper)
fcst_export_trade$lower <- exp(fcst_export_trade$lower)
fcst_export_trade$x <- exp(fcst_export_trade$x)
autoplot(fcst_export_trade) +
  ggtitle("U.S. Trade in Goods with China - Exports (Forecasted from Jul 2019 to Dec 2021)")
+
  ylab("Millions of U.S. Dollars")

############################################################
############################################################
# 3 Forecast of GDP, CPI, unemployment rate in the following 3 years
############################################################
############################################################

# Load the data from Excel (3 datasets except for trade)
gdp_dataset <- read_xlsx("GDP.xlsx")
cpi_dataset <- read_xlsx("CPI.xlsx")
ur_dataset <- read_xlsx("Unemployment Rate.xlsx")

# Basic statistics
describe(gdp_dataset$USA)
```

```
describe(gdp_dataset$China)
describe(cpi_dataset$USA)
describe(cpi_dataset$China)
describe(ur_dataset$USA)
describe(ur_dataset$China)

# Combine the actual data [Jan 1985 - Jun 2019] and forecasted data [Jul 2019 - Dec 2021]
fc_import <- ts(fcst_import_trade$mean, frequency = 12, start = c(2019,7))
fc_import_all <- ts(c(import_trade, fc_import), frequency = frequency(import_trade), start =
start(import_trade))
fc_export <- ts(fcst_export_trade$mean, frequency = 12, start = c(2019,7))
fc_export_all <- ts(c(export_trade, fc_export), frequency = frequency(export_trade), start =
start(export_trade))

# Change monthly time series import&export to yearly
import_yearly <- aggregate(fc_import_all, nfrequency = 1)
export_yearly <- aggregate(fc_export_all, nfrequency = 1)
trade_yearly <- cbind(import_yearly, export_yearly)

# Store the other variables as time-series objects
gdp_usa <- ts(gdp_dataset$USA, frequency = 1, start = 1985)
gdp_china <- ts(gdp_dataset$China, frequency = 1, start = 1985)
cpi_usa <- ts(cpi_dataset$USA, frequency = 1, start = 1985)
cpi_china <- ts(cpi_dataset$China, frequency = 1, start = 1985)
ur_usa <- ts(ur_dataset$USA, frequency = 1, start = 1985)
```

```
ur_china <- ts(ur_dataset$China, frequency = 1, start = 1985)

##########################################################
# Preliminary analysis
##########################################################
# Time plot of original data
ggplot(gdp_dataset) +
  geom_line(aes(x = Year,y = USA, colour = "USA"), size = 1) +
  geom_line(aes(x = Year,y = China,colour ="China"),size=1) +
  scale_colour_manual("", values = c("China" = "red","USA" = "blue")) +
  xlab("Year") + ylab("Millions of U.S. Dollars") +
  ggtitle("Time Plot: GDP of China v.s. USA")
#*A drop of USA GDP in 2008-2009, should be due to Great Recession
#*Monotonic increasing of China GDP (the degree of increase constantly increases)

ggplot(cpi_dataset) +
  geom_line(aes(x = Year,y = USA, colour = "USA"), size = 1) +
  geom_line(aes(x = Year,y = China,colour ="China"),size=1) +
  scale_colour_manual("", values = c("China" = "red","USA" = "blue")) +
  xlab("Year") + ylab("Annual Growth Rate %") +
  ggtitle("Time Plot: CPI of China v.s. USA")
#*Analysis should be written in the dissertation
#*As time series goes on, large fluctuations appear

ggplot(ur_dataset) +
```

```
  geom_line(aes(x = Year,y = USA, colour = "USA"), size = 1) +
  geom_line(aes(x = Year,y = China,colour ="China"),size=1) +
  scale_colour_manual("", values = c("China" = "red","USA" = "blue")) +
  xlab("Year") + ylab("% of Labour Force") +
  ggtitle("Time Plot: Unemployment Rate of China v.s. USA")
#*Fluctuations appears in the U.S.
#*General pattern shows an increasing trend in China

#############################################################
# Both GDP have trend and no seasonality
# Both CPI have no trend and no seasonality
# USA unemployment rate has no trend and no seasonality
# China unemployment rate has trend and no seasonality
#############################################################
# Forecast using dynamic regression models
#############################################################
# 1 GDP
##ARIMA
arima_gdp_usa <- auto.arima(gdp_usa, d = 1, xreg = trade_yearly[1:34, ], stepwise = FALSE,
approximation = FALSE, trace = TRUE)
#*d = 1: take 1st difference
#*xreg: a numerical matrix of external regressors - import&export
#*stepwise = F: make our model try every combination of the model
#*approximation = F: make our model more accurate using the exact AIC instead of
approximate AIC
```

```
#*trace = T: print out all the models
print(summary(arima_gdp_usa))
#*ARIMA(2,1,0) errors
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(9.58e+09) = 97877.47
checkresiduals(arima_gdp_usa)
#*ACF shows all lags are inside the 95% CI
accuracy(arima_gdp_usa)
#*ME       RMSE      MAE       MPE       MAPE      MASE       ACF1
#*1757.571 88821.65 71350.91 -0.1166889 0.7232579 0.1411369 0.01121269

arima_gdp_china <- auto.arima(gdp_china, d = 1, xreg = trade_yearly[1:34, ], stepwise = FALSE, approximation = FALSE, trace = TRUE)
#*xreg: a numerical matrix of external regressors - import&export
#*stepwise = F: make our model try every combination of the model
#*approximation = F: make our model more accurate using the exact AIC instead of approximate AIC
#*trace = T: print out all the models
print(summary(arima_gdp_china))
#*ARIMA(1,1,1) errors
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(1.636e+10) = 127906.2
checkresiduals(arima_gdp_china)
#*ACF shows all lags are inside the 95% CI
accuracy(arima_gdp_china)
#*ME       RMSE      MAE       MPE       MAPE      MASE       ACF1
#*37948.5 116075.6 82223.14 0.07348095 1.70852 0.1102773 -0.08223658
```

```
##NNAR

set.seed(25784)

nnar_gdp_usa <- nnetar(gdp_usa, xreg = trade_yearly[1:34, ])

nnar_gdp_usa

#*NNAR(1,2)

#*Residual SD = sqrt(sigma^2 estimated) = sqrt(6.123e-05) = 0.00782496

#*p = 1: last 1 observation is used as predictors

#*k = 2: the number of hidden nodes (2 neurons in the hidden layer)

accuracy(nnar_gdp_usa)

#*ME      RMSE      MAE      MPE         MAPE      MASE       ACF1

#*-62.46487 61332.4 45159.5 -0.01988756 0.5317358 0.08932856 0.1281458


nnar_gdp_china <- nnetar(gdp_china,  xreg = trade_yearly[1:34, ])

nnar_gdp_china

#*NNAR(1,2)

#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.000246) = 0.01568439

#*p = 1: last 1 observation are used as predictors

#*k = 2: the number of hidden nodes (2 neurons in the hidden layer)

accuracy(nnar_gdp_china)

#*ME      RMSE      MAE      MPE      MAPE      MASE       ACF1

#*2076.398 90525.71 57578.96 -0.01405055 1.059446 0.07722465 0.05336912


#*Both GDP in US and China using NNAR
```

```
# 2 CPI
##ARIMA
arima_cpi_usa <- auto.arima(cpi_usa, xreg = trade_yearly[1:34, ], stepwise = FALSE,
approximation = FALSE, trace = TRUE)
#*xreg: a numerical matrix of external regressors - import&export
#*stepwise = F: make our model try every combination of the model
#*approximation = F: make our model more accurate using the exact AIC instead of
approximate AIC
#*trace = T: print out all the models
print(summary(arima_cpi_usa))
#*ARIMA(0,0,1) errors
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(1.031) = 1.015382
checkresiduals(arima_cpi_usa)
#*ACF shows all lags are inside the 95% CI
accuracy(arima_cpi_usa)
#*ME         RMSE      MAE       MPE       MAPE      MASE       ACF1
#*-0.00676133 0.9539593 0.6913773 -14.91935 88.32274 0.7611922 -0.02273644

arima_cpi_china <- auto.arima(cpi_china, xreg = trade_yearly[1:34, ], stepwise = FALSE,
approximation = FALSE, trace = TRUE)
#*xreg: a numerical matrix of external regressors - import&export
#*stepwise = F: make our model try every combination of the model
#*approximation = F: make our model more accurate using the exact AIC instead of
approximate AIC
#*trace = T: print out all the models
```

```
print(summary(arima_cpi_china))
#*ARIMA(0,0,1) errors
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(16.24) = 4.029888
checkresiduals(arima_cpi_china)
#*ACF shows all lags are inside the 95% CI
accuracy(arima_cpi_china)
#*ME      RMSE     MAE      MPE      MAPE     MASE      ACF1
#*-0.01429449 3.785105 2.801339 25.57312 140.3367 0.8358424 0.2022386

##NNAR
set.seed(25784)
nnar_cpi_usa <- nnetar(cpi_usa, xreg = trade_yearly[1:34, ])
nnar_cpi_usa
#*NNAR(1,2)
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.4665) = 0.6830081
#*p = 1: last 1 observation is used as predictors
#*k = 2: the number of hidden nodes (2 neurons in the hidden layer)
accuracy(nnar_cpi_usa)
#*ME       RMSE     MAE      MPE       MAPE     MASE      ACF1
#*0.001236831 0.6829751 0.5172169 -19.75173 66.38162 0.5694453 -0.05088162

nnar_cpi_china <- nnetar(cpi_china, xreg = trade_yearly[1:34, ])
nnar_cpi_china
#*NNAR(5,4)
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.06626) = 0.2574102
```

#*p = 5: last 5 observation are used as predictors

#*k = 4: the number of hidden nodes (4 neurons in the hidden layer)

accuracy(nnar_cpi_china)

#*ME RMSE MAE MPE MAPE MASE ACF1

#*-0.0007777047 0.2574062 0.1751069 5.382673 10.78762 0.05224709 -0.2453657

#*Both CPI in US and China using NNAR

3 Unemployment Rate

##ARIMA

arima_ur_usa <- auto.arima(ur_usa, xreg = trade_yearly[1:34,], stepwise = FALSE, approximation = FALSE, trace = TRUE)

#*xreg: a numerical matrix of external regressors - import&export

#*stepwise = F: make our model try every combination of the model

#*approximation = F: make our model more accurate using the exact AIC instead of approximate AIC

#*trace = T: print out all the models

print(summary(arima_ur_usa))

#*ARIMA(2,0,1) errors

#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.2862) = 0.5349766

checkresiduals(arima_ur_usa)

#*ACF shows all lags are inside the 95% CI

accuracy(arima_ur_usa)

#*ME RMSE MAE MPE MAPE MASE ACF1

#*0.04029842 0.4854454 0.3490715 0.8105623 5.892881 0.5290177 0.05104611

```
arima_ur_china <- auto.arima(ur_china, d = 1, xreg = trade_yearly[1:34, ], stepwise = FALSE, approximation = FALSE, trace = TRUE)
#*xreg: a numerical matrix of external regressors - import&export
#*stepwise = F: make our model try every combination of the model
#*approximation = F: make our model more accurate using the exact AIC instead of approximate AIC
#*trace = T: print out all the models
print(summary(arima_ur_china))
#*ARIMA(0,1,0) errors
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.03418) = 0.1848783
checkresiduals(arima_ur_china)
#*ACF shows all lags are inside the 95% CI
accuracy(arima_ur_china)
#*ME          RMSE      MAE       MPE        MAPE     MASE      ACF1
#*5.018642e-05 0.1736537 0.1271638 -0.0693511 4.074366 0.999144 0.1830708

##NNAR
set.seed(25784)
nnar_ur_usa <- nnetar(ur_usa, xreg = trade_yearly[1:34, ])
nnar_ur_usa
#*NNAR(2,2)
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.003791) = 0.0615711
#*p = 2: last 1 observation is used as predictors
#*k = 2: the number of hidden nodes (2 neurons in the hidden layer)
```

```
accuracy(nnar_ur_usa)
#*ME        RMSE      MAE       MPE         MAPE      MASE       ACF1
#*-0.001250892 0.2834774 0.2275057 -0.4227489 4.108182 0.3447848 0.1872391

nnar_ur_china <- nnetar(ur_china, xreg = trade_yearly[1:34,])
nnar_ur_china
#*NNAR(1,2)
#*Residual SD = sqrt(sigma^2 estimated) = sqrt(0.001817) = 0.04262628
#*p = 1: last 1 observation are used as predictors
#*k = 2: the number of hidden nodes (1 neurons in the hidden layer)
accuracy(nnar_ur_china)
#*ME       RMSE      MAE       MPE       MAPE      MASE       ACF1
#*-0.0001851183 0.1078269 0.08266885 -0.1901174 2.83701 0.649541 -0.0491004

#*Both Unemployment Rate in US and China using NNAR
###############################################################
# Forecast using time series models (without impacts of trade war)
###############################################################
# 1 GDP
arima_gdp_usa_n <- auto.arima(gdp_usa, d = 1, stepwise = FALSE, approximation = FALSE,
trace = TRUE)
#*ARIMA(1,1,0) with drift
print(summary(arima_gdp_usa_n))
#*Residual SD = sqrt(4.238e+10)
```

```
arima_gdp_china_n <- auto.arima(gdp_china, d = 1, stepwise = FALSE, approximation =
FALSE, trace = TRUE)
#*ARIMA(2,1,2)
print(summary(arima_gdp_china_n))
#*Residual SD = sqrt(1.665e+10)
accuracy(arima_gdp_usa_n)
#*ME      RMSE      MAE      MPE    MAPE      MASE      ACF1
#*5511.667 196565.1 137178.5 -0.2429258 1.23884 0.2713484 0.08572064
accuracy(arima_gdp_china_n)
#*ME       RMSE      MAE      MPE     MAPE     MASE       ACF1
#*33951.02 117082.9 81287.5 -0.09074421 1.730513 0.1090224 -0.07803587

set.seed(25784)
nnar_gdp_usa_n <- nnetar(gdp_usa)
nnar_gdp_usa_n
#*NNAR(1,1)
#*Residual SD = sqrt(0.0002723)
nnar_gdp_china_n <- nnetar(gdp_china)
nnar_gdp_china_n
#*NNAR(1,1)
#*Residual SD = sqrt(0.0005222)
accuracy(nnar_gdp_usa_n)
#*ME       RMSE      MAE       MPE     MAPE      MASE      ACF1
#*3114.823 228081.5 142060.7 -0.01849107 1.194269 0.2810058 0.4259529
accuracy(nnar_gdp_china_n)
```

```
#*ME        RMSE     MAE       MPE     MAPE     MASE     ACF1
#*7168.831 182282.5 111342.5 -0.04912824 1.832167 0.149332 0.423674

#*Best model should be ARIMA when forecasting GDP in both countries.

fcst_gdp_usa_n <- forecast(arima_gdp_usa_n, h = 3)
fcst_gdp_china_n <- forecast(arima_gdp_china_n, h = 3)

# 2 CPI
arima_cpi_usa_n <- auto.arima(cpi_usa, stepwise = FALSE, approximation = FALSE, trace =
TRUE)
#*ARIMA(0,1,2)
print(summary(arima_cpi_usa_n))
#*Residual SD = sqrt(1.123)
arima_cpi_china_n <- auto.arima(cpi_china, stepwise = FALSE, approximation = FALSE,
trace = TRUE)
#*ARIMA(0,1,2)
print(summary(arima_cpi_china_n))
#*Residual SD = sqrt(16.37)
accuracy(arima_cpi_usa_n)
#*ME         RMSE      MAE      MPE    MAPE      MASE      ACF1
#*-0.193704 1.012062 0.7433498 -21.56326 100.4545 0.818413 -0.07482249
accuracy(arima_cpi_china_n)
#*ME        RMSE      MAE      MPE     MAPE     MASE       ACF1
#*-0.5114925 3.863039 2.861922 25.83405 135.8875 0.8539189 0.1444656
```

```
set.seed(25784)

nnar_cpi_usa_n <- nnetar(cpi_usa)

nnar_cpi_usa_n

#*NNAR(1,1)

#*Residual SD = sqrt(1.001)

nnar_cpi_china_n <- nnetar(cpi_china)

nnar_cpi_china_n

#*NNAR(5,3)

#*Residual SD = sqrt(0.7689)

accuracy(nnar_cpi_usa_n)

#*ME          RMSE      MAE       MPE     MAPE      MASE      ACF1

#*0.001083309 1.000271 0.7233561 -22.51689 101.6376 0.7964003 0.05681852

accuracy(nnar_cpi_china_n)

#*ME          RMSE      MAE       MPE     MAPE      MASE      ACF1

#*0.003091029 0.876869 0.64863 13.75952 41.13341 0.1935334 -0.06113646


#*Best model should be NNAR when forecasting CPI in both countries.


fcst_cpi_usa_n <- forecast(nnar_cpi_usa_n, PI = TRUE, h = 3)

fcst_cpi_china_n <- forecast(nnar_cpi_china_n, PI = TRUE, h = 3)


# 3 Unemployment Rate

arima_ur_usa_n <- auto.arima(ur_usa, stepwise = FALSE, approximation = FALSE, trace =
TRUE)
```

```
#*ARIMA(2,0,0)
print(summary(arima_ur_usa_n))
#*Residual SD = sqrt(0.4382)
arima_ur_china_n <- auto.arima(ur_china, d = 1, stepwise = FALSE, approximation = FALSE,
trace = TRUE)
#*ARIMA(0,1,1)
print(summary(arima_ur_china_n))
#*Residual SD = sqrt(0.03522)
accuracy(arima_ur_usa_n)
#*ME          RMSE       MAE       MPE    MAPE      MASE       ACF1
#*-0.006916699 0.63207 0.4333709 -1.284165 7.11417 0.6567733 0.09630501
accuracy(arima_ur_china_n)
#*ME         RMSE       MAE       MPE     MAPE     MASE       ACF1
#*0.04292576 0.182061 0.1208995 1.469917 3.877175 0.949925 -0.07350245

set.seed(25784)
nnar_ur_usa_n <- nnetar(ur_usa)
nnar_ur_usa_n
#*NNAR(2,2)
#*Residual SD = sqrt(0.006787)
nnar_ur_china_n <- nnetar(ur_china)
nnar_ur_china_n
#*NNAR(1,1)
#*Residual SD = sqrt(0.02568)
accuracy(nnar_ur_usa_n)
```

```
#*ME          RMSE      MAE       MPE     MAPE      MASE      ACF1
#*0.0008549603 0.5224743 0.3699153 -0.6922858 6.279768 0.5606064 0.3377347
accuracy(nnar_ur_china_n)
#*ME          RMSE      MAE       MPE     MAPE      MASE      ACF1
#*4.920407e-07 0.1602561 0.125162 -0.3232209 4.148301 0.983416 0.201808

#*Best model should be NNAR when forecasting Unemployment Rate in USA, ARIMA in China.

fcst_ur_usa_n <- forecast(nnar_ur_usa_n, PI = TRUE, h = 3)
fcst_ur_china_n <- forecast(arima_ur_china_n, h = 3)

#############################################################
# Forecast 2019 - 2021
#############################################################
fcst_gdp_usa <- forecast(nnar_gdp_usa, PI = TRUE, xreg = trade_yearly[35:37, ], h = 3)
autoplot(fcst_gdp_usa) +
  ggtitle("GDP - USA (Forecasted from 2019 to 2021)") +
  ylab("Millions of U.S. Dollars")+
  autolayer(fcst_gdp_usa_n$mean)

fcst_gdp_china <- forecast(nnar_gdp_china, PI = TRUE, xreg = trade_yearly[35:37, ], h = 3)
autoplot(fcst_gdp_china) +
  ggtitle("GDP - China (Forecasted from 2019 to 2021)") +
  ylab("Millions of U.S. Dollars")+
```

```
  autolayer(fcst_gdp_china_n$mean)

fcst_cpi_usa <- forecast(nnar_cpi_usa, PI = TRUE, xreg = trade_yearly[35:37, ], h = 3)
autoplot(fcst_cpi_usa) +
  ggtitle("CPI - USA (Forecasted from 2019 to 2021)") +
  ylab("Annual Growth Rate %")+
  autolayer(fcst_cpi_usa_n$mean)

fcst_cpi_china <- forecast(nnar_cpi_china, PI = TRUE, xreg = trade_yearly[35:37, ], h = 3)
autoplot(fcst_cpi_china) +
  ggtitle("CPI - China (Forecasted from 2019 to 2021)") +
  ylab("Annual Growth Rate %")+
  autolayer(fcst_cpi_china_n$mean)

fcst_ur_usa <- forecast(nnar_ur_usa, PI = TRUE, xreg = trade_yearly[35:37, ], h = 3)
autoplot(fcst_ur_usa) +
  ggtitle("Unemployment Rate - USA (Forecasted from 2019 to 2021)") +
  ylab("% of labour force")+
  autolayer(fcst_ur_usa_n$mean)

fcst_ur_china <- forecast(nnar_ur_china, PI = TRUE, xreg = trade_yearly[35:37, ], h = 3)
autoplot(fcst_ur_china) +
  ggtitle("Unemployment Rate - China (Forecasted from 2019 to 2021)") +
  ylab("% of labour force") +
  autolayer(fcst_ur_china_n$mean)
```

C – LIST OF ARIMA MODELS WITH AICC

C – 1 ARIMA for Imports

Models	AICc
ARIMA(0,1,0)(0,1,0)[12]	-657.4163
ARIMA(0,1,0)(0,1,1)[12]	-841.9566
ARIMA(0,1,0)(0,1,2)[12]	-842.1447
ARIMA(0,1,0)(1,1,0)[12]	-768.763
ARIMA(0,1,0)(1,1,1)[12]	-841.705
ARIMA(0,1,0)(1,1,2)[12]	-840.683
ARIMA(0,1,0)(2,1,0)[12]	-831.8233
ARIMA(0,1,0)(2,1,1)[12]	-843.0135
ARIMA(0,1,0)(2,1,2)[12]	-849.8554
ARIMA(0,1,1)(0,1,0)[12]	-772.0322
ARIMA(0,1,1)(0,1,1)[12]	-921.0352
ARIMA(0,1,1)(0,1,2)[12]	-921.3083
ARIMA(0,1,1)(1,1,0)[12]	-881.771
ARIMA(0,1,1)(1,1,1)[12]	-921.1123
ARIMA(0,1,1)(1,1,2)[12]	-917.4287
ARIMA(0,1,1)(2,1,0)[12]	-921.0698
ARIMA(0,1,1)(2,1,1)[12]	-919.9908
ARIMA(0,1,1)(2,1,2)[12]	-923.6178
ARIMA(0,1,2)(0,1,0)[12]	-771.059
ARIMA(0,1,2)(0,1,1)[12]	-919.4382

ARIMA(0,1,2)(0,1,2)[12]	-919.4807
ARIMA(0,1,2)(1,1,0)[12]	-880.7083
ARIMA(0,1,2)(1,1,1)[12]	-919.2989
ARIMA(0,1,2)(1,1,2)[12]	-915.9437
ARIMA(0,1,2)(2,1,0)[12]	-919.0168
ARIMA(0,1,2)(2,1,1)[12]	-918.1267
ARIMA(0,1,3)(0,1,0)[12]	-775.732
ARIMA(0,1,3)(0,1,1)[12]	-917.943
ARIMA(0,1,3)(0,1,2)[12]	-917.9647
ARIMA(0,1,3)(1,1,0)[12]	-882.7992
ARIMA(0,1,3)(1,1,1)[12]	-917.7968
ARIMA(0,1,3)(2,1,0)[12]	-918.4511
ARIMA(0,1,4)(0,1,0)[12]	-774.9087
ARIMA(0,1,4)(0,1,1)[12]	-923.0441
ARIMA(0,1,4)(1,1,0)[12]	-886.2196
ARIMA(0,1,5)(0,1,0)[12]	-773.4947
ARIMA(1,1,0)(0,1,0)[12]	-734.7284
ARIMA(1,1,0)(0,1,1)[12]	-895.8019
ARIMA(1,1,0)(0,1,2)[12]	-896.9957
ARIMA(1,1,0)(1,1,0)[12]	-847.0734
ARIMA(1,1,0)(1,1,1)[12]	-896.5288
ARIMA(1,1,0)(1,1,2)[12]	-892.3887
ARIMA(1,1,0)(2,1,0)[12]	-895.4324
ARIMA(1,1,0)(2,1,1)[12]	-896.3987

ARIMA(1,1,0)(2,1,2)[12]	-900.8114
ARIMA(1,1,1)(0,1,0)[12]	-770.6707
ARIMA(1,1,1)(0,1,1)[12]	-919.3841
ARIMA(1,1,1)(0,1,2)[12]	-919.4506
ARIMA(1,1,1)(1,1,0)[12]	-880.3654
ARIMA(1,1,1)(1,1,1)[12]	Inf
ARIMA(1,1,1)(1,1,2)[12]	-915.8753
ARIMA(1,1,1)(2,1,0)[12]	Inf
ARIMA(1,1,1)(2,1,1)[12]	Inf
ARIMA(1,1,2)(0,1,0)[12]	-770.7774
ARIMA(1,1,2)(0,1,1)[12]	-920.155
ARIMA(1,1,2)(0,1,2)[12]	-920.0336
ARIMA(1,1,2)(1,1,0)[12]	Inf
ARIMA(1,1,2)(1,1,1)[12]	-918.8187
ARIMA(1,1,2)(2,1,0)[12]	Inf
ARIMA(1,1,3)(0,1,0)[12]	Inf
ARIMA(1,1,3)(0,1,1)[12]	-918.2372
ARIMA(1,1,3)(1,1,0)[12]	Inf
ARIMA(1,1,4)(0,1,0)[12]	-789.0561
ARIMA(2,1,0)(0,1,0)[12]	-777.9887
ARIMA(2,1,0)(0,1,1)[12]	-922.3772
ARIMA(2,1,0)(0,1,2)[12]	-923.3388
ARIMA(2,1,0)(1,1,0)[12]	-891.2704
ARIMA(2,1,0)(1,1,1)[12]	-923.1672

ARIMA(2,1,0)(1,1,2)[12]	-921.2753
ARIMA(2,1,0)(2,1,0)[12]	-925.2348
ARIMA(2,1,0)(2,1,1)[12]	-924.9506
ARIMA(2,1,1)(0,1,0)[12]	-776.312
ARIMA(2,1,1)(0,1,1)[12]	-920.4398
ARIMA(2,1,1)(0,1,2)[12]	-921.5925
ARIMA(2,1,1)(1,1,0)[12]	-889.5579
ARIMA(2,1,1)(1,1,1)[12]	-921.4116
ARIMA(2,1,1)(2,1,0)[12]	-923.8976
ARIMA(2,1,2)(0,1,0)[12]	-775.6973
ARIMA(2,1,2)(0,1,1)[12]	-919.2238
ARIMA(2,1,2)(1,1,0)[12]	-887.851
ARIMA(2,1,3)(0,1,0)[12]	Inf
ARIMA(3,1,0)(0,1,0)[12]	-776.1229
ARIMA(3,1,0)(0,1,1)[12]	-920.3785
ARIMA(3,1,0)(0,1,2)[12]	-921.455
ARIMA(3,1,0)(1,1,0)[12]	-889.4534
ARIMA(3,1,0)(1,1,1)[12]	-921.2781
ARIMA(3,1,0)(2,1,0)[12]	-923.6168
ARIMA(3,1,1)(0,1,0)[12]	-788.6589
ARIMA(3,1,1)(0,1,1)[12]	-918.4855
ARIMA(3,1,1)(1,1,0)[12]	-887.5679
ARIMA(3,1,2)(0,1,0)[12]	-773.7619
ARIMA(4,1,0)(0,1,0)[12]	-777.0612

ARIMA(4,1,0)(0,1,1)[12]	-920.8679
ARIMA(4,1,0)(1,1,0)[12]	-888.8141
ARIMA(4,1,1)(0,1,0)[12]	-774.9977
ARIMA(5,1,0)(0,1,0)[12]	-774.9988

C – 2 ARIMA for Exports

Models	AICc
ARIMA(0,1,0)	-217.2418
ARIMA(0,1,0) with drift	-216.0991
ARIMA(0,1,0)(0,0,1)[12]	-243.3122
ARIMA(0,1,0)(0,0,1)[12] with drift	-241.8873
ARIMA(0,1,0)(0,0,2)[12]	-251.4251
ARIMA(0,1,0)(0,0,2)[12] with drift	-249.8445
ARIMA(0,1,0)(1,0,0)[12]	-251.8417
ARIMA(0,1,0)(1,0,0)[12] with drift	-250.264
ARIMA(0,1,0)(1,0,1)[12]	Inf
ARIMA(0,1,0)(1,0,1)[12] with drift	Inf
ARIMA(0,1,0)(1,0,2)[12]	Inf
ARIMA(0,1,0)(1,0,2)[12] with drift	Inf
ARIMA(0,1,0)(2,0,0)[12]	-256.5408
ARIMA(0,1,0)(2,0,0)[12] with drift	-254.8325
ARIMA(0,1,0)(2,0,1)[12]	Inf
ARIMA(0,1,0)(2,0,1)[12] with drift	Inf
ARIMA(0,1,0)(2,0,2)[12]	Inf

ARIMA(0,1,0)(2,0,2)[12] with drift	Inf
ARIMA(0,1,1)	-331.7127
ARIMA(0,1,1) with drift	-340.2078
ARIMA(0,1,1)(0,0,1)[12]	-361.1026
ARIMA(0,1,1)(0,0,1)[12] with drift	-365.7577
ARIMA(0,1,1)(0,0,2)[12]	-367.2321
ARIMA(0,1,1)(0,0,2)[12] with drift	-370.1931
ARIMA(0,1,1)(1,0,0)[12]	-369.0377
ARIMA(0,1,1)(1,0,0)[12] with drift	-371.9502
ARIMA(0,1,1)(1,0,1)[12]	Inf
ARIMA(0,1,1)(1,0,1)[12] with drift	Inf
ARIMA(0,1,1)(1,0,2)[12]	Inf
ARIMA(0,1,1)(1,0,2)[12] with drift	Inf
ARIMA(0,1,1)(2,0,0)[12]	-370.7726
ARIMA(0,1,1)(2,0,0)[12] with drift	-372.7121
ARIMA(0,1,1)(2,0,1)[12]	Inf
ARIMA(0,1,1)(2,0,1)[12] with drift	Inf
ARIMA(0,1,1)(2,0,2)[12]	Inf
ARIMA(0,1,1)(2,0,2)[12] with drift	Inf
ARIMA(0,1,2)	-330.1998
ARIMA(0,1,2) with drift	-340.5027
ARIMA(0,1,2)(0,0,1)[12]	-359.1554
ARIMA(0,1,2)(0,0,1)[12] with drift	-364.425
ARIMA(0,1,2)(0,0,2)[12]	-365.2484

ARIMA(0,1,2)(0,0,2)[12] with drift	-368.5882
ARIMA(0,1,2)(1,0,0)[12]	-367.0717
ARIMA(0,1,2)(1,0,0)[12] with drift	-370.3726
ARIMA(0,1,2)(1,0,1)[12]	Inf
ARIMA(0,1,2)(1,0,1)[12] with drift	Inf
ARIMA(0,1,2)(1,0,2)[12]	Inf
ARIMA(0,1,2)(1,0,2)[12] with drift	Inf
ARIMA(0,1,2)(2,0,0)[12]	-368.9342
ARIMA(0,1,2)(2,0,0)[12] with drift	-371.2615
ARIMA(0,1,2)(2,0,1)[12]	Inf
ARIMA(0,1,2)(2,0,1)[12] with drift	Inf
ARIMA(0,1,3)	-332.3285
ARIMA(0,1,3) with drift	-345.8474
ARIMA(0,1,3)(0,0,1)[12]	-361.3535
ARIMA(0,1,3)(0,0,1)[12] with drift	-369.3976
ARIMA(0,1,3)(0,0,2)[12]	-369.1732
ARIMA(0,1,3)(0,0,2)[12] with drift	-374.4806
ARIMA(0,1,3)(1,0,0)[12]	-370.2114
ARIMA(0,1,3)(1,0,0)[12] with drift	-375.6513
ARIMA(0,1,3)(1,0,1)[12]	Inf
ARIMA(0,1,3)(1,0,1)[12] with drift	Inf
ARIMA(0,1,3)(2,0,0)[12]	-373.5367
ARIMA(0,1,3)(2,0,0)[12] with drift	-377.4429
ARIMA(0,1,4)	-331.6331

ARIMA(0,1,4) with drift	-344.1915
ARIMA(0,1,4)(0,0,1)[12]	-360.0244
ARIMA(0,1,4)(0,0,1)[12] with drift	-367.4185
ARIMA(0,1,4)(1,0,0)[12]	-368.7532
ARIMA(0,1,4)(1,0,0)[12] with drift	-373.6875
ARIMA(0,1,5)	-329.7609
ARIMA(0,1,5) with drift	-343.2006
ARIMA(1,1,0)	-304.0256
ARIMA(1,1,0) with drift	-304.4714
ARIMA(1,1,0)(0,0,1)[12]	-335.3067
ARIMA(1,1,0)(0,0,1)[12] with drift	-335.0113
ARIMA(1,1,0)(0,0,2)[12]	-345.2338
ARIMA(1,1,0)(0,0,2)[12] with drift	-344.4744
ARIMA(1,1,0)(1,0,0)[12]	-345.0006
ARIMA(1,1,0)(1,0,0)[12] with drift	-344.2466
ARIMA(1,1,0)(1,0,1)[12]	Inf
ARIMA(1,1,0)(1,0,1)[12] with drift	Inf
ARIMA(1,1,0)(1,0,2)[12]	Inf
ARIMA(1,1,0)(1,0,2)[12] with drift	Inf
ARIMA(1,1,0)(2,0,0)[12]	-347.6445
ARIMA(1,1,0)(2,0,0)[12] with drift	-346.5949
ARIMA(1,1,0)(2,0,1)[12]	Inf
ARIMA(1,1,0)(2,0,1)[12] with drift	Inf
ARIMA(1,1,0)(2,0,2)[12]	Inf

ARIMA(1,1,0)(2,0,2)[12] with drift	Inf
ARIMA(1,1,1)	-330.4088
ARIMA(1,1,1) with drift	-341.7005
ARIMA(1,1,1)(0,0,1)[12]	-359.1973
ARIMA(1,1,1)(0,0,1)[12] with drift	-364.8715
ARIMA(1,1,1)(0,0,2)[12]	-365.2861
ARIMA(1,1,1)(0,0,2)[12] with drift	-368.8961
ARIMA(1,1,1)(1,0,0)[12]	-367.1097
ARIMA(1,1,1)(1,0,0)[12] with drift	-370.6777
ARIMA(1,1,1)(1,0,1)[12]	Inf
ARIMA(1,1,1)(1,0,1)[12] with drift	Inf
ARIMA(1,1,1)(1,0,2)[12]	Inf
ARIMA(1,1,1)(1,0,2)[12] with drift	Inf
ARIMA(1,1,1)(2,0,0)[12]	Inf
ARIMA(1,1,1)(2,0,0)[12] with drift	-371.6759
ARIMA(1,1,1)(2,0,1)[12]	-367.3093
ARIMA(1,1,1)(2,0,1)[12] with drift	Inf
ARIMA(1,1,2)	Inf
ARIMA(1,1,2) with drift	-343.1932
ARIMA(1,1,2)(0,0,1)[12]	Inf
ARIMA(1,1,2)(0,0,1)[12] with drift	Inf
ARIMA(1,1,2)(0,0,2)[12]	-365.2728
ARIMA(1,1,2)(0,0,2)[12] with drift	-367.8179
ARIMA(1,1,2)(1,0,0)[12]	Inf

ARIMA(1,1,2)(1,0,0)[12] with drift	Inf
ARIMA(1,1,2)(1,0,1)[12]	Inf
ARIMA(1,1,2)(1,0,1)[12] with drift	Inf
ARIMA(1,1,2)(2,0,0)[12]	-369.2685
ARIMA(1,1,2)(2,0,0)[12] with drift	Inf
ARIMA(1,1,3)	-331.6998
ARIMA(1,1,3) with drift	-344.45
ARIMA(1,1,3)(0,0,1)[12]	-360.0541
ARIMA(1,1,3)(0,0,1)[12] with drift	-367.5281
ARIMA(1,1,3)(1,0,0)[12]	Inf
ARIMA(1,1,3)(1,0,0)[12] with drift	-373.768
ARIMA(1,1,4)	-329.673
ARIMA(1,1,4) with drift	Inf
ARIMA(2,1,0)	-311.3596
ARIMA(2,1,0) with drift	-312.8405
ARIMA(2,1,0)(0,0,1)[12]	-343.1046
ARIMA(2,1,0)(0,0,1)[12] with drift	-343.5444
ARIMA(2,1,0)(0,0,2)[12]	-350.6428
ARIMA(2,1,0)(0,0,2)[12] with drift	-350.4179
ARIMA(2,1,0)(1,0,0)[12]	-351.8489
ARIMA(2,1,0)(1,0,0)[12] with drift	-351.6296
ARIMA(2,1,0)(1,0,1)[12]	Inf
ARIMA(2,1,0)(1,0,1)[12] with drift	Inf
ARIMA(2,1,0)(1,0,2)[12]	Inf

ARIMA(2,1,0)(1,0,2)[12] with drift	Inf
ARIMA(2,1,0)(2,0,0)[12]	-353.3453
ARIMA(2,1,0)(2,0,0)[12] with drift	-352.7347
ARIMA(2,1,0)(2,0,1)[12]	Inf
ARIMA(2,1,0)(2,0,1)[12] with drift	Inf
ARIMA(2,1,1)	-331.4426
ARIMA(2,1,1) with drift	-345.4931
ARIMA(2,1,1)(0,0,1)[12]	-360.9543
ARIMA(2,1,1)(0,0,1)[12] with drift	-371.3502
ARIMA(2,1,1)(0,0,2)[12]	-368.353
ARIMA(2,1,1)(0,0,2)[12] with drift	-376.5848
ARIMA(2,1,1)(1,0,0)[12]	-369.7718
ARIMA(2,1,1)(1,0,0)[12] with drift	-378.3982
ARIMA(2,1,1)(1,0,1)[12]	Inf
ARIMA(2,1,1)(1,0,1)[12] with drift	Inf
ARIMA(2,1,1)(2,0,0)[12]	-372.6089
ARIMA(2,1,1)(2,0,0)[12] with drift	-379.6035
ARIMA(2,1,2)	Inf
ARIMA(2,1,2) with drift	Inf
ARIMA(2,1,2)(0,0,1)[12]	-360.078
ARIMA(2,1,2)(0,0,1)[12] with drift	-369.5348
ARIMA(2,1,2)(1,0,0)[12]	-368.581
ARIMA(2,1,2)(1,0,0)[12] with drift	-376.95
ARIMA(2,1,3)	Inf

ARIMA(2,1,3) with drift	Inf
ARIMA(3,1,0)	-325.255
ARIMA(3,1,0) with drift	-328.7239
ARIMA(3,1,0)(0,0,1)[12]	-354.2717
ARIMA(3,1,0)(0,0,1)[12] with drift	-356.0021
ARIMA(3,1,0)(0,0,2)[12]	-360.7467
ARIMA(3,1,0)(0,0,2)[12] with drift	-361.499
ARIMA(3,1,0)(1,0,0)[12]	-361.9461
ARIMA(3,1,0)(1,0,0)[12] with drift	-362.7202
ARIMA(3,1,0)(1,0,1)[12]	Inf
ARIMA(3,1,0)(1,0,1)[12] with drift	Inf
ARIMA(3,1,0)(2,0,0)[12]	-363.2233
ARIMA(3,1,0)(2,0,0)[12] with drift	-363.4299
ARIMA(3,1,1)	-331.3462
ARIMA(3,1,1) with drift	-344.2833
ARIMA(3,1,1)(0,0,1)[12]	-359.8012
ARIMA(3,1,1)(0,0,1)[12] with drift	-369.3096
ARIMA(3,1,1)(1,0,0)[12]	-368.4739
ARIMA(3,1,1)(1,0,0)[12] with drift	-376.4783
ARIMA(3,1,2)	-331.9973
ARIMA(3,1,2) with drift	Inf
ARIMA(4,1,0)	-326.2495
ARIMA(4,1,0) with drift	-330.933
ARIMA(4,1,0)(0,0,1)[12]	-355.9313

ARIMA(4,1,0)(0,0,1)[12] with drift	-358.5451
ARIMA(4,1,0)(1,0,0)[12]	-364.5119
ARIMA(4,1,0)(1,0,0)[12] with drift	-365.9555
ARIMA(4,1,1)	-329.6262
ARIMA(4,1,1) with drift	-343.3143
ARIMA(5,1,0)	-325.3777
ARIMA(5,1,0) with drift	-331.0028

C – 3 ARIMA for GDP in the USA with regressors

Models	AICc
ARIMA(0,1,0)	934.7163
Regression with ARIMA(0,1,0) errors	877.7812
ARIMA(0,1,1)	Inf
Regression with ARIMA(0,1,1) errors	864.7971
ARIMA(0,1,2)	Inf
Regression with ARIMA(0,1,2) errors	863.5133
ARIMA(0,1,3)	Inf
Regression with ARIMA(0,1,3) errors	866.4357
ARIMA(0,1,4)	Inf
Regression with ARIMA(0,1,4) errors	Inf
ARIMA(0,1,5)	Inf
Regression with ARIMA(0,1,5) errors	Inf
ARIMA(1,1,0)	868.4894
Regression with ARIMA(1,1,0) errors	864.9983

ARIMA(1,1,1)	869.31
Regression with ARIMA(1,1,1) errors	863.9834
ARIMA(1,1,2)	Inf
Regression with ARIMA(1,1,2) errors	866.3103
ARIMA(1,1,3)	Inf
Regression with ARIMA(1,1,3) errors	869.8302
ARIMA(1,1,4)	Inf
Regression with ARIMA(1,1,4) errors	Inf
ARIMA(2,1,0)	869.9824
Regression with ARIMA(2,1,0) errors	862.9581
ARIMA(2,1,1)	872.2813
Regression with ARIMA(2,1,1) errors	866.1831
ARIMA(2,1,2)	875.0811
Regression with ARIMA(2,1,2) errors	869.5962
ARIMA(2,1,3)	Inf
Regression with ARIMA(2,1,3) errors	Inf
ARIMA(3,1,0)	Inf
Regression with ARIMA(3,1,0) errors	866.1701
ARIMA(3,1,1)	Inf
Regression with ARIMA(3,1,1) errors	869.709
ARIMA(3,1,2)	878.7484
Regression with ARIMA(3,1,2) errors	873.3505
ARIMA(4,1,0)	Inf
Regression with ARIMA(4,1,0) errors	869.3694

ARIMA(4,1,1)	Inf
Regression with ARIMA(4,1,1) errors	873.3066
ARIMA(5,1,0)	Inf
Regression with ARIMA(5,1,0) errors	872.8292

C – 4 ARIMA for GDP in China with regressors

Models	AICc
ARIMA(0,1,0)	988.3658
Regression with ARIMA(0,1,0) errors	975.4145
ARIMA(0,1,1)	Inf
Regression with ARIMA(0,1,1) errors	Inf
ARIMA(0,1,2)	Inf
Regression with ARIMA(0,1,2) errors	Inf
ARIMA(0,1,3)	Inf
Regression with ARIMA(0,1,3) errors	Inf
ARIMA(0,1,4)	Inf
Regression with ARIMA(0,1,4) errors	Inf
ARIMA(0,1,5)	Inf
Regression with ARIMA(0,1,5) errors	Inf
ARIMA(1,1,0)	Inf
ARIMA(1,1,0) with drift	Inf
ARIMA(1,1,1)	Inf
Regression with ARIMA(1,1,1) errors	883.9525
ARIMA(1,1,2)	Inf

Regression with ARIMA(1,1,2) errors	Inf
ARIMA(1,1,3)	Inf
Regression with ARIMA(1,1,3) errors	Inf
ARIMA(1,1,4)	Inf
ARIMA(1,1,4) with drift	Inf
ARIMA(2,1,0)	Inf
ARIMA(2,1,0) with drift	Inf
ARIMA(2,1,1)	Inf
ARIMA(2,1,1) with drift	Inf
ARIMA(2,1,2)	Inf
Regression with ARIMA(2,1,2) errors	Inf
ARIMA(2,1,3)	Inf
Regression with ARIMA(2,1,3) errors	Inf
ARIMA(3,1,0)	Inf
ARIMA(3,1,0) with drift	Inf
ARIMA(3,1,1)	Inf
ARIMA(3,1,1) with drift	Inf
ARIMA(3,1,2)	Inf
Regression with ARIMA(3,1,2) errors	Inf
ARIMA(4,1,0)	Inf
ARIMA(4,1,0) with drift	Inf
ARIMA(4,1,1)	Inf
ARIMA(4,1,1) with drift	Inf
ARIMA(5,1,0)	Inf

ARIMA(5,1,0) with drift	Inf

C – 5 ARIMA for GDP in the USA without regressors

Models	AICc
ARIMA(0,1,0)	967.1684
ARIMA(0,1,0) with drift	913.5647
ARIMA(0,1,1)	943.5526
ARIMA(0,1,1) with drift	906.8374
ARIMA(0,1,2)	929.7184
ARIMA(0,1,2) with drift	907.7017
ARIMA(0,1,3)	933.6437
ARIMA(0,1,3) with drift	910.4428
ARIMA(0,1,4)	Inf
ARIMA(0,1,4) with drift	913.4035
ARIMA(0,1,5)	924.8158
ARIMA(0,1,5) with drift	Inf
ARIMA(1,1,0)	911.8043
ARIMA(1,1,0) with drift	906.2764
ARIMA(1,1,1)	913.9768
ARIMA(1,1,1) with drift	908.1044
ARIMA(1,1,2)	Inf
ARIMA(1,1,2) with drift	910.4563
ARIMA(1,1,3)	Inf
ARIMA(1,1,3) with drift	913.4444

ARIMA(1,1,4)	927.0862
ARIMA(1,1,4) with drift	916.6991
ARIMA(2,1,0)	914.0912
ARIMA(2,1,0) with drift	907.9215
ARIMA(2,1,1)	Inf
ARIMA(2,1,1) with drift	910.7007
ARIMA(2,1,2)	Inf
ARIMA(2,1,2) with drift	Inf
ARIMA(2,1,3)	Inf
ARIMA(2,1,3) with drift	Inf
ARIMA(3,1,0)	915.6159
ARIMA(3,1,0) with drift	910.6927
ARIMA(3,1,1)	Inf
ARIMA(3,1,1) with drift	Inf
ARIMA(3,1,2)	Inf
ARIMA(3,1,2) with drift	Inf
ARIMA(4,1,0)	Inf
ARIMA(4,1,0) with drift	913.6294
ARIMA(4,1,1)	Inf
ARIMA(4,1,1) with drift	Inf
ARIMA(5,1,0)	Inf
ARIMA(5,1,0) with drift	916.8763

C – 6 ARIMA for GDP in China without regressors

Models	AICc
ARIMA(0,1,0)	1004.892
ARIMA(0,1,0) with drift	976.6345
ARIMA(0,1,1)	Inf
ARIMA(0,1,1) with drift	Inf
ARIMA(0,1,2)	Inf
ARIMA(0,1,2) with drift	Inf
ARIMA(0,1,3)	924.0633
ARIMA(0,1,3) with drift	908.9015
ARIMA(0,1,4)	917.6838
ARIMA(0,1,4) with drift	905.9564
ARIMA(0,1,5)	Inf
ARIMA(0,1,5) with drift	899.1851
ARIMA(1,1,0)	Inf
ARIMA(1,1,0) with drift	Inf
ARIMA(1,1,1)	Inf
ARIMA(1,1,1) with drift	Inf
ARIMA(1,1,2)	Inf
ARIMA(1,1,2) with drift	Inf
ARIMA(1,1,3)	Inf
ARIMA(1,1,3) with drift	Inf
ARIMA(1,1,4)	Inf
ARIMA(1,1,4) with drift	Inf

ARIMA(2,1,0)	Inf
ARIMA(2,1,0) with drift	Inf
ARIMA(2,1,1)	Inf
ARIMA(2,1,1) with drift	Inf
ARIMA(2,1,2)	Inf
ARIMA(2,1,2) with drift	884.6957
ARIMA(2,1,3)	Inf
ARIMA(2,1,3) with drift	887.7644
ARIMA(3,1,0)	Inf
ARIMA(3,1,0) with drift	Inf
ARIMA(3,1,1)	Inf
ARIMA(3,1,1) with drift	Inf
ARIMA(3,1,2)	Inf
ARIMA(3,1,2) with drift	Inf
ARIMA(4,1,0)	Inf
ARIMA(4,1,0) with drift	Inf
ARIMA(4,1,1)	Inf
ARIMA(4,1,1) with drift	Inf
ARIMA(5,1,0)	Inf
ARIMA(5,1,0) with drift	Inf

C – 7 ARIMA for CPI in the USA with regressors

Models	AICc
ARIMA(0,0,0) with zero mean	162.2433

ARIMA(0,0,0) with non-zero mean	106.2119
ARIMA(0,0,1) with zero mean	139.4739
ARIMA(0,0,1) with non-zero mean	105.5611
ARIMA(0,0,2) with zero mean	135.8791
ARIMA(0,0,2) with non-zero mean	108.3279
ARIMA(0,0,3) with zero mean	Inf
ARIMA(0,0,3) with non-zero mean	111.5242
ARIMA(0,0,4) with zero mean	Inf
ARIMA(0,0,4) with non-zero mean	114.7571
ARIMA(0,0,5) with zero mean	Inf
ARIMA(0,0,5) with non-zero mean	Inf
ARIMA(1,0,0) with zero mean	114.2428
ARIMA(1,0,0) with non-zero mean	106.2977
ARIMA(1,0,1) with zero mean	114.3149
ARIMA(1,0,1) with non-zero mean	108.3299
ARIMA(1,0,2) with zero mean	Inf
ARIMA(1,0,2) with non-zero mean	Inf
ARIMA(1,0,3) with zero mean	Inf
ARIMA(1,0,3) with non-zero mean	114.8104
ARIMA(1,0,4) with zero mean	Inf
ARIMA(1,0,4) with non-zero mean	Inf
ARIMA(2,0,0) with zero mean	115.5799
ARIMA(2,0,0) with non-zero mean	108.5256
ARIMA(2,0,1) with zero mean	Inf

ARIMA(2,0,1) with non-zero mean	111.5257
ARIMA(2,0,2) with zero mean	Inf
ARIMA(2,0,2) with non-zero mean	Inf
ARIMA(2,0,3) with zero mean	Inf
ARIMA(2,0,3) with non-zero mean	Inf
ARIMA(3,0,0) with zero mean	116.3778
ARIMA(3,0,0) with non-zero mean	111.7175
ARIMA(3,0,1) with zero mean	119.3348
ARIMA(3,0,1) with non-zero mean	114.9747
ARIMA(3,0,2) with zero mean	122.6477
ARIMA(3,0,2) with non-zero mean	Inf
ARIMA(4,0,0) with zero mean	119.5724
ARIMA(4,0,0) with non-zero mean	114.451
ARIMA(4,0,1) with zero mean	122.7683
ARIMA(4,0,1) with non-zero mean	Inf
ARIMA(5,0,0) with zero mean	120.0648
ARIMA(5,0,0) with non-zero mean	117.8439

C – 8 ARIMA for CPI in China with regressors

Models	AICc
ARIMA(0,0,0) with zero mean	243.3676
ARIMA(0,0,0) with non-zero mean	218.9462
ARIMA(0,0,1) with zero mean	Inf
ARIMA(0,0,1) with non-zero mean	200.3025

ARIMA(0,0,2) with zero mean	206.9169
ARIMA(0,0,2) with non-zero mean	201.2389
ARIMA(0,0,3) with zero mean	208.3281
ARIMA(0,0,3) with non-zero mean	204.3949
ARIMA(0,0,4) with zero mean	209.5956
ARIMA(0,0,4) with non-zero mean	207.847
ARIMA(0,0,5) with zero mean	Inf
ARIMA(0,0,5) with non-zero mean	Inf
ARIMA(1,0,0) with zero mean	211.3948
ARIMA(1,0,0) with non-zero mean	209.7301
ARIMA(1,0,1) with zero mean	203.3143
ARIMA(1,0,1) with non-zero mean	201.5258
ARIMA(1,0,2) with zero mean	Inf
ARIMA(1,0,2) with non-zero mean	Inf
ARIMA(1,0,3) with zero mean	Inf
ARIMA(1,0,3) with non-zero mean	Inf
ARIMA(1,0,4) with zero mean	210.7151
ARIMA(1,0,4) with non-zero mean	Inf
ARIMA(2,0,0) with zero mean	210.9731
ARIMA(2,0,0) with non-zero mean	204.1149
ARIMA(2,0,1) with zero mean	Inf
ARIMA(2,0,1) with non-zero mean	204.3179
ARIMA(2,0,2) with zero mean	Inf
ARIMA(2,0,2) with non-zero mean	Inf

ARIMA(2,0,3) with zero mean	Inf
ARIMA(2,0,3) with non-zero mean	Inf
ARIMA(3,0,0) with zero mean	208.6914
ARIMA(3,0,0) with non-zero mean	206.6392
ARIMA(3,0,1) with zero mean	Inf
ARIMA(3,0,1) with non-zero mean	207.6058
ARIMA(3,0,2) with zero mean	Inf
ARIMA(3,0,2) with non-zero mean	211.2536
ARIMA(4,0,0) with zero mean	211.8878
ARIMA(4,0,0) with non-zero mean	209.0262
ARIMA(4,0,1) with zero mean	Inf
ARIMA(4,0,1) with non-zero mean	210.9584
ARIMA(5,0,0) with zero mean	209.723
ARIMA(5,0,0) with non-zero mean	210.8682

C – 9 ARIMA for CPI in the USA without regressors

Models	AICc
ARIMA(0,1,0)	107.2122
ARIMA(0,1,0) with drift	109.4571
ARIMA(0,1,1)	103.4578
ARIMA(0,1,1) with drift	Inf
ARIMA(0,1,2)	103.013
ARIMA(0,1,2) with drift	Inf
ARIMA(0,1,3)	105.5125

ARIMA(0,1,3) with drift	Inf
ARIMA(0,1,4)	108.2901
ARIMA(0,1,4) with drift	Inf
ARIMA(0,1,5)	111.1482
ARIMA(0,1,5) with drift	Inf
ARIMA(1,1,0)	107.1843
ARIMA(1,1,0) with drift	109.5866
ARIMA(1,1,1)	103.6059
ARIMA(1,1,1) with drift	Inf
ARIMA(1,1,2)	105.4995
ARIMA(1,1,2) with drift	Inf
ARIMA(1,1,3)	108.2899
ARIMA(1,1,3) with drift	Inf
ARIMA(1,1,4)	111.1415
ARIMA(1,1,4) with drift	Inf
ARIMA(2,1,0)	106.3019
ARIMA(2,1,0) with drift	108.8171
ARIMA(2,1,1)	105.7433
ARIMA(2,1,1) with drift	Inf
ARIMA(2,1,2)	108.2884
ARIMA(2,1,2) with drift	Inf
ARIMA(2,1,3)	111.2966
ARIMA(2,1,3) with drift	Inf
ARIMA(3,1,0)	108.5446

ARIMA(3,1,0) with drift	111.189
ARIMA(3,1,1)	108.5159
ARIMA(3,1,1) with drift	Inf
ARIMA(3,1,2)	111.2923
ARIMA(3,1,2) with drift	Inf
ARIMA(4,1,0)	108.3063
ARIMA(4,1,0) with drift	110.7515
ARIMA(4,1,1)	110.0751
ARIMA(4,1,1) with drift	Inf
ARIMA(5,1,0)	109.2651
ARIMA(5,1,0) with drift	110.9246

C – 10 ARIMA for CPI in China without regressors

Models	AICc
ARIMA(0,1,0)	201.2535
ARIMA(0,1,0) with drift	203.4601
ARIMA(0,1,1)	197.7677
ARIMA(0,1,1) with drift	200.1714
ARIMA(0,1,2)	192.0181
ARIMA(0,1,2) with drift	Inf
ARIMA(0,1,3)	192.8426
ARIMA(0,1,3) with drift	Inf
ARIMA(0,1,4)	195.6316
ARIMA(0,1,4) with drift	Inf

ARIMA(0,1,5)	198.6371
ARIMA(0,1,5) with drift	Inf
ARIMA(1,1,0)	202.4966
ARIMA(1,1,0) with drift	204.8731
ARIMA(1,1,1)	197.5962
ARIMA(1,1,1) with drift	200.1591
ARIMA(1,1,2)	193.0393
ARIMA(1,1,2) with drift	Inf
ARIMA(1,1,3)	Inf
ARIMA(1,1,3) with drift	Inf
ARIMA(1,1,4)	Inf
ARIMA(1,1,4) with drift	Inf
ARIMA(2,1,0)	196.537
ARIMA(2,1,0) with drift	199.016
ARIMA(2,1,1)	196.5831
ARIMA(2,1,1) with drift	Inf
ARIMA(2,1,2)	195.5686
ARIMA(2,1,2) with drift	Inf
ARIMA(2,1,3)	198.3338
ARIMA(2,1,3) with drift	Inf
ARIMA(3,1,0)	198.8542
ARIMA(3,1,0) with drift	201.4607
ARIMA(3,1,1)	198.9911
ARIMA(3,1,1) with drift	Inf

ARIMA(3,1,2)	198.3526
ARIMA(3,1,2) with drift	Inf
ARIMA(4,1,0)	194.4322
ARIMA(4,1,0) with drift	196.7489
ARIMA(4,1,1)	196.5456
ARIMA(4,1,1) with drift	199.1765
ARIMA(5,1,0)	196.649
ARIMA(5,1,0) with drift	199.3244

C – 11 ARIMA for Unemployment Rate in the USA with regressors

Models	AICc
ARIMA(0,0,0) with zero mean	201.1453
ARIMA(0,0,0) with non-zero mean	122.0267
ARIMA(0,0,1) with zero mean	166.8023
ARIMA(0,0,1) with non-zero mean	Inf
ARIMA(0,0,2) with zero mean	143.0443
ARIMA(0,0,2) with non-zero mean	82.26672
ARIMA(0,0,3) with zero mean	129.4669
ARIMA(0,0,3) with non-zero mean	80.94697
ARIMA(0,0,4) with zero mean	Inf
ARIMA(0,0,4) with non-zero mean	81.10388
ARIMA(0,0,5) with zero mean	Inf
ARIMA(0,0,5) with non-zero mean	83.68802
ARIMA(1,0,0) with zero mean	Inf

ARIMA(1,0,0) with non-zero mean	90.0942
ARIMA(1,0,1) with zero mean	Inf
ARIMA(1,0,1) with non-zero mean	Inf
ARIMA(1,0,2) with zero mean	Inf
ARIMA(1,0,2) with non-zero mean	71.33389
ARIMA(1,0,3) with zero mean	Inf
ARIMA(1,0,3) with non-zero mean	74.25915
ARIMA(1,0,4) with zero mean	Inf
ARIMA(1,0,4) with non-zero mean	Inf
ARIMA(2,0,0) with zero mean	Inf
ARIMA(2,0,0) with non-zero mean	77.02336
ARIMA(2,0,1) with zero mean	Inf
ARIMA(2,0,1) with non-zero mean	70.94392
ARIMA(2,0,2) with zero mean	Inf
ARIMA(2,0,2) with non-zero mean	74.22347
ARIMA(2,0,3) with zero mean	Inf
ARIMA(2,0,3) with non-zero mean	77.94063
ARIMA(3,0,0) with zero mean	Inf
ARIMA(3,0,0) with non-zero mean	72.54944
ARIMA(3,0,1) with zero mean	Inf
ARIMA(3,0,1) with non-zero mean	74.18636
ARIMA(3,0,2) with zero mean	Inf
ARIMA(3,0,2) with non-zero mean	Inf
ARIMA(4,0,0) with zero mean	Inf

ARIMA(4,0,0) with non-zero mean	74.55671
ARIMA(4,0,1) with zero mean	Inf
ARIMA(4,0,1) with non-zero mean	77.91999
ARIMA(5,0,0) with zero mean	Inf
ARIMA(5,0,0) with non-zero mean	78.22177

C – 12 ARIMA for Unemployment Rate in China with regressors

Models	AICc
ARIMA(0,1,0)	-7.351084
Regression with ARIMA(0,1,0) errors	-11.48212
ARIMA(0,1,1)	-8.72313
Regression with ARIMA(0,1,1) errors	-10.40318
ARIMA(0,1,2)	-5.930991
Regression with ARIMA(0,1,2) errors	-7.887181
ARIMA(0,1,3)	-2.928087
Regression with ARIMA(0,1,3) errors	-4.989769
ARIMA(0,1,4)	Inf
Regression with ARIMA(0,1,4) errors	Inf
ARIMA(0,1,5)	Inf
Regression with ARIMA(0,1,5) errors	Inf
ARIMA(1,1,0)	-8.146067
Regression with ARIMA(1,1,0) errors	-9.822353
ARIMA(1,1,1)	-5.930893
Regression with ARIMA(1,1,1) errors	-7.6578

ARIMA(1,1,2)	-2.921276
Regression with ARIMA(1,1,2) errors	-4.781966
ARIMA(1,1,3)	Inf
Regression with ARIMA(1,1,3) errors	-1.659366
ARIMA(1,1,4)	0.1853112
Regression with ARIMA(1,1,4) errors	Inf
ARIMA(2,1,0)	-5.71159
Regression with ARIMA(2,1,0) errors	-8.175467
ARIMA(2,1,1)	-2.926912
Regression with ARIMA(2,1,1) errors	-4.92835
ARIMA(2,1,2)	-1.673849
ARIMA(2,1,2) with drift	Inf
ARIMA(2,1,3)	0.4097123
Regression with ARIMA(2,1,3) errors	Inf
ARIMA(3,1,0)	-3.549201
Regression with ARIMA(3,1,0) errors	-4.929072
ARIMA(3,1,1)	-2.544217
Regression with ARIMA(3,1,1) errors	Inf
ARIMA(3,1,2)	Inf
Regression with ARIMA(3,1,2) errors	1.959797
ARIMA(4,1,0)	-0.9916856
Regression with ARIMA(4,1,0) errors	-1.440398
ARIMA(4,1,1)	Inf
Regression with ARIMA(4,1,1) errors	Inf

ARIMA(5,1,0)	2.527841
Regression with ARIMA(5,1,0) errors	1.949763

C – 13 ARIMA for Unemployment Rate in the USA without regressors

Models	AICc
ARIMA(0,0,0) with zero mean	221.9964
ARIMA(0,0,0) with non-zero mean	126.5324
ARIMA(0,0,1) with zero mean	Inf
ARIMA(0,0,1) with non-zero mean	98.5471
ARIMA(0,0,2) with zero mean	Inf
ARIMA(0,0,2) with non-zero mean	83.14756
ARIMA(0,0,3) with zero mean	Inf
ARIMA(0,0,3) with non-zero mean	80.40841
ARIMA(0,0,4) with zero mean	123.914
ARIMA(0,0,4) with non-zero mean	83.06047
ARIMA(0,0,5) with zero mean	113.9543
ARIMA(0,0,5) with non-zero mean	84.3594
ARIMA(1,0,0) with zero mean	95.91115
ARIMA(1,0,0) with non-zero mean	92.87237
ARIMA(1,0,1) with zero mean	86.24275
ARIMA(1,0,1) with non-zero mean	81.83091
ARIMA(1,0,2) with zero mean	86.64017
ARIMA(1,0,2) with non-zero mean	79.74646
ARIMA(1,0,3) with zero mean	88.72919

ARIMA(1,0,3) with non-zero mean	82.61893
ARIMA(1,0,4) with zero mean	Inf
ARIMA(1,0,4) with non-zero mean	85.67548
ARIMA(2,0,0) with zero mean	87.98757
ARIMA(2,0,0) with non-zero mean	76.88177
ARIMA(2,0,1) with zero mean	87.61232
ARIMA(2,0,1) with non-zero mean	79.08207
ARIMA(2,0,2) with zero mean	89.02228
ARIMA(2,0,2) with non-zero mean	82.00086
ARIMA(2,0,3) with zero mean	92.21683
ARIMA(2,0,3) with non-zero mean	Inf
ARIMA(3,0,0) with zero mean	85.91897
ARIMA(3,0,0) with non-zero mean	79.19805
ARIMA(3,0,1) with zero mean	Inf
ARIMA(3,0,1) with non-zero mean	82.04108
ARIMA(3,0,2) with zero mean	91.67413
ARIMA(3,0,2) with non-zero mean	84.93917
ARIMA(4,0,0) with zero mean	88.40061
ARIMA(4,0,0) with non-zero mean	81.82553
ARIMA(4,0,1) with zero mean	91.36133
ARIMA(4,0,1) with non-zero mean	85.28003
ARIMA(5,0,0) with zero mean	91.02473
ARIMA(5,0,0) with non-zero mean	84.85656

C – 14 ARIMA for Unemployment Rate in China without regressors

Models	AICc
ARIMA(0,1,0)	-11.97909
ARIMA(0,1,0) with drift	-13.04598
ARIMA(0,1,1)	-13.26076
ARIMA(0,1,1) with drift	-12.94841
ARIMA(0,1,2)	-10.85631
ARIMA(0,1,2) with drift	-10.70841
ARIMA(0,1,3)	-8.346302
ARIMA(0,1,3) with drift	-8.502537
ARIMA(0,1,4)	-6.264535
ARIMA(0,1,4) with drift	-5.904282
ARIMA(0,1,5)	-3.352019
ARIMA(0,1,5) with drift	-2.686129
ARIMA(1,1,0)	-12.55005
ARIMA(1,1,0) with drift	-12.1486
ARIMA(1,1,1)	-10.85099
ARIMA(1,1,1) with drift	-10.52428
ARIMA(1,1,2)	-8.262472
ARIMA(1,1,2) with drift	-8.11169
ARIMA(1,1,3)	Inf
ARIMA(1,1,3) with drift	-5.769007
ARIMA(1,1,4)	-5.626463
ARIMA(1,1,4) with drift	-3.33475

ARIMA(2,1,0)	-10.78935
ARIMA(2,1,0) with drift	-11.17991
ARIMA(2,1,1)	-8.321547
ARIMA(2,1,1) with drift	-8.386365
ARIMA(2,1,2)	Inf
ARIMA(2,1,2) with drift	Inf
ARIMA(2,1,3)	Inf
ARIMA(2,1,3) with drift	Inf
ARIMA(3,1,0)	-8.518024
ARIMA(3,1,0) with drift	-8.386393
ARIMA(3,1,1)	Inf
ARIMA(3,1,1) with drift	Inf
ARIMA(3,1,2)	Inf
ARIMA(3,1,2) with drift	Inf
ARIMA(4,1,0)	-6.135312
ARIMA(4,1,0) with drift	-5.414878
ARIMA(4,1,1)	Inf
ARIMA(4,1,1) with drift	Inf
ARIMA(5,1,0)	-3.141408
ARIMA(5,1,0) with drift	-2.523584