ECON 144 Project 2

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I. Introduction

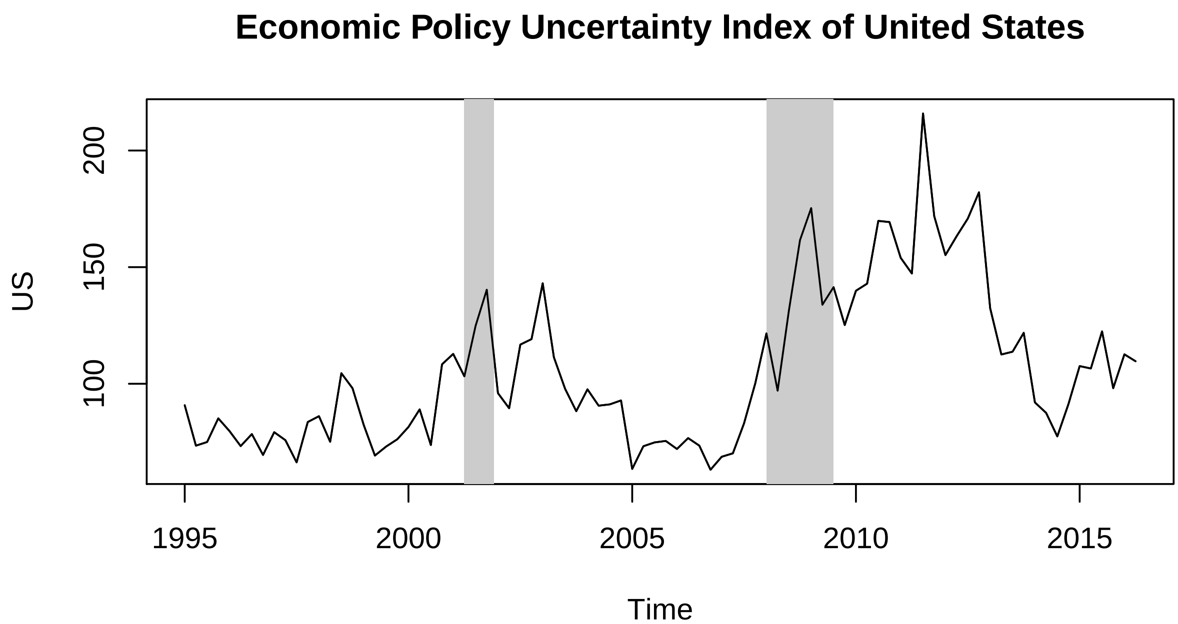
According to a recent article published by the New York Times, the relationship between the United States and China is like a "mutually dependent, frequently dysfunctional economic partnership" (Neil). The world's first and second largest economies are like a married couple, who would constantly fight with each other, but still could not live without each other.

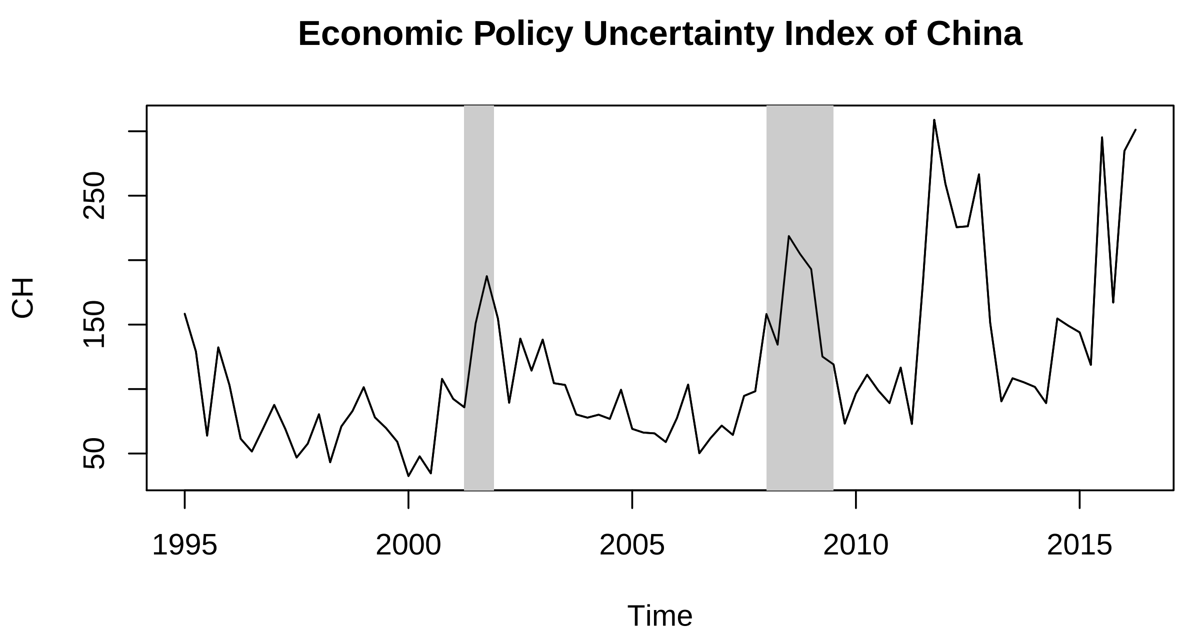
Therefore, our team has decided to focus this project on the topic of the economic relationship between these two countries. Additionally, due to the large uncertainty in the new political leadership within U.S. as well as the rising concerns about the policy uncertainty in the wake of the Global Financial Crisis and serial crises in the Eurozone, we have decided to collect the data "Economic Policy Uncertainty Index" for both countries to see how these two countries' uncertainty index would trace each other, and whether one could potentially influence the other.

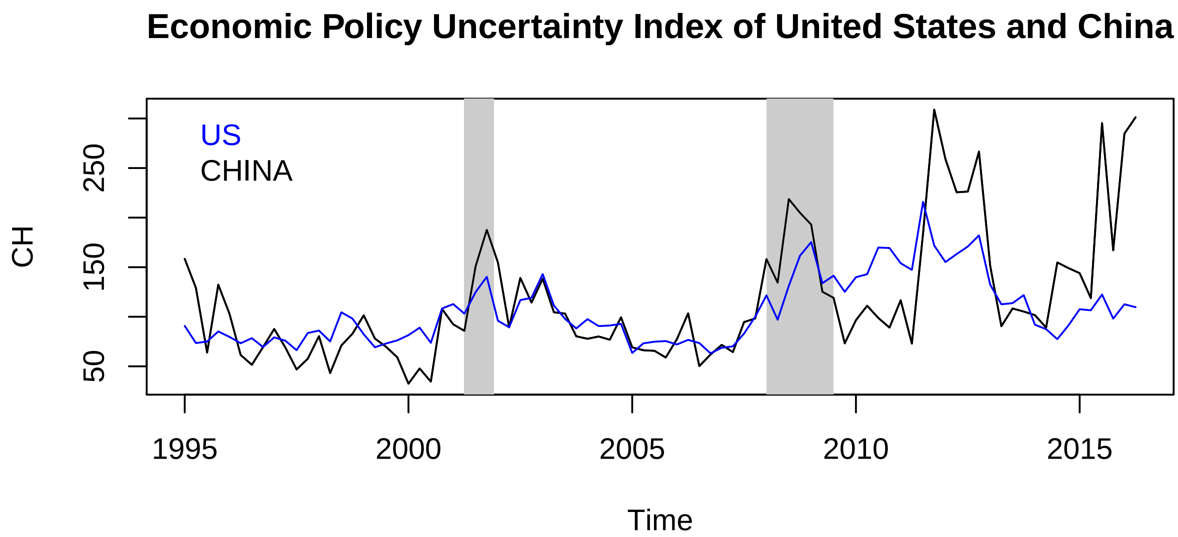
The Economic Policy Uncertainty Index is an index, which was first developed by Baker, Scott, Nicholas Bloom and Steven Davis (2012) for the United States in order to examine its evolution since 1985. The Index is designed to capture the uncertainty about who will make the economic policy decisions, what economic policy actions could be undertaken, and when, and most importantly, the economic effects of the policy actions.

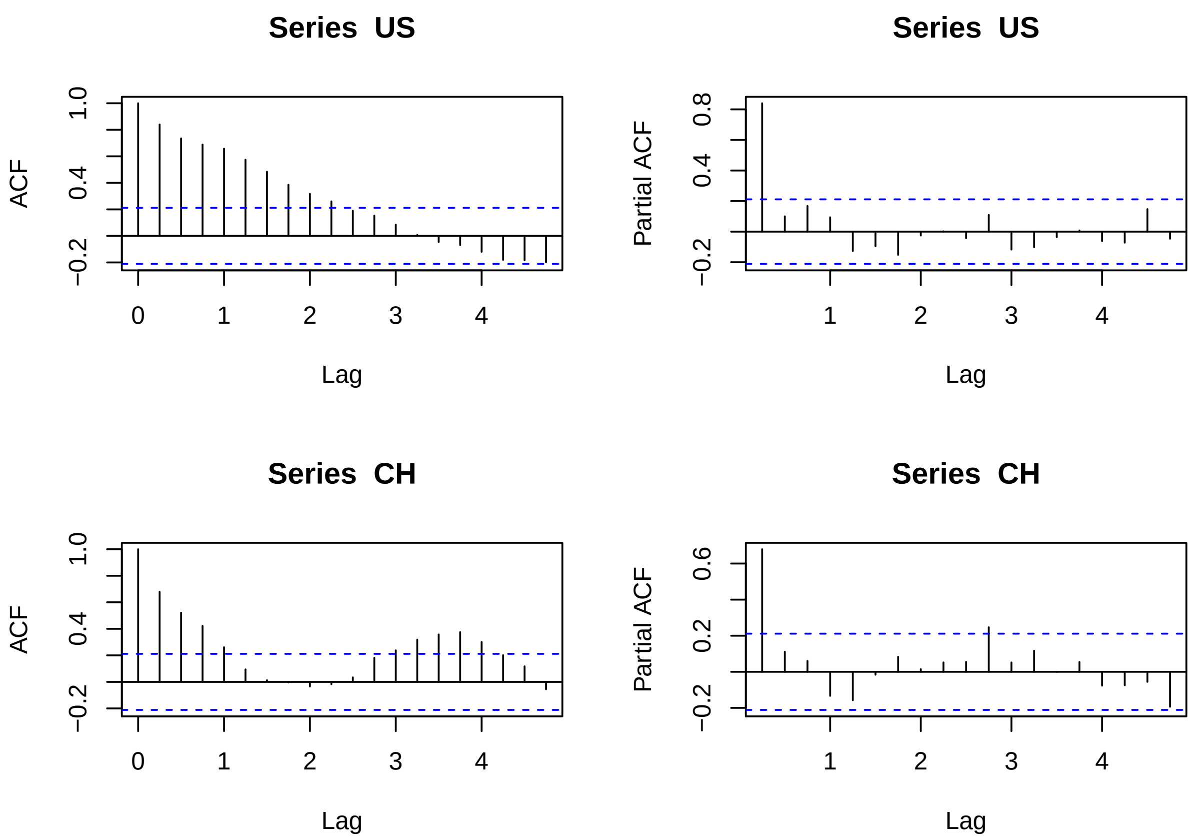
II. Results

(a) Plot Time Series with ACF & PACF







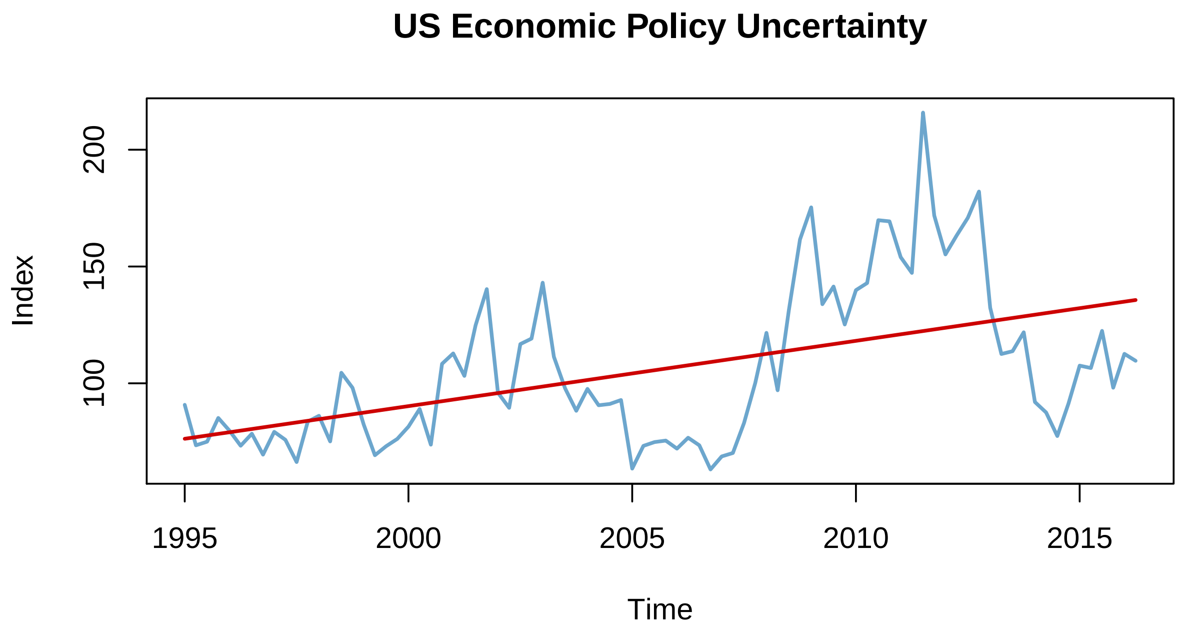


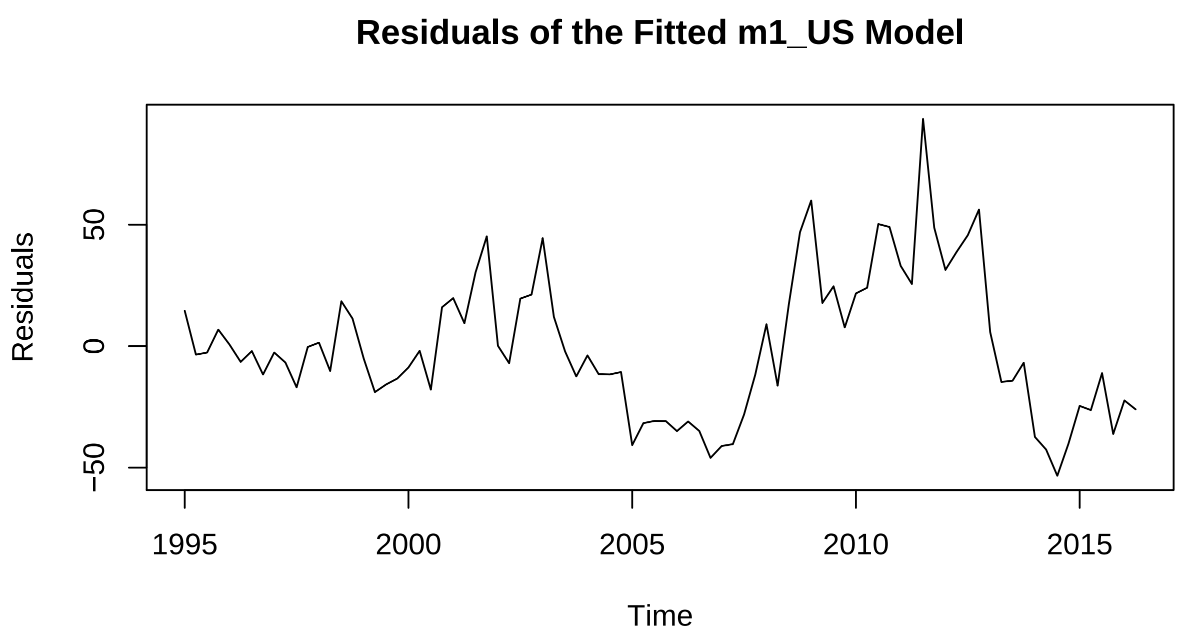
Time series plots of Economic Policy Uncertainty Index for China and the U.S are shown above; ACF anf PACF plots of each series are provided for preliminary analysis. At the first glance, by looking at two time series together with ACF & PACF plots, both series appear to be some-what covariance stationary with clear increasing trend, seasonality, and clcyles.

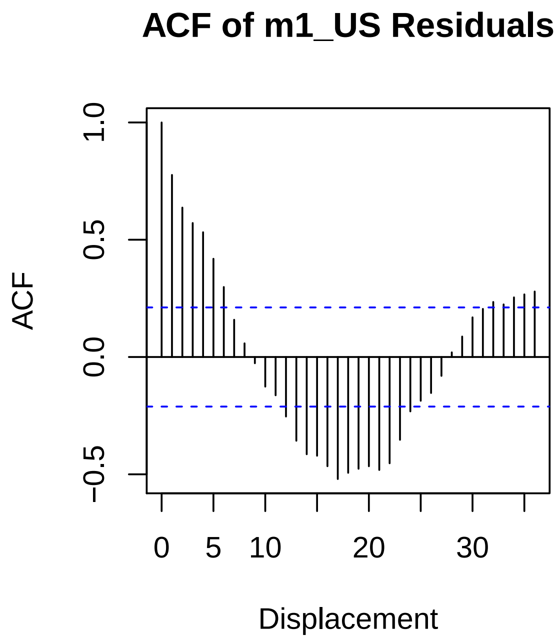
(b) Integrated Model Selection and Improvement

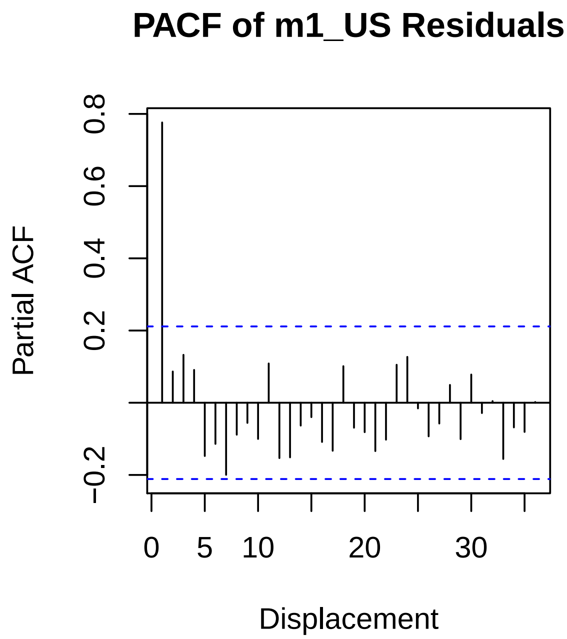
* For U.S

Linear Trend



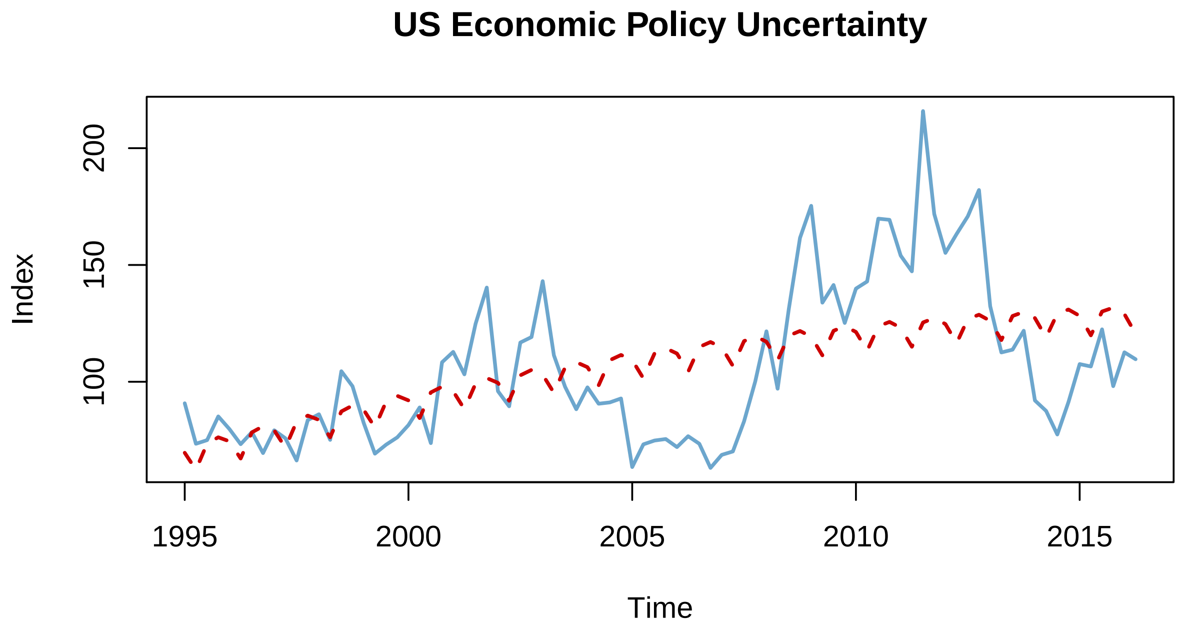


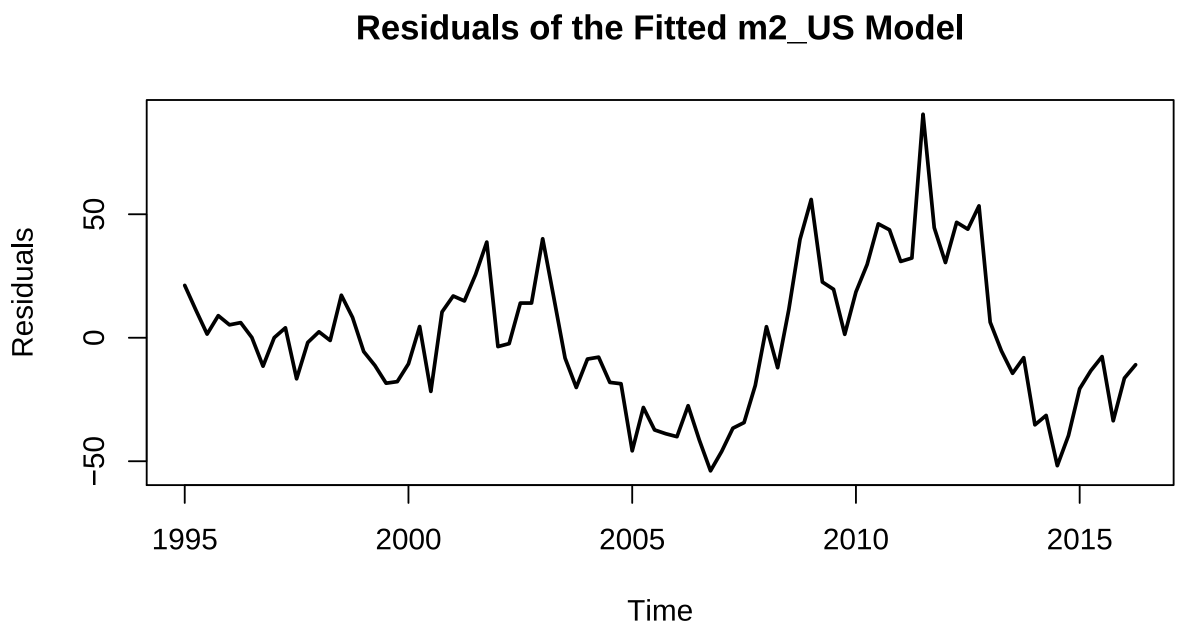


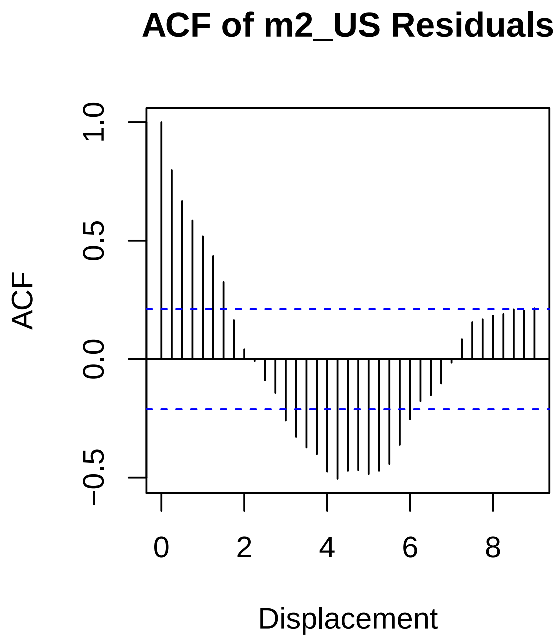


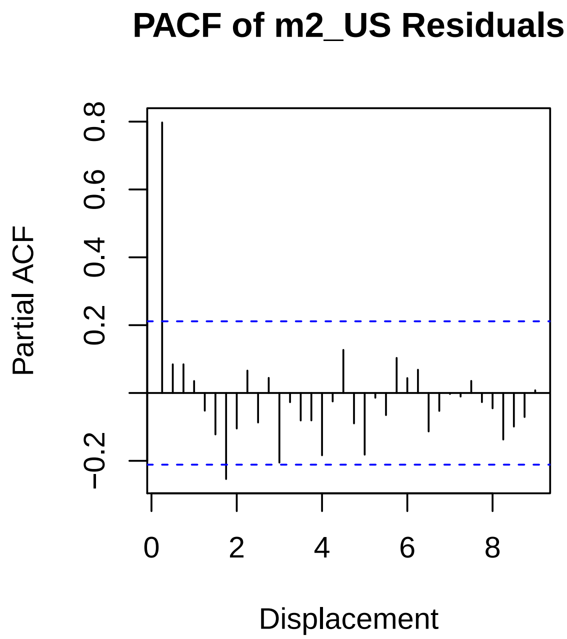
First, we have just fitted a simple trend with t for our model. As we can observed from the fitted plot that the trend does capture the upward movement of the original plot, however, it still lacks much, such as capturing the seasonality and cyclical. Second, from the Residual plot, it still has structures. Moreover, we can also observe from its ACF and PACF plots that they do not resemble the white noise. Therefore, to sum up, these all indicate that we can do much better with our model.

Quadratic Trend + Seasonal Dummies





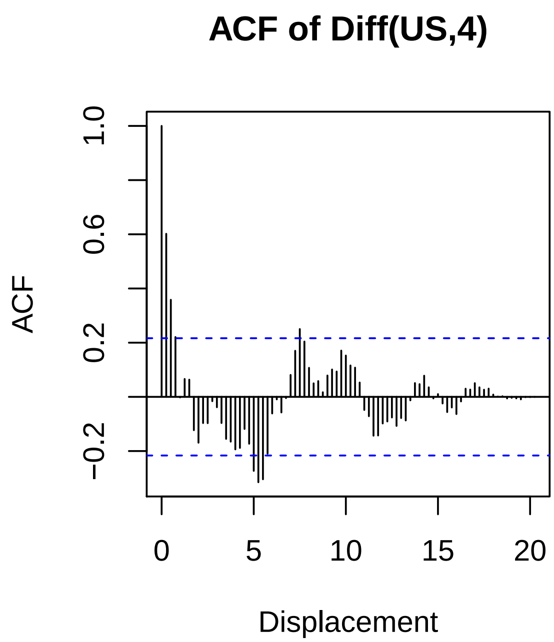


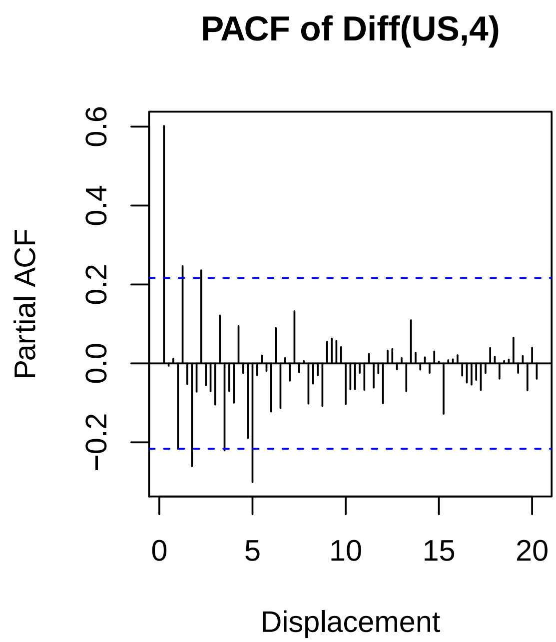


Then, we fitted t, tˆ2, and seasonal dummies into our model. Similar to the previous model, though the fitted plot captures the upward movement of the original plot, but it still could not capture all the seasonality and cyclical components. Furthermore, the Residual Plot and ACF and PACF all suggest that our model still need more work.

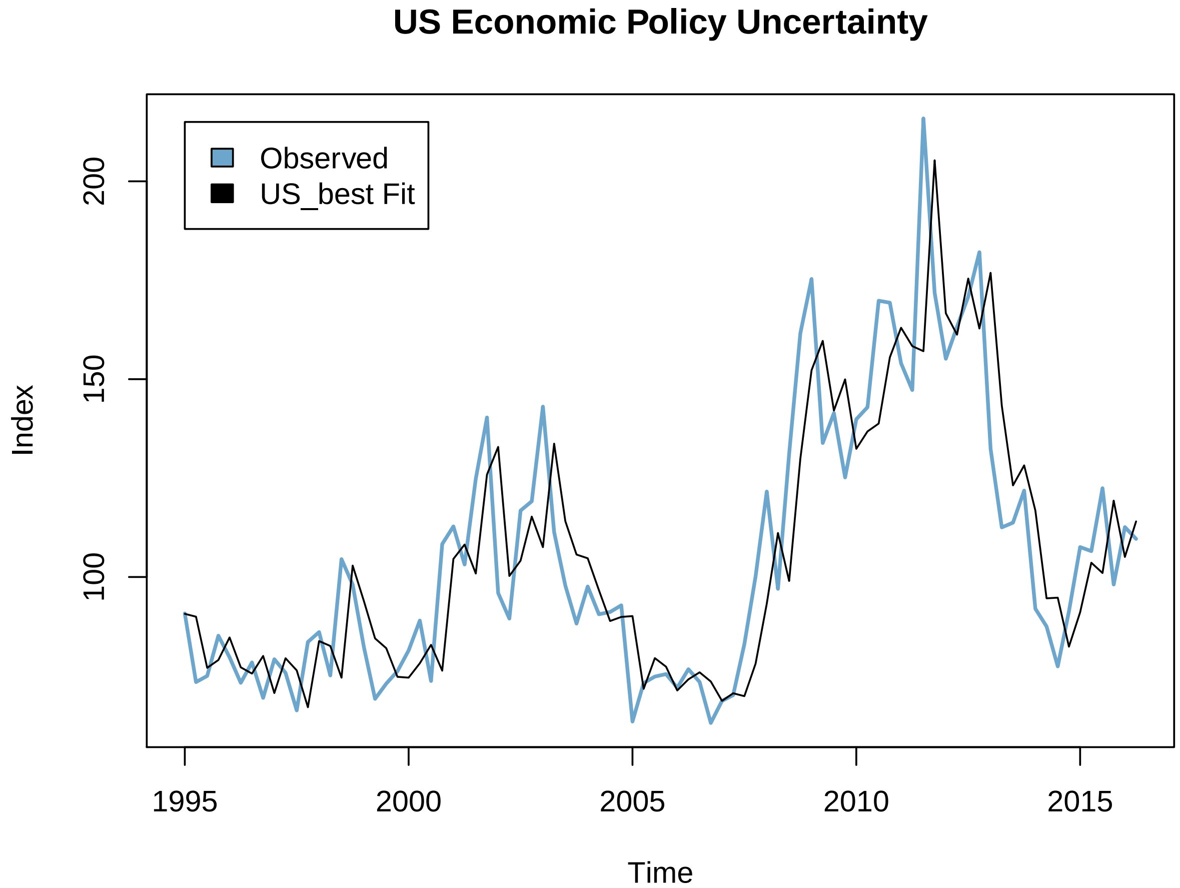
R's auto.arima

```
## Series: US
## ARIMA(0,1,2)(0,0,1)[4]
##
## Coefficients:
##           ma1      ma2    sma1
##       -0.2473  -0.1691  0.2060
## s.e.   0.1083   0.1106  0.1178
##
## sigma^2 estimated as 329.7:  log likelihood=-365.64
## AIC=739.29   AICc=739.79   BIC=749.06
```





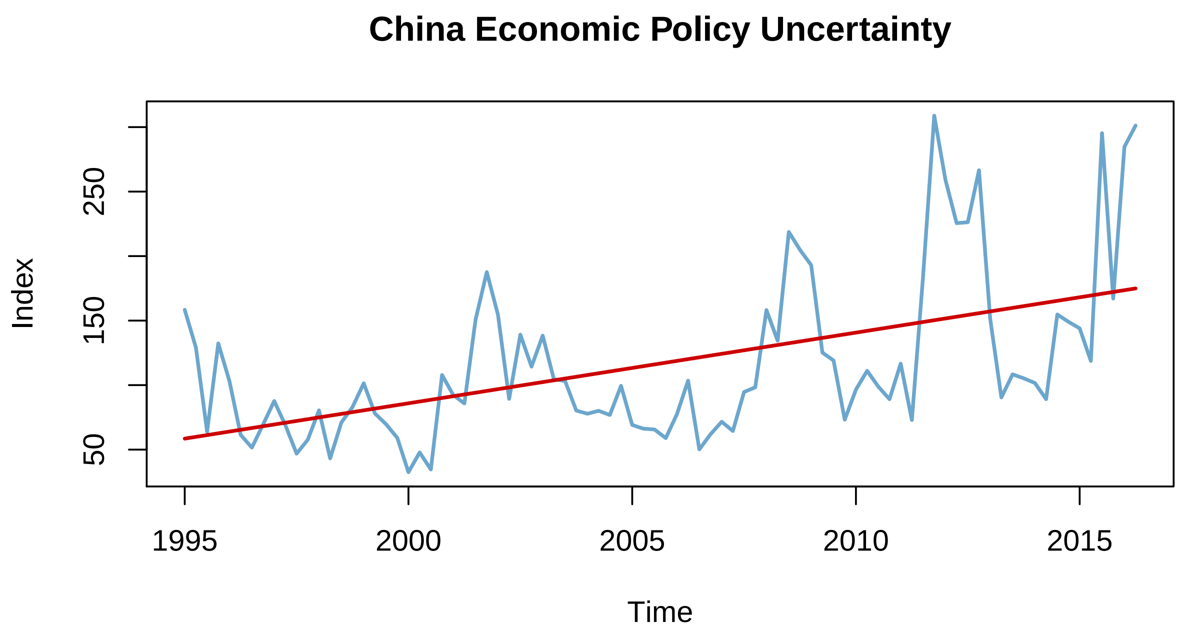
Third, we utilized Auto Arima in order to obtain the optimal cyclical components Arima(0,1,2). Furthermore, we also used the ACF and PACF plots of the diff(US, 4) to find the optimal seasonal component for our ARIMA. The ACF and PACF graphs suggested an Arima(2,0,1) process for its seasonal structures.

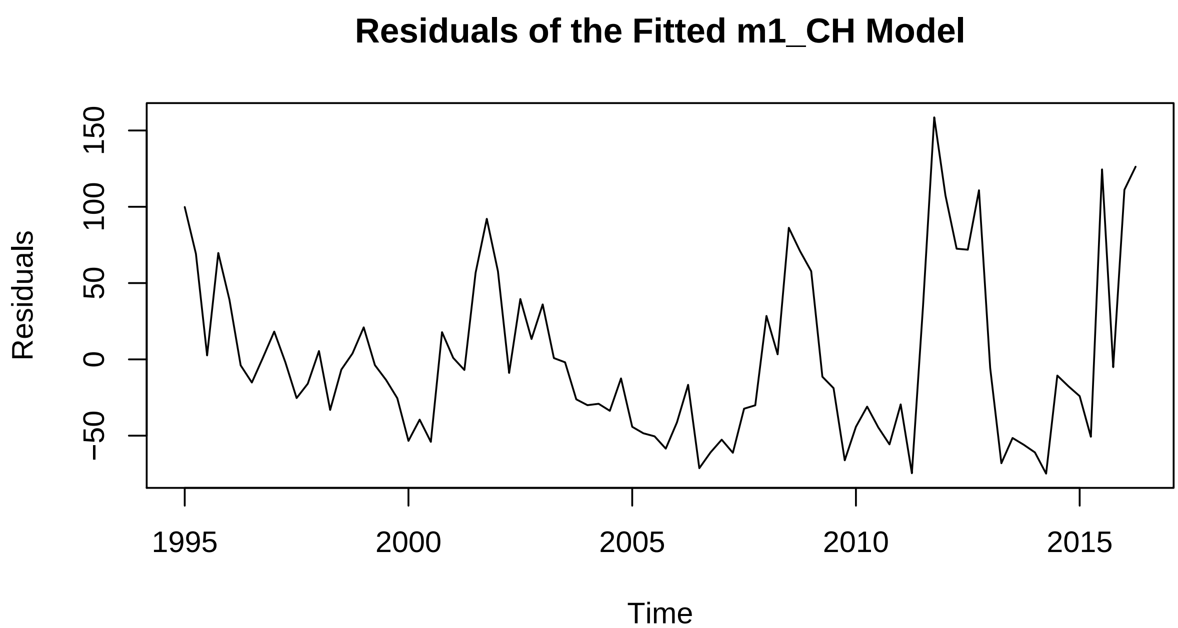


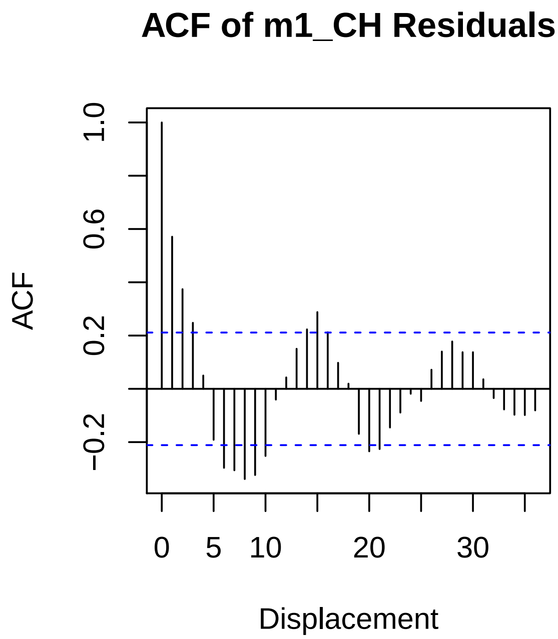
Lastly, our final model for the U.S Economic Policy Uncertainty Index is constructed by combining the seasonal arima with the cyclic arima order suggested by the auto.arima function, and the linear trend. The reason why we decide to choose the linear trend ~ t is because of parsimony. Since the second model we tried did not improve much from the first one, we would like to keep it simple, and only include t in the final model. As the fitted plot has shown that our final model really traced out the data well. Moreover, the Residuals, ACF and PACF plots will be provided in later sub-sections to test the validity of this chosen model.

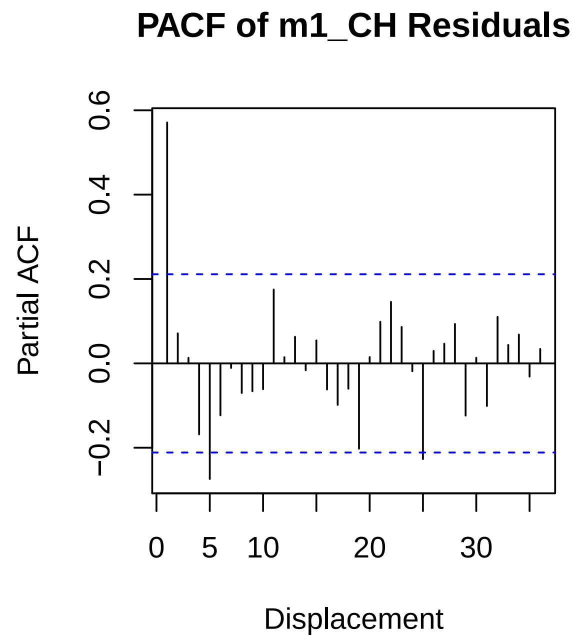
*** For China**

Linear Trend



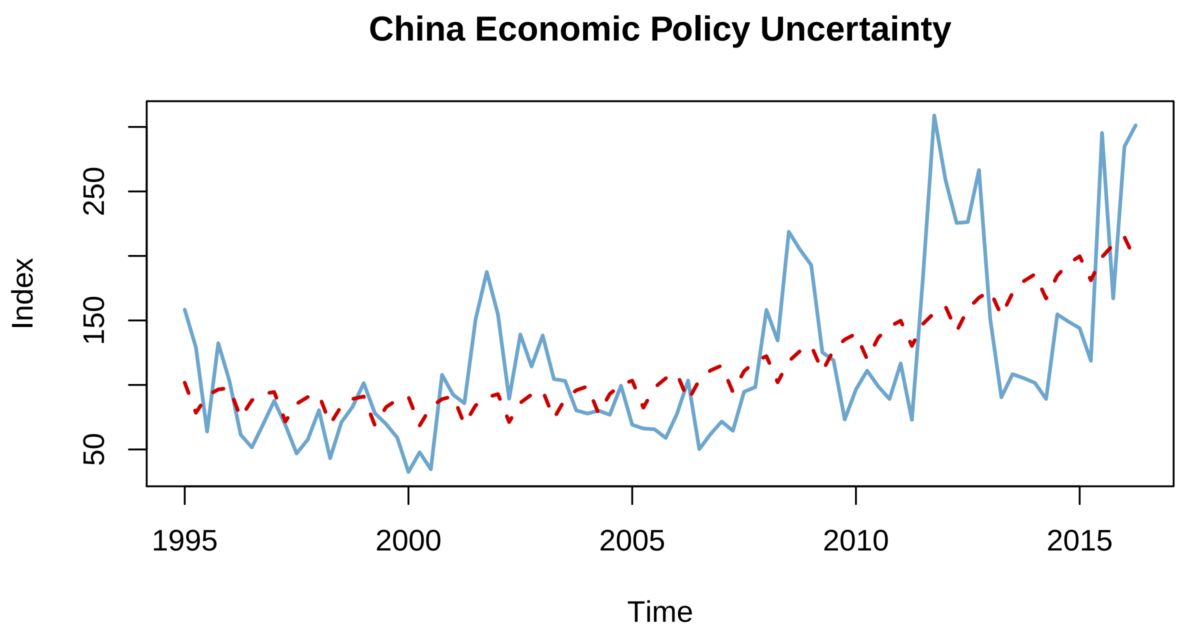


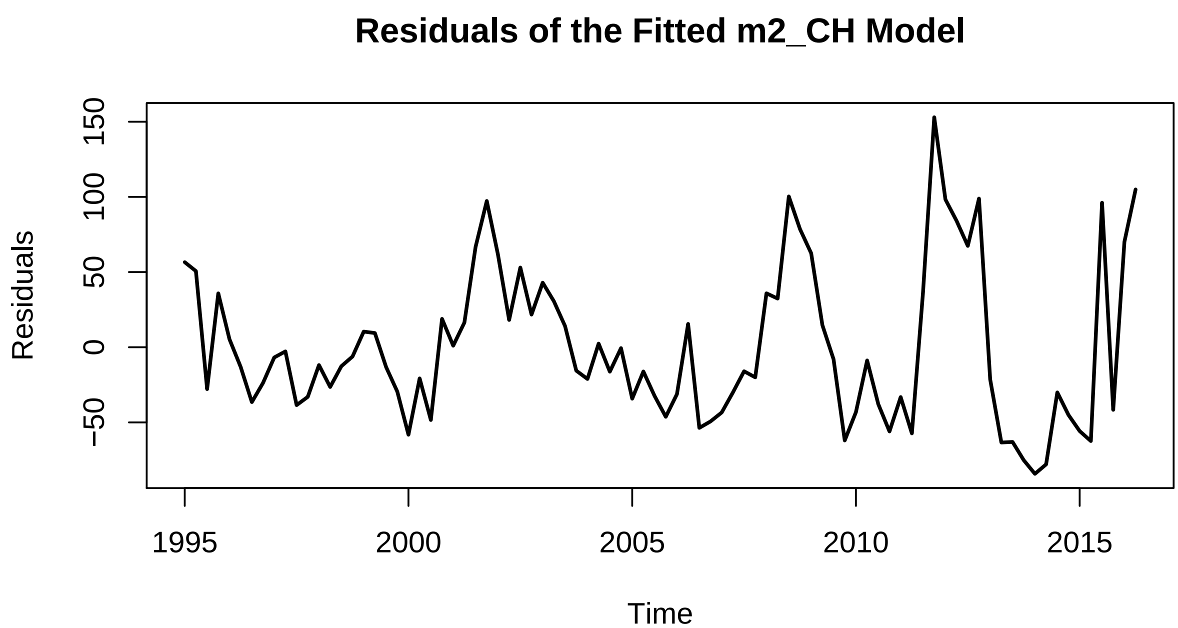


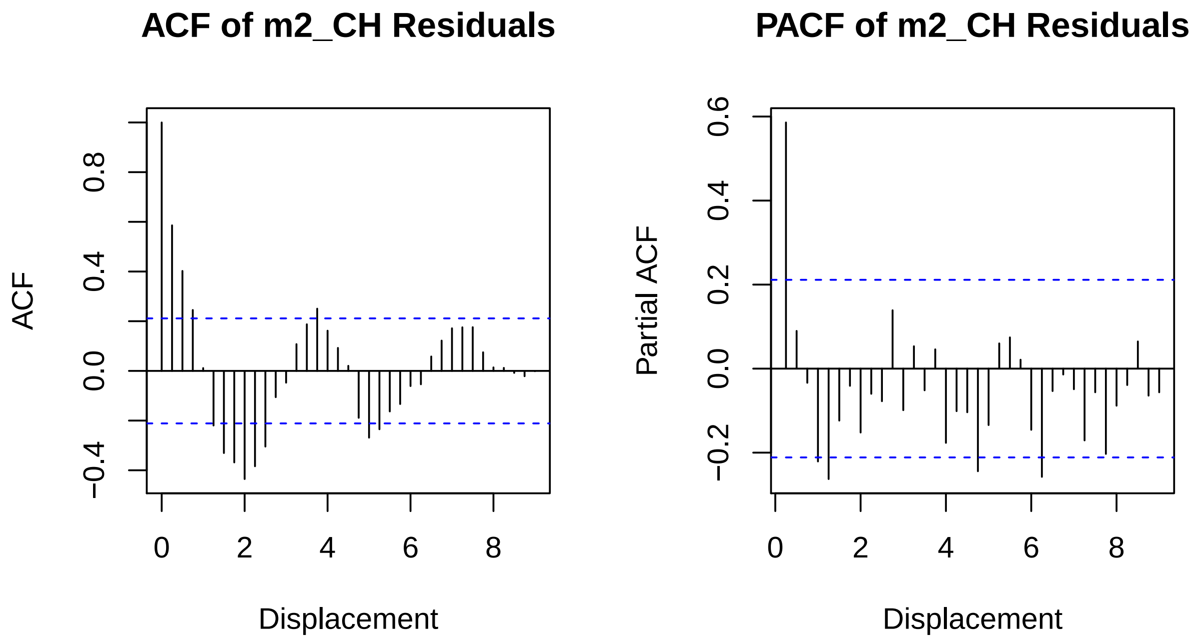


Similar to the U.S case, first, we have just fitted a simple trend with t for our model. As we can observed from the fitted plot that the trend does capture the upward movement of the original plot, however, it still lacks much, such as capturing the seasonality and cyclical. Second, from the Residual plot, it still has structures. Moreover, we can also observe from its ACF and PACF plots that they do not resemble the white noise. Therefore, to sum up, these all indicate that we can do much better with our model.

Quadratic Trend + Seasonal Dummies



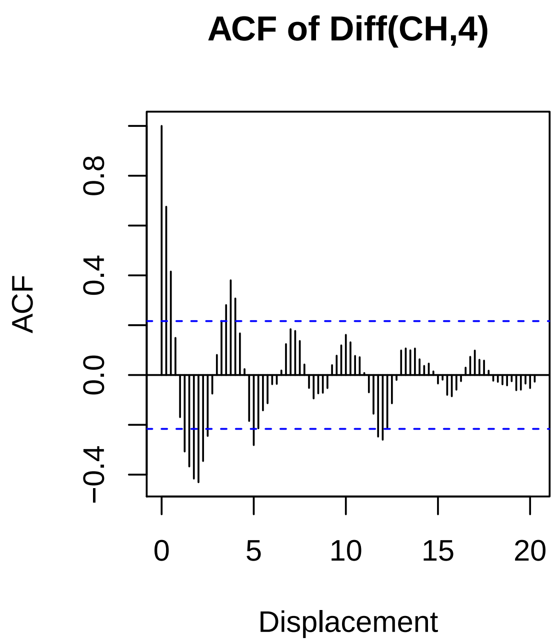


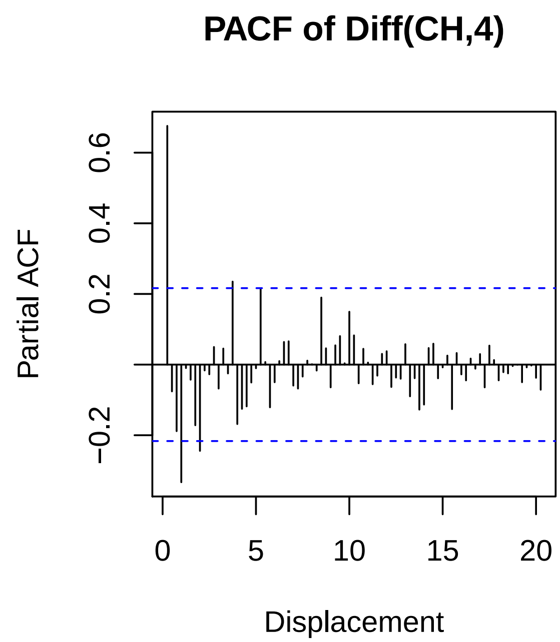


Then, we fitted t, t^2, and seasonal dummies into our model. Similar to the previous model, though the fitted plot could capture the upward movement of the original plot, it still could not capture the seasonality and cyclical. Furthermore, the Residual Plot and ACF and PACF all suggest that our model still need more work.

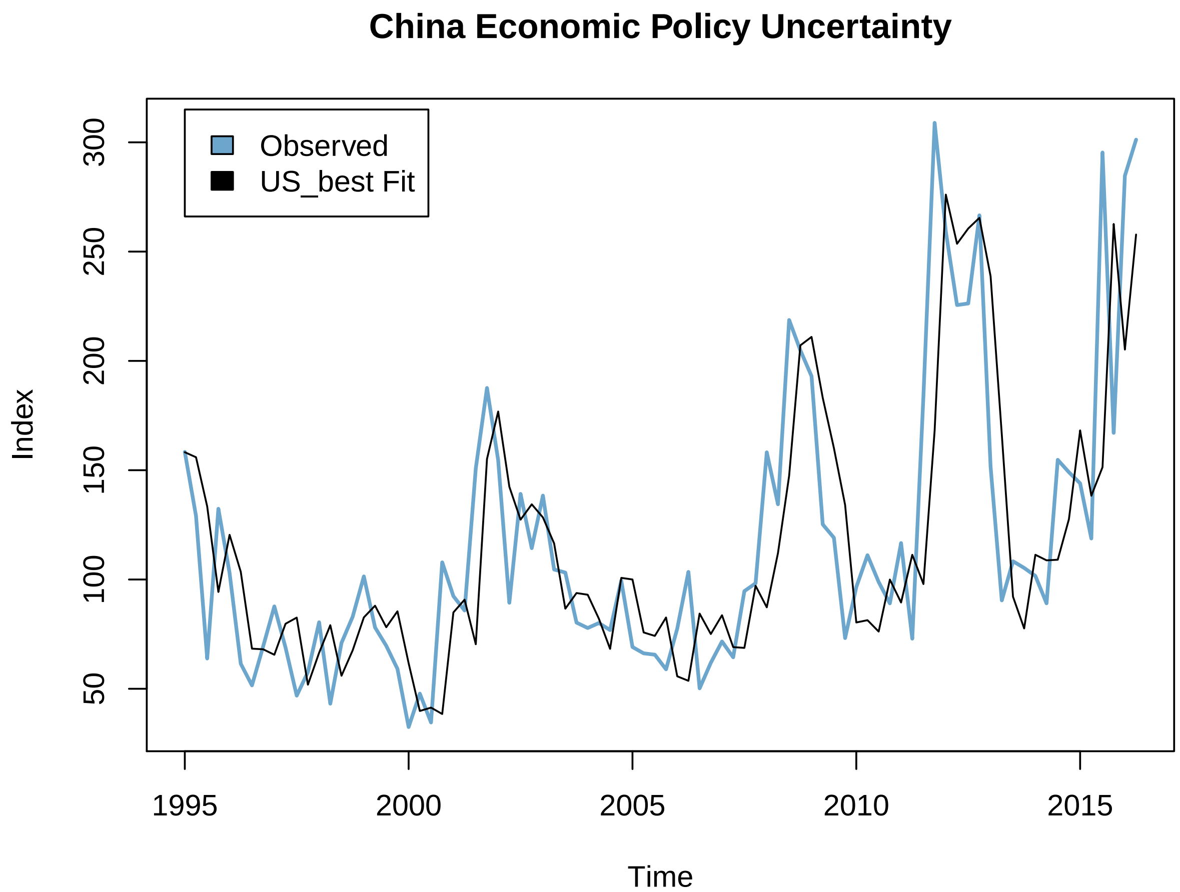
R's auto.arima

```
## Series: CH
## ARIMA(0,1,1)(0,0,1)[4]
##
## Coefficients:
##           ma1     sma1
##       -0.2401   0.2491
## s.e.   0.1066   0.1297
##
## sigma^2 estimated as 1989:  log likelihood=-442.56
## AIC=891.11   AICc=891.41   BIC=898.44
```





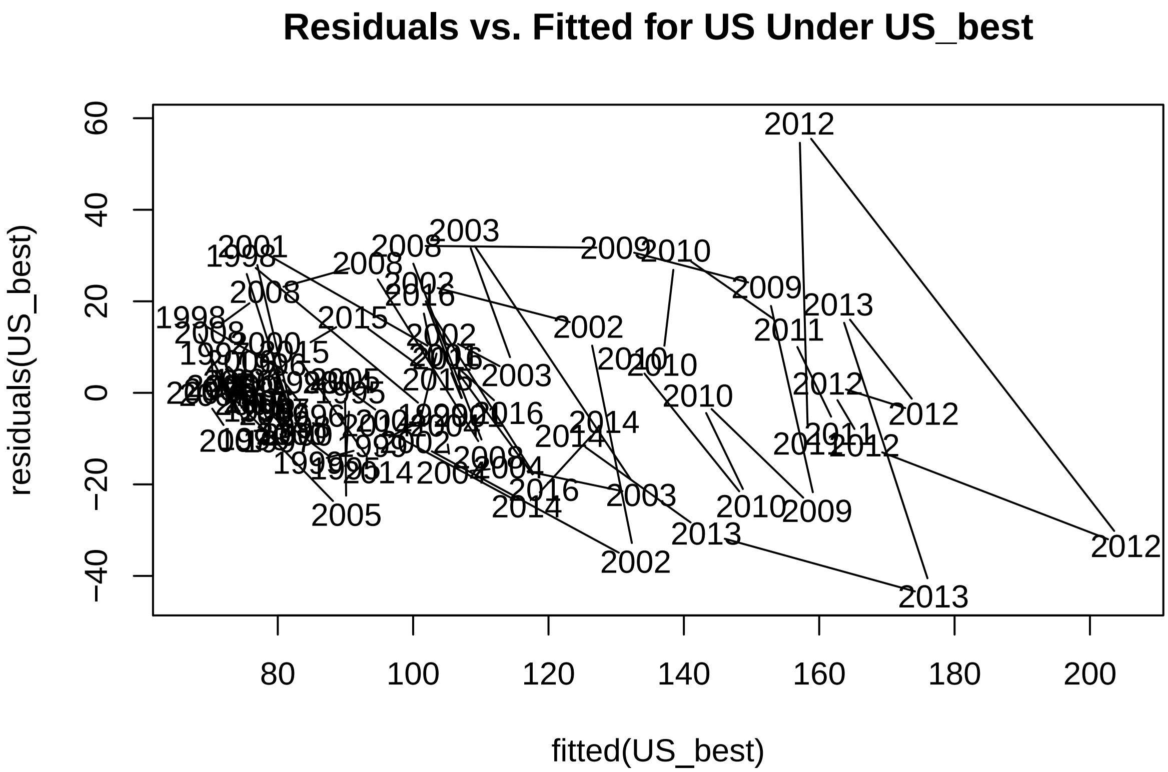
Third, we utilized Auto Arima in order to receive the optimal process representing its cycles: Arima(0,1,1). We also used the ACF and PACF plots of the diff(CH, 4) to find the optimal seasonal components: the ACF and PACF graphs suggested an Arima(2,0,4) process for its seasonal structures.



Lastly, our final model for China Economic Policy Uncertainty Index is constructed by combining its seasonal arima with the cyclic arima suggested by the auto.arima function, and the linear trend. The reason why we decide to choose the linear trend $\sim$ t is because of parsimony. Since the second model we tried did not improve much from the first one, we would like to keep it simple, and only include t in the final model. As the fitted plot has shown that our final model really traced out the data well. Moreover, the Residuals, ACF and PACF plots will be provided in later sub-sections to test the validity of this chosen model.

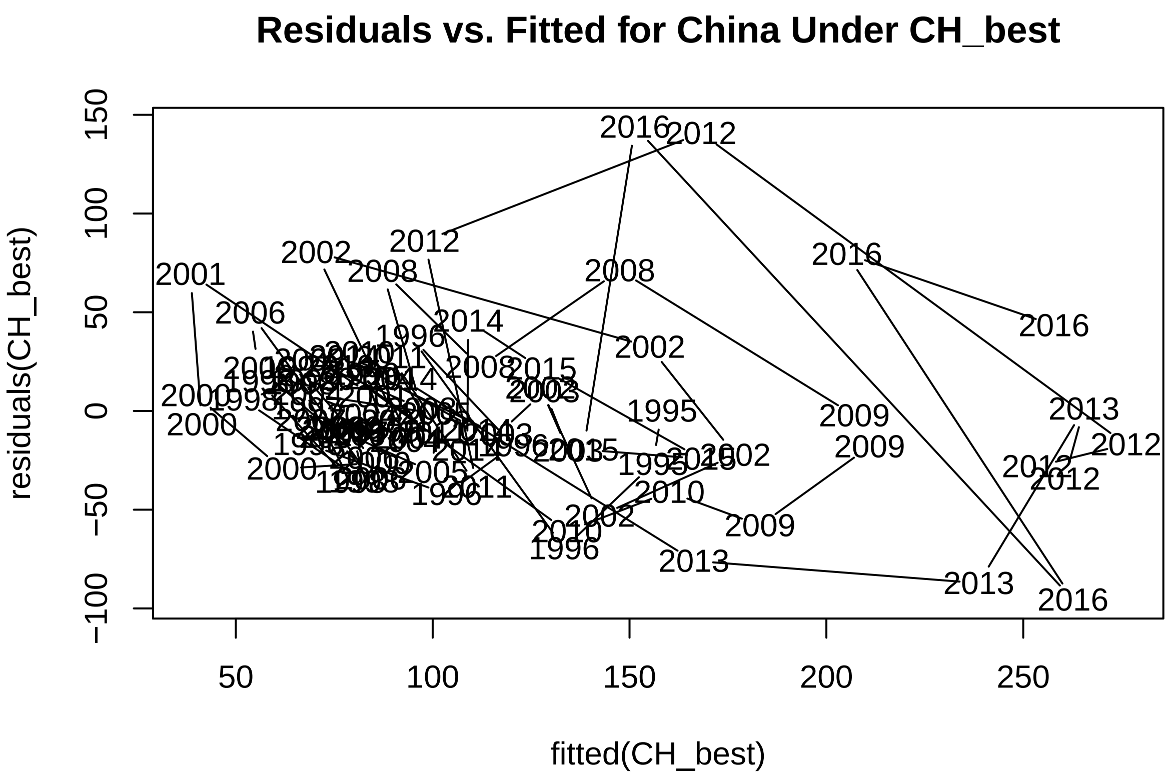
(c) Residuals vs. Fitted Analysis

*** For U.S**



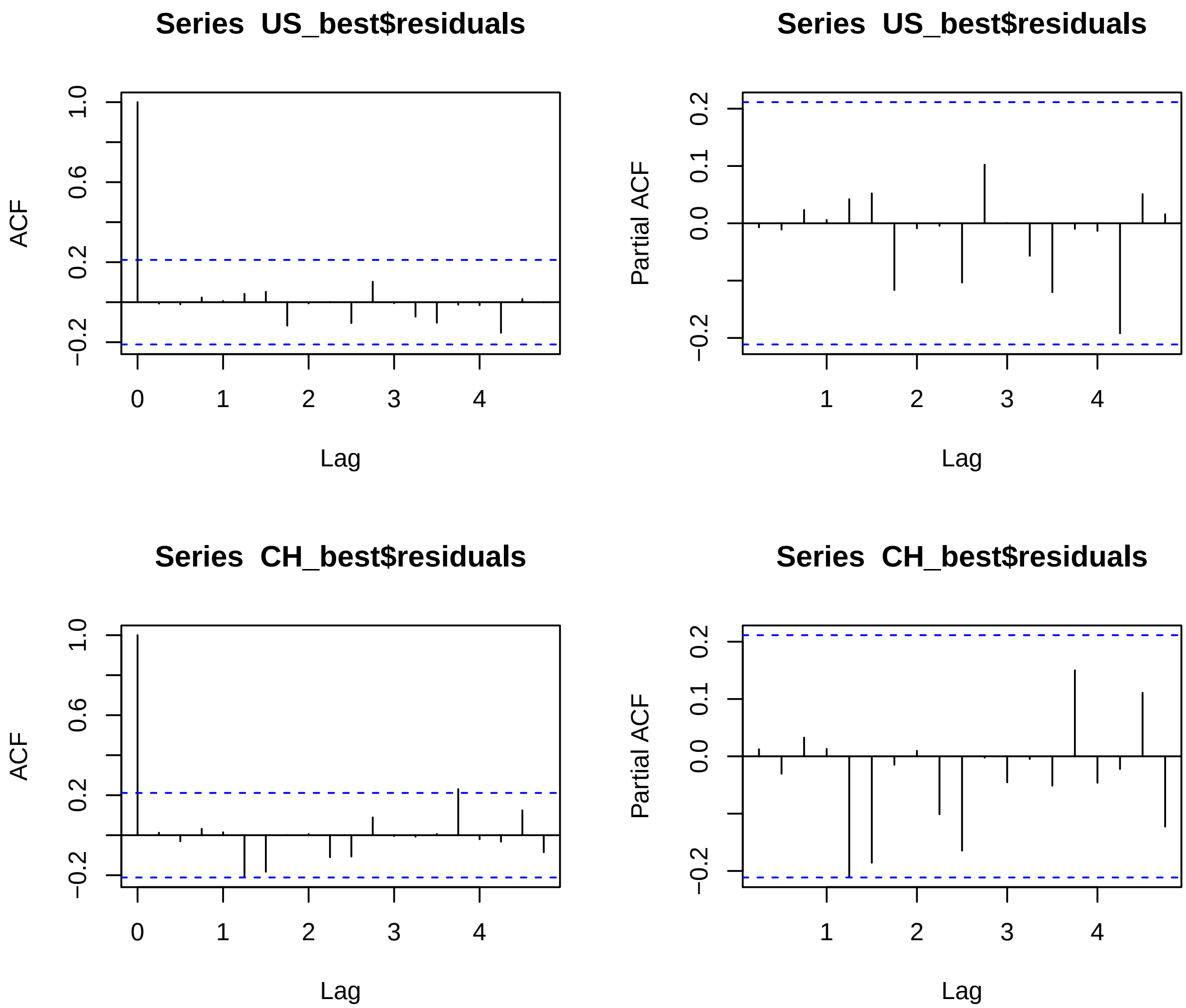
we observe that this residual vs. fitted value plot is a well-behaved one because the residuals are bouncing randomly around the red 0 line, which suggests that the relationship is reasonable. In addition, only few residuals actually stand out as possible outliers.

*** For China**



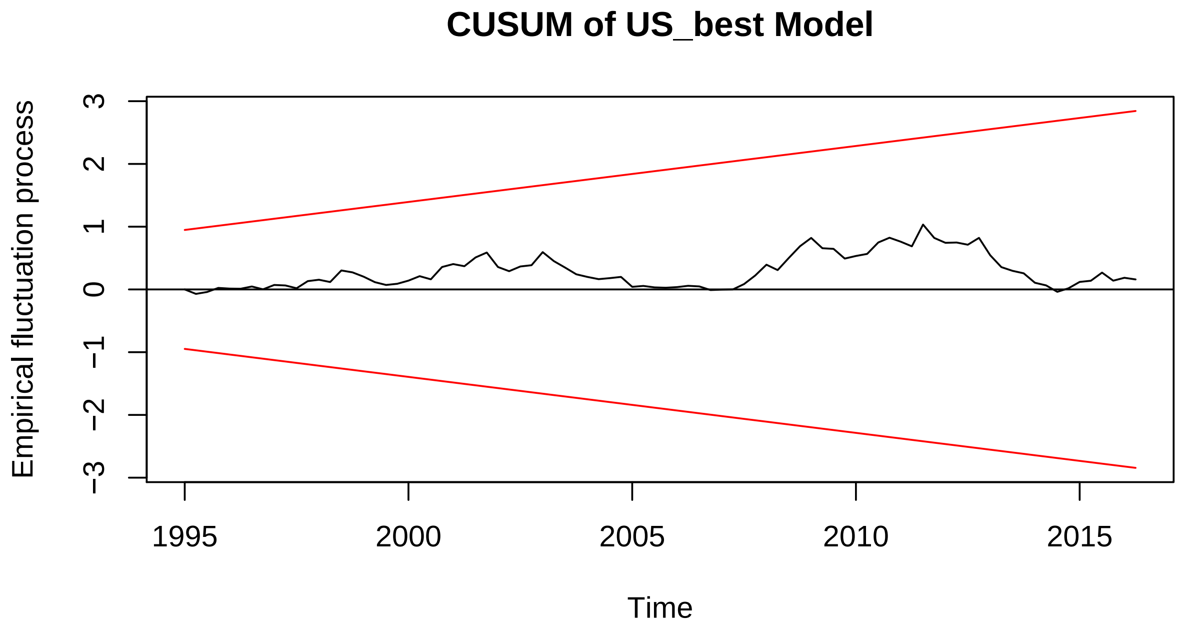
Just like the residuals under the US_best model, the residuals for CH_best model are also well-behaved in the same fashion.

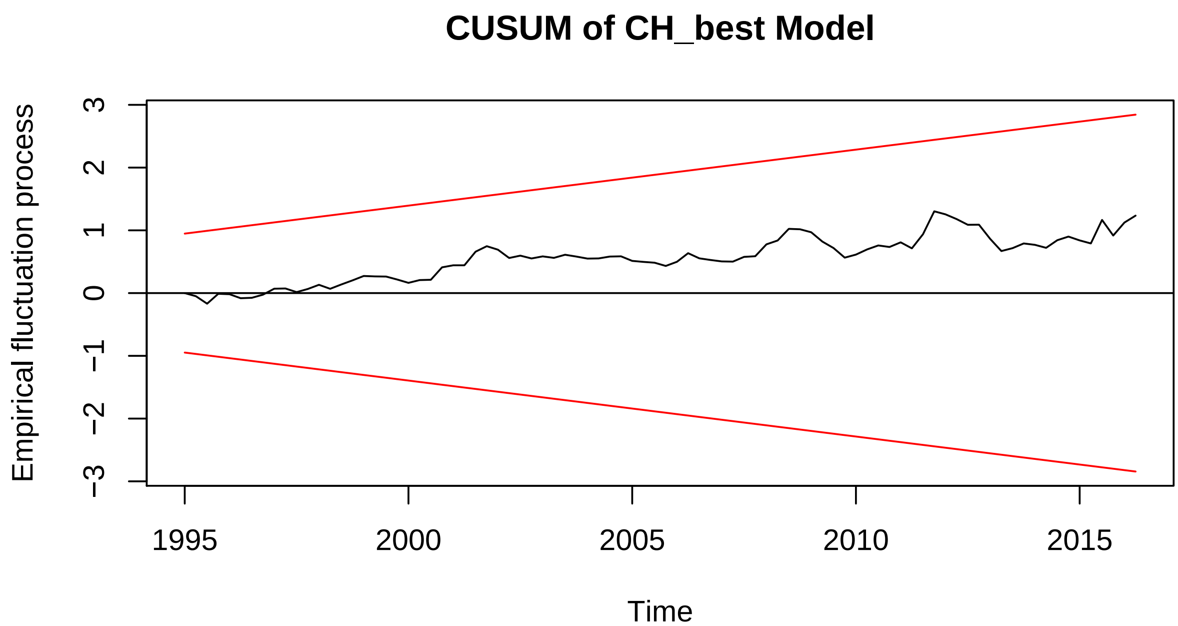
(d) ACF & PACF Analysis on Residuals



The ACF and PACF of residuals for both US_best and CH_best are consistent with white noises, which indicates that the two modles are very good fits, and they have captured all seasonal and cyclic structures of the respective time series.

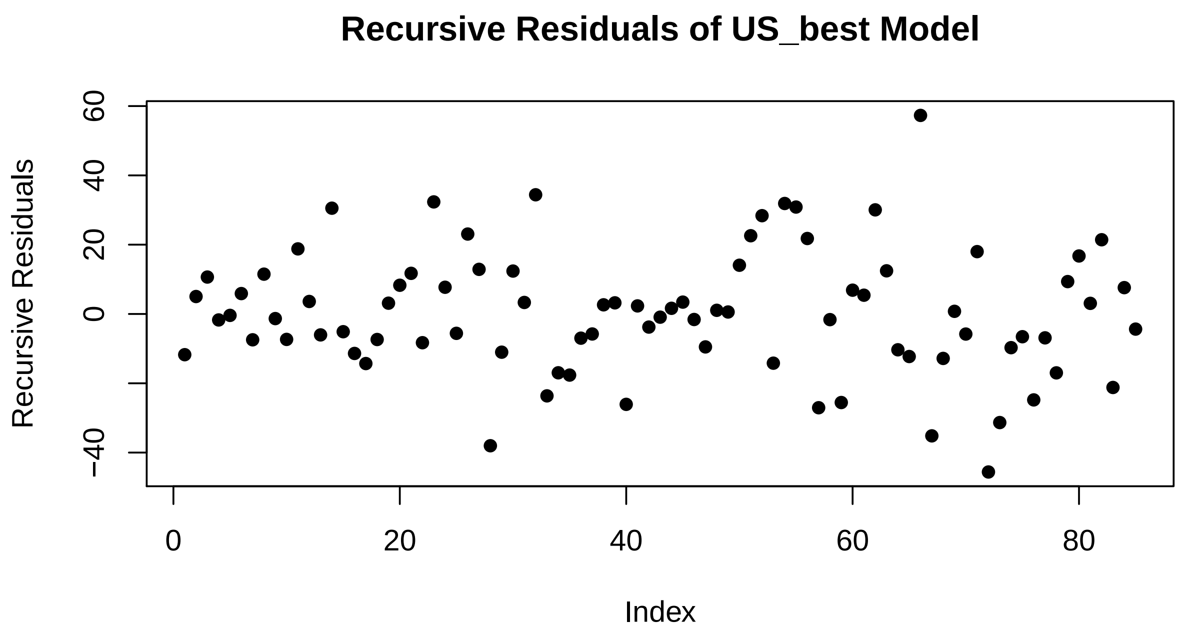
(e) CUSUM Evaluation

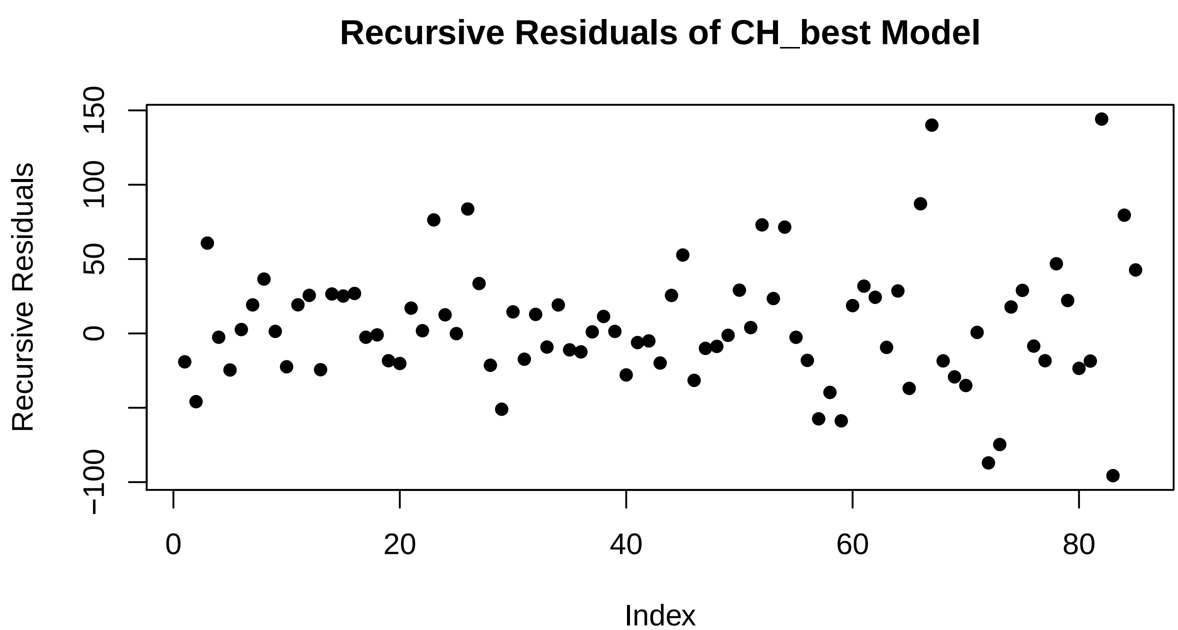




As we can observe from the CUSUM plot, we further confirm that our models for both China and US Economic Policy Uncertainty Indices are structurally fine because they do not break out of the bounds.

(f) Recursive Residuals Evaluation





As observed from the above two plots, for both models, the recursive residuals appear to behave following a random manner. That affrims these two models are very good fits in term of capturing non-linearity and as well for structural changes.

(g) Diagnostic Statistics (p-value).

```
## Series: US
## ARIMA(0,1,2)(2,0,1)[4] with drift
##
## Coefficients:
##           ma1      ma2     sar1     sar2    sma1   drift
##       -0.2530  -0.1643  -0.0794  -0.0483  0.2729  0.2773
## s.e.   0.1092   0.1110   0.8090   0.1902  0.8041  1.2810
##
## sigma^2 estimated as 340.5:  log likelihood=-365.46
## AIC=744.91   AICc=746.37   BIC=762.01
##
## Training set error measures:
##                       ME     RMSE      MAE       MPE     MAPE      MASE
## Training set -0.0753101 17.68682 13.38319 -1.649581 12.29845 0.6133268
##                       ACF1
## Training set -0.007117966
```

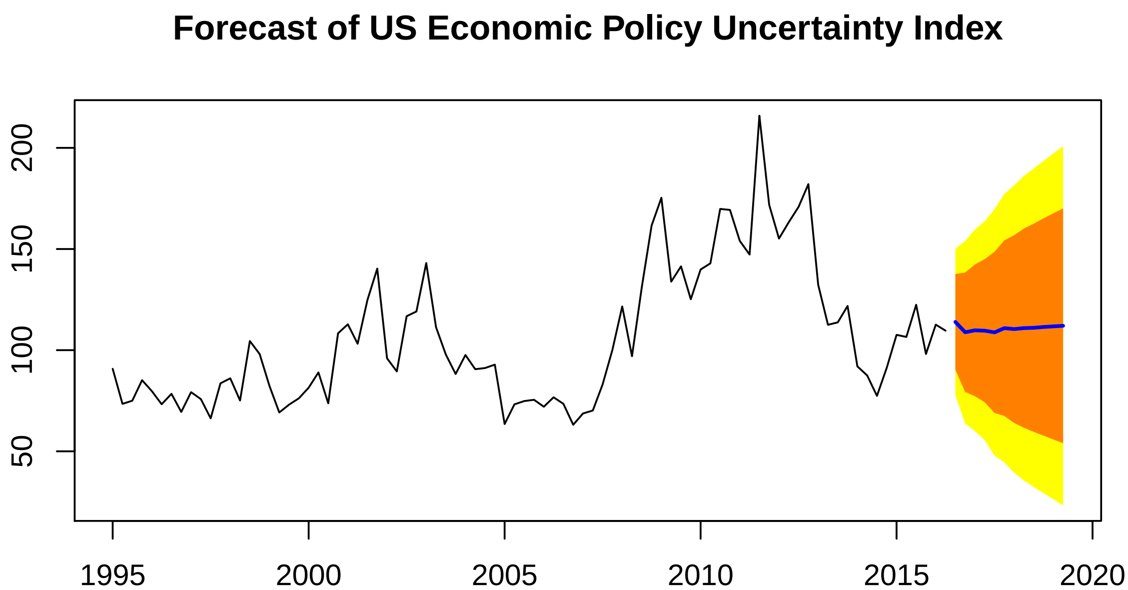
z-score of each coefficients 2.32211, 1.48, 0.098, 0.25, 0.33934, 0.2164

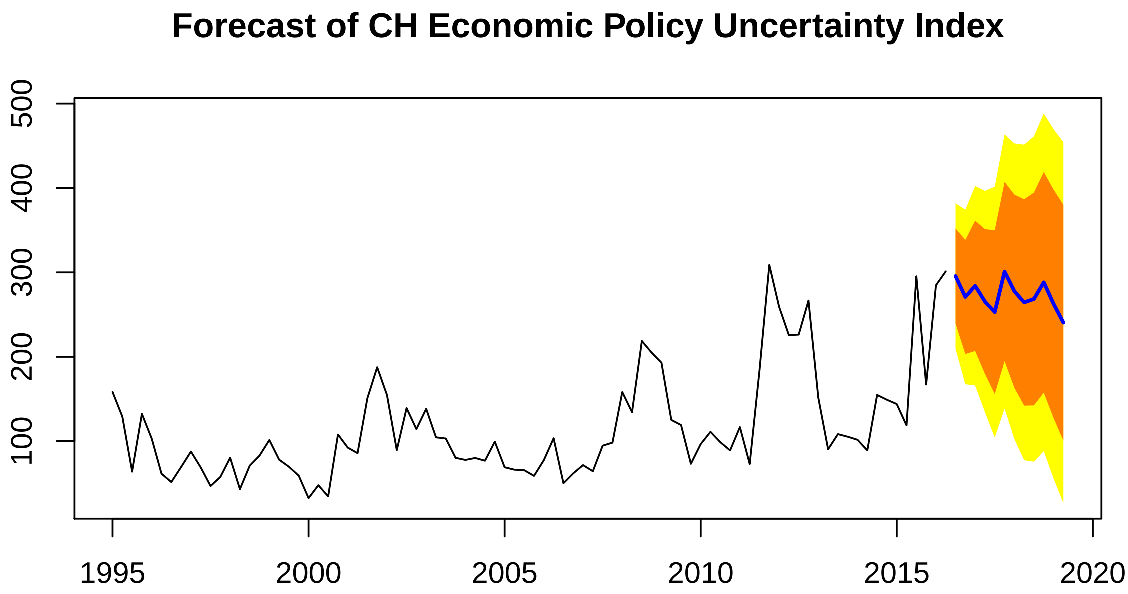
```
## Series: CH
## ARIMA(0,1,1)(2,0,4)[4] with drift
##
## Coefficients:
##           ma1    sar1    sar2     sma1     sma2     sma3    sma4   drift
##       -0.3385  0.2556  0.6563  -0.1075  -0.9078  -0.1479  0.3767  1.5665
## s.e.   0.1277  0.3669  0.3479   0.4369   0.2857   0.1662  0.1774  4.8214
##
## sigma^2 estimated as 1937:  log likelihood=-439.83
## AIC=897.66   AICc=900.06   BIC=919.64
##
## Training set error measures:
##                      ME     RMSE      MAE       MPE     MAPE      MASE
## Training set 0.9612354 41.64014 30.20497 -7.112578 28.08536 0.5767825
##                    ACF1
## Training set 0.01233897
```

z-score of each coefficients 2.65, 0.69, 1.886, 0.2459, 3.17, 0.88989, 2.1234, 0.3246

By computing z scores for each coefficients, under each model, many of the coefficients are not statistically significant. Such a result might be caused by the relative small number of observations and the small values of these coefficient themselves. Despite this potential drawback, currently within the limits our knowledge, US_best and CH_best are the best models that we can produce for each time series.

(h) Forecast under ARIMA Model

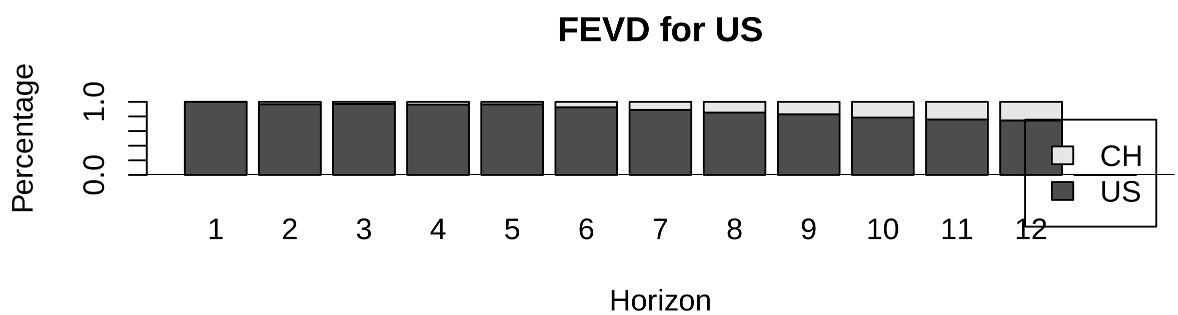


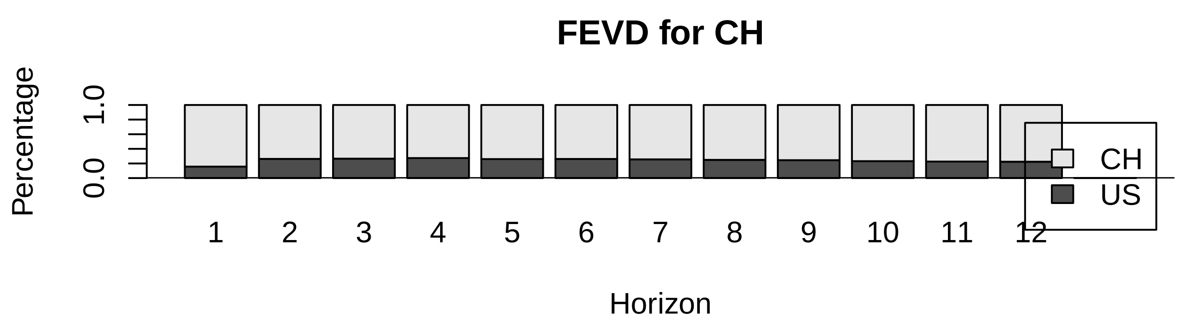


The 12-step ahead forecast for each time series using ARIMA with respective error bands are shown above. The forecast for US Policy Uncertainty Index is more stable as compared to China's more fluctuating forecast results.

(i) Fitting VAR model

```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      5      1      1      5
##
## $criteria
##                   1            2            3            4            5
## AIC(n)     13.29263     13.30771     13.35106     13.42581     13.23195
## HQ(n)      13.39068     13.45479     13.54716     13.67093     13.52610
## SC(n)      13.53797     13.67572     13.84174     14.03916     13.96797
## FPE(n) 592923.64371 602216.31453 629466.51969 679341.67666 560890.93169
##                   6            7            8            9           10
## AIC(n)     13.26884     13.25482     13.34176     13.39500     13.49176
## HQ(n)      13.61202     13.64702     13.78298     13.88525     14.03103
## SC(n)      14.12753     14.23619     14.44579     14.62170     14.84113
## FPE(n) 583822.27228 578160.91364 634184.25209 673578.01034 748502.07024
```

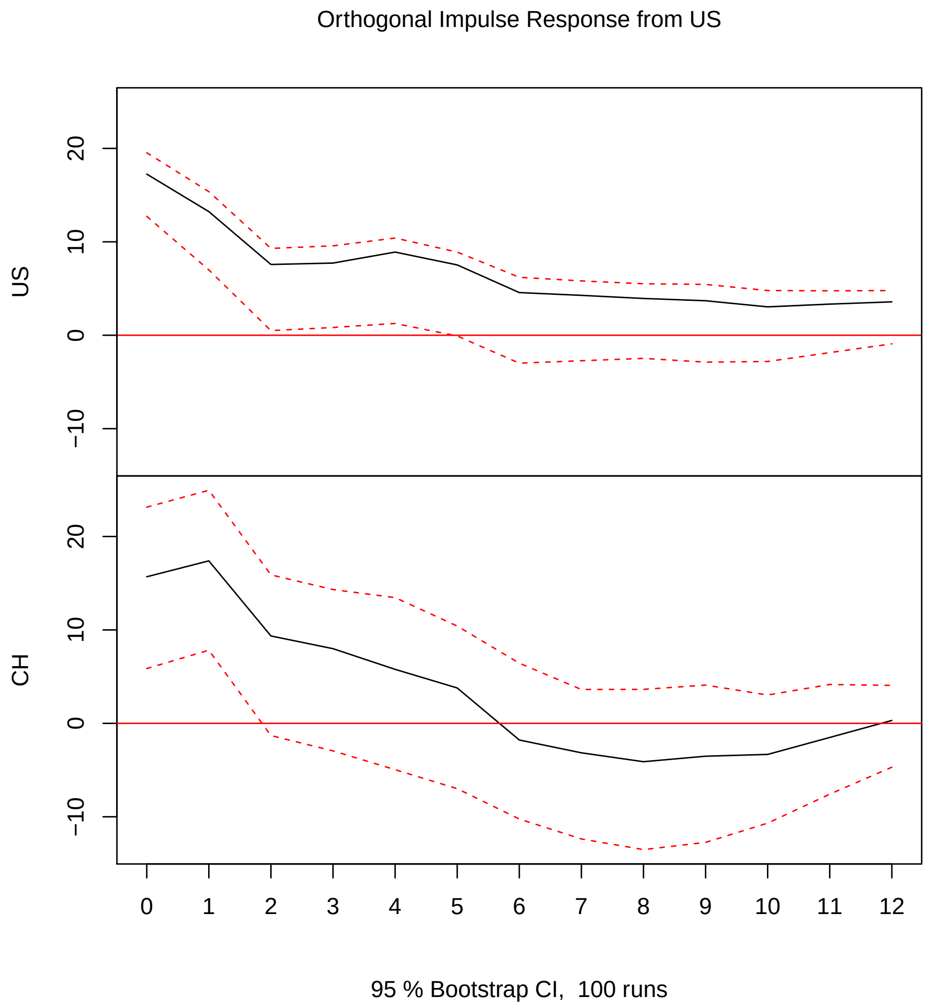


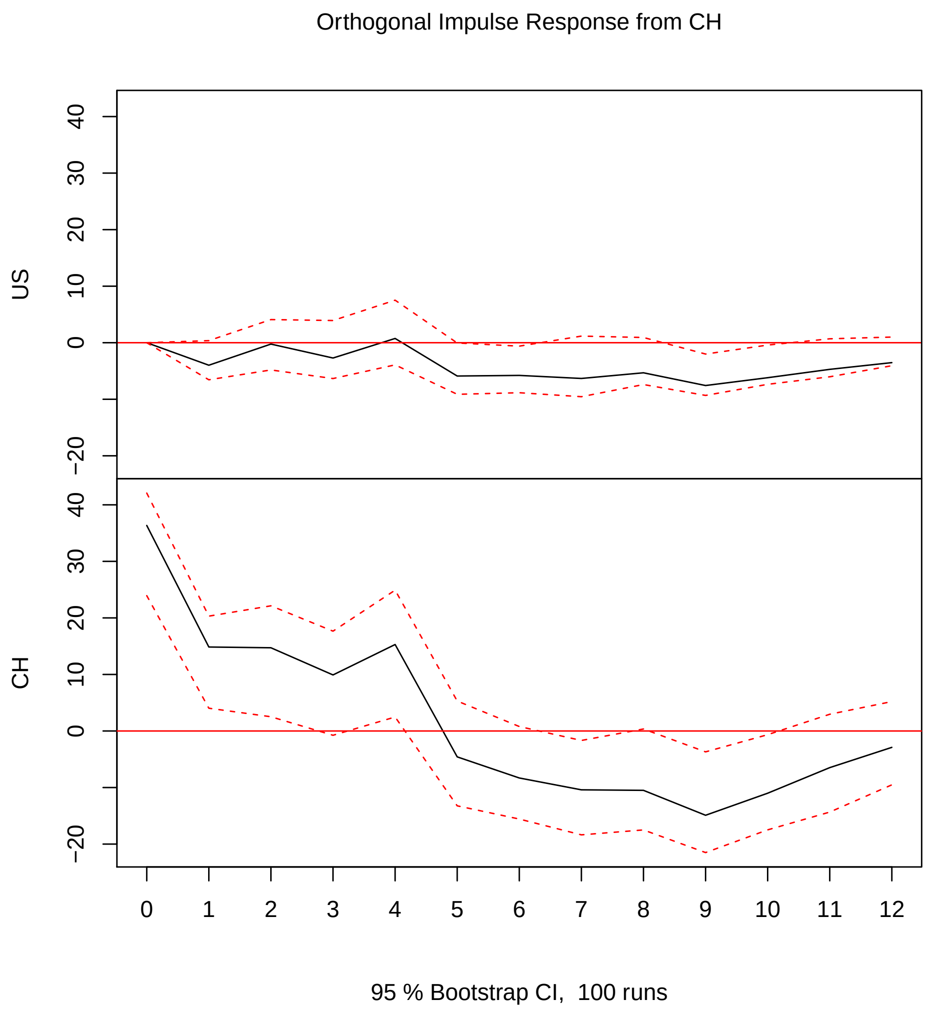


Given a maximum of 10 lags, the VARselect function suggests that p = 5, and then this value is used in fitting the VAR model.

As we explore the Forecast Error Variance Decomposition, we can see that the Economic Policy Uncertainty Index in China has been strongly influenced by the US component (about 20%~25%) but no so much the other way around.

(j) Impulse Response Functions Analysis





By analyzing the above Impulse Response Functions, we can visually observe that an unanticipated change in U.S economic policies will affect China's economic policies with significant magnitude for a couple calendar quarters then such impact dissolves within 6 quarters.

On the other hand, an unanticipated change in China's economic policies does not affect U.S economic policies much.

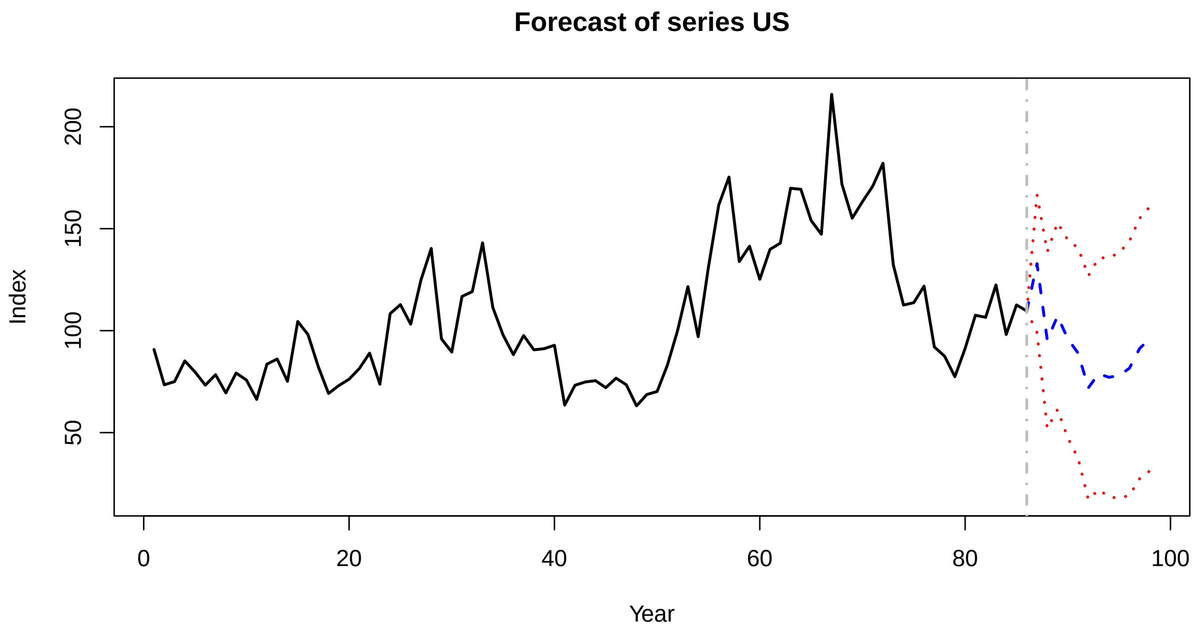
(k) Granger-Causality Test

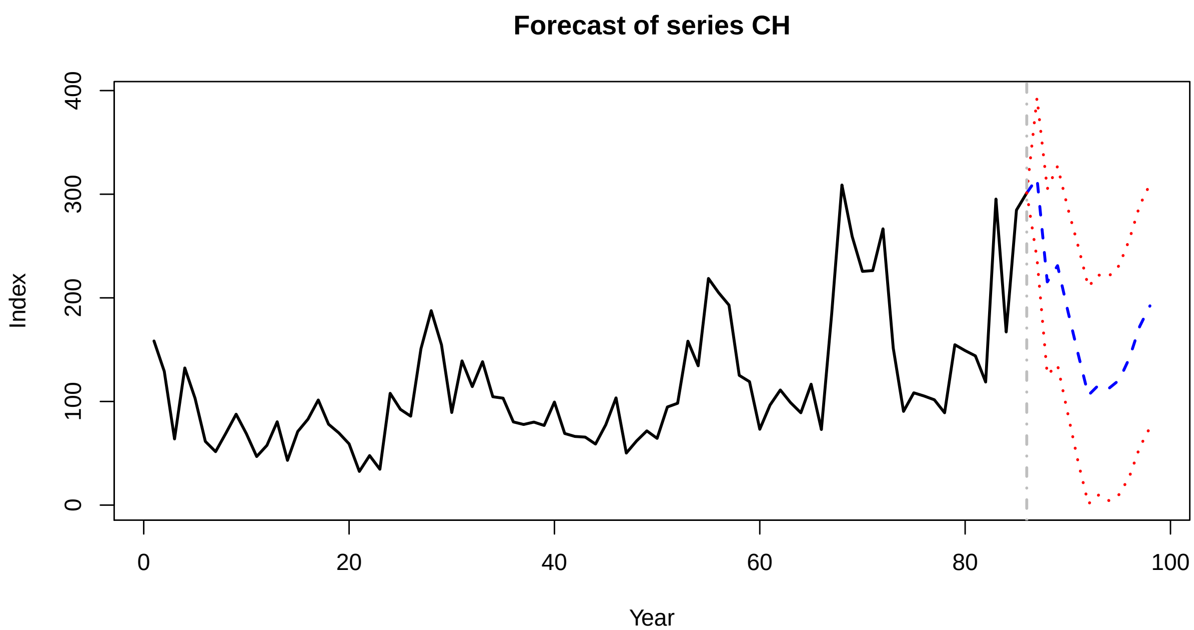
```
## Granger causality test
##
## Model 1: US ~ Lags(US, 1:5) + Lags(CH, 1:5)
## Model 2: US ~ Lags(US, 1:5)
##   Res.Df Df      F  Pr(>F)
## 1     70
## 2     75 -5 2.8496 0.02123 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Granger causality test
##
## Model 1: CH ~ Lags(CH, 1:5) + Lags(US, 1:5)
## Model 2: CH ~ Lags(CH, 1:5)
##   Res.Df Df      F Pr(>F)
## 1     70
## 2     75 -5 1.5787 0.1774
```

Interestingly enough, the Impulse Response Functions show that the U.S affects China's economic policies with greater impact, yet the granger-causality test reveals that there is no statistic significance supporting that finding, but changes in China's policies actually granger-cause changes in U.S economic policies with statistical significance. This interestingn finding will be discussed again in the Conclusions and Future Work section.

(l) Forecast under VAR Model





The 12-step ahead forecast for each time series using VAR with respective error bands are shown above. Under ARIMA forecast, predicted future values have much less fluctuations as compared to predicted values under VAR. In some ways, it seems that VAR is better in forecasting mutiple-step ahead predictions while maintaining the time series' original structures in its forecast.

III. Conclusions and Future Work.

* Conclusions

In the first part, when we are trying to fit a model that includes trend, seasonality and cyclical components, we have fitted an ARIMA Model for both US and China Economic Policy Uncertainty Index, and this model also includes the linear trend t, as well as the seasonal component, whose order is observed from the difference's ACF and PACF.

Moreover, after displaying the Residual V.S. Fitted plots where the residuals are bouncing around zero, the Residual plots where they scatter randomly, and the ACF and PACF plots of the residuals where there is no significant spikes, we can further confirm that our ARIMA Model, that was mentioned above, is an appropriate fit for both time series. In addition, with the help from CUSUM where nothing exceeds the red lines, and the Recursive Residual plots which is also random, we can be more certain that the relationship we are proposing here is appropriate.

Furthermore, when we are using our ARIMA model to forecast, the US forecast seems to be a little flatter, while the China forecast seems to be more robust, and catches the seasonality. Indeed, this discovery corresponds to our ACF and PACF plots for taking the differences within each plot. In the US plots, the seasonal component was not that obvious; however, in the China plots, we can easily see a quarterly seasonality.

In the second part, when we are trying to fit a VAR model, we have discovered that the China Economic Policy Uncertainty granger-cause the US Index, while the vice versa is not statistically significant. On the contrary, the Impulse Response Function suggested that when China is experiencing a shock, it rarely has any influence on the US Index, but when US is experiencing an impulse, it does influence the China Index.

These two findings are rather intriguing to our team. For the Impulse Response Function, where the US Index shock could influence China Index while the vice versa does not could be explained by the fact that United States has a much stronger and larger economic foundation, which could affect the China Index in a larger magnitude. Moreover, for the granger-causality test, which suggested the China Index granger cause the US Index, could be explained by the increasing presence of the Chinese economy in the Global Market. According to a research paper, written by Chen, Jian, Fuwei Jiang and Guoshi Tong, they have discovered that a high level of policy uncertainty and lack of accurate feedback could amplify investor behavioral biases, which could creates a larger speculative component in stock price under short sales constraint (Chen, Jian, Fuwei Jiang and Guoshi Tong 2016). Therefore, when the uncertainty in the Chinese economy rises, it could possibly motivate investor to take behavioral biases, which could have further impact in the Global Economy setting.

* Future Works

when trying to fit a model that includes trend, seasonality and cyclical components, though ARIMA does appear to be a good model, in the fitted value plot, we could see that there is a delay compared to the original data. After searching through the internet, we have discovered that it could be due to the fact that ARIMA model approximation can be flawed by the presence of deterministic structure in the data. And such deterministic structure can include Pulses , Level/Step shifts; Seasonal Pulses and/or Time Trends. In other words, it could suggest us to use a hybrid model incorporating not only ARIMA, but also other models to make it a better fit, and such model could be VARMA, the combination for VAR and ARIMA.

In addition, according to the coefficient significance, which we performed in the discussion of the associated diagnostic statistics, there are a couple coefficients that do not stand out even when they are suggested by Auto ARIMA. Therefore, this further suggests that a hybrid model incorporating not just ARIMA could be a better model.

Last but not least, this data can only be traced back to 1985, therefore, to nowadays, we only have 32 years of data, and it will be very interesting how the Index would change under the new political leaders in the future, and how the policy uncertainty could affect our microeconomics and macroeconomics in the long run. Furthermore, with our granger-causality test, which suggested that China Index granger causes the US Index, along with our Impulse Response function, which suggested that the shock on the US Index has a bigger impact on the China Index, further studies as well as datas will be needed to understand and develop a deeper cause-effect relationship between these two countries' Economic Policy Uncertainty Indexes.

IV. References

- Baker, Scott, Nicholas Bloom, and Steven Davis. "Measuring Economic Policy Uncertainty." (2015): n. pag. Web. 31 May 2017.
- Irwin, Neil. "How Trump Can Improve the Messy U.S.-Chinese Economic Relationship."Www.nytimes.com. N.p., 6 Apr. 2017. Web. 31 May 2017.
- Chen, Jian, Fuwei Jiang, and Guoshi Tong. "Economic Policy Uncertainty in China and Stock Market Expected Returns." SSRN Electronic Journal (n.d.): n. pag. Web. 1 June 2017.
- Data is obtained from the Fred Economic Research, Economic Policy Uncertainty. Both of the data from US and China is quarterly data, starting from 1995.01.01 to 2016.04.01.
- Data Source URL: https://fred.stlouisfed.org/search?st=economic+policy+uncertainty

V. R Source code.

Loading & Reading

```
#Load Libraries
library(fOptions)
library(nlstools)
library(tseries)
library(Quandl)
library(zoo)
library(PerformanceAnalytics)
library(quantmod)
library(car)
library(FinTS)
library(forecast)
library(stats)
library(strucchange)
library(stockPortfolio)
library(vars)
library(XML)
library(pastecs)
library(fBasics)
library(timsac)
library(TTR)
library(lattice)
library(MASS)
library(stats4)
library(KernSmooth)
library(fastICA)
library(cluster)
library(leaps)
library(mgcv)
library(rpart)
library(graphics)
library(RColorBrewer)
library(DAAG)
library(tis)
library(lmtest)
library(corrplot)
library(quantmod)
```

```r
#Read Data
my_q1 <- read.csv("Data/fredgraph.csv")

#Delete Unneeded rows
my_q1 <- my_q1[c(14:99),]

#Assign Proper class to variables
US_Values <- as.numeric(as.character(my_q1$X))
CH_Values <- as.numeric(as.character(my_q1$X.1))

#Assign Time Series class
US <-ts(US_Values,start=c(1995),freq=4)
CH <-ts(CH_Values,start=c(1995),freq=4)

#Create time sequence
t<-seq(1995, 2016.25,length=length(US))
```

II.(a)

```r
#Plot Time Series
plot(US,main="Economic Policy Uncertainty Index of United States")
nberShade()
lines(US,ylab="")
plot(CH,main="Economic Policy Uncertainty Index of China")
nberShade()
lines(CH,ylab="")
```

```r
#Plot Time Series Overlay on top of each other
plot(CH, main="Economic Policy Uncertainty Index of United States and China")
nberShade()
lines(CH,ylab="Economic Policy Uncertainty Index")
lines(US ,col="blue")
legend("topleft",legend=c("US","CHINA"),text.col=c("blue","black"),bty="n")
```

```r
#Plot ACF & PACF
par(mfrow=c(2,2))
acf(US)
pacf(US)
acf(CH)
pacf(CH)
```

II.(b)

* For U.S

Linear Trend

```
#Fit linear trend
m1_US <- lm(US~t)

#Plot Time series overlay fitted trend
plot(US, main = "US Economic Policy Uncertainty",
     ylab = "Index", xlab="Time", lwd=2, col='skyblue3')
lines(t,m1_US$fit,col="red3",lwd=2)

#Plot Residuals of the Fit
plot(t,m1_US$res, main = "Residuals of the Fitted m1_US Model",
     ylab ="Residuals", xlab ="Time", type='l')

#Plot ACF anf PACF of m1_US Residuals
par(mfrow=c(1,2))
acf(m1_US$res,lag=36,main="ACF of m1_US Residuals",xlab="Displacement")
pacf(m1_US$res,lag=36,main="PACF of m1_US Residuals", xlab="Displacement")
```

Quadratic Trend + Seasonal Dummies

```
#Fit a quadratic trend + seasonality model (no y-intercept)
t2 <- t^2
m2_US <- tslm(US~0+t+t2+season)
plot(US, main = "US Economic Policy Uncertainty",
     ylab="Index", xlab="Time", lwd=2, col='skyblue3')
lines(t,m2_US$fit,col="red3",lwd=2,lty=2)

#Plot Residuals of the Fit
plot(t,m2_US$res, main = "Residuals of the Fitted m2_US Model",
     ylab="Residuals",type='l',xlab="Time",lwd=2)

# Look at the ACF and PACF of m2_US Residuals
par(mfrow=c(1,2))
acf(m2_US$res,lag=36,main="ACF of m2_US Residuals",xlab="Displacement")
pacf(m2_US$res,lag=36,main="PACF of m2_US Residuals", xlab="Displacement")
```

R's auto.arima

```
#Fit Auto Arima Model
US_auto <- auto.arima(US)
US_auto

#We will use the following to check for the Seasonality in the ARIMA Model
par(mfrow=c(1,2))
acf(diff(US,4),lag=360,main="ACF of Diff(US,4)",xlab="Displacement")
pacf(diff(US,4),lag=360,main="PACF of Diff(US,4)", xlab="Displacement")
```

```
# Model: Quadratic Trend + Seasonality + Cycles (from the Auto Arima)
US_best <- Arima(US,order=c(0,1,2), include.drift=TRUE,seasonal=list(order=c(2,0,1)))

plot(US, main = "US Economic Policy Uncertainty",
     ylab="Index", xlab="Time", lwd=2, col='skyblue3')
lines(fitted(US_best),col="black")
legend(1995,215, c("Observed", "US_best Fit"),
fill = c("skyblue3", "black"))
```

*** For China**

Linear Trend

```
#Fit linear trend
m1_CH <- lm(CH~t)

#Plot Time series overlay fitted trend
plot(CH, main = "China Economic Policy Uncertainty",
     ylab = "Index", xlab="Time", lwd=2, col='skyblue3')
lines(t,m1_CH$fit,col="red3",lwd=2)

#Plot Residuals of the Fit
plot(t,m1_CH$res, main = "Residuals of the Fitted m1_CH Model",
     ylab ="Residuals", xlab ="Time", type='l')

#Plot ACF anf PACF of m1_CH Residuals
par(mfrow=c(1,2))
acf(m1_CH$res,lag=36,main="ACF of m1_CH Residuals",xlab="Displacement")
pacf(m1_CH$res,lag=36,main="PACF of m1_CH Residuals", xlab="Displacement")
```

Quadratic Trend + Seasonal Dummies

```
#Fit a quadrtaic trend + seasonality model (no y-intercept)
m2_CH <- tslm(CH~0+t+t2+season)
plot(CH, main = "China Economic Policy Uncertainty",
     ylab="Index", xlab="Time", lwd=2, col='skyblue3')
lines(t,m2_CH$fit,col="red3",lwd=2,lty=2)

#Plot Residuals of the Fit
plot(t,m2_CH$res, main = "Residuals of the Fitted m2_CH Model",
     ylab="Residuals",type='l',xlab="Time",lwd=2)

# Look at the ACF and PACF of M2 Residuals
par(mfrow=c(1,2))
acf(m2_CH$res,lag=36,main="ACF of m2_CH Residuals",xlab="Displacement")
pacf(m2_CH$res,lag=36,main="PACF of m2_CH Residuals", xlab="Displacement")
```

R's auto.arima

```
#Fit Auto Arima Model
CH_auto <- auto.arima(CH)
CH_auto

#We will use the following to check for the Seasonality in the ARIMA Model
par(mfrow=c(1,2))
acf(diff(CH,4),lag=360,main="ACF of Diff(CH,4)",xlab="Displacement")
pacf(diff(CH,4),lag=360,main="PACF of Diff(CH,4)", xlab="Displacement")
```

```
# Model: Quadratic Trend + Seasonality + Cycles (from the Auto Arima)
CH_best <- Arima(CH,order=c(0,1,1),include.drift=TRUE,seasonal=list(order=c(2,0,4)))

plot(CH, main = "China Economic Policy Uncertainty",
     ylab="Index", xlab="Time", lwd=2, col='skyblue3')
lines(fitted(CH_best),col="black")
legend(1995,315, c("Observed", "US_best Fit"),
fill = c("skyblue3", "black"))
```

II.(c)

* For U.S

```
#Plot Fitted vs. Residuals for US
plot(fitted(US_best), residuals(US_best))
title("Residuals vs. Fitted for US Under US_best")
```

* For China

```
#Plot Fitted vs. Residuals for China
plot(fitted(CH_best), residuals(CH_best))
title("Residuals vs. Fitted for China Under CH_best")
```

II.(d)

```
#Plot ACF & PACF of residuals
par(mfrow=c(2,2))
acf(US_best$residuals)
pacf(US_best$residuals)
acf(CH_best$residuals)
pacf(CH_best$residuals)
```

II.(e)

```
#Plot CUSUM plot
par(mfrow=c(2,1))
plot(efp(US_best$res~1, type = "Rec-CUSUM"), main = "CUSUM of US_best Model")
plot(efp(CH_best$res~1, type = "Rec-CUSUM"), main = "CUSUM of CH_best Model")
```

II.(f)

```
#Compute and Plot Recursive Residuals
x <- recresid(US_best$res~1)
y <- recresid(CH_best$res~1)

par(mfrow=c(2,1))
plot(x, pch=16, ylab= "Recursive Residuals",
     main = "Recursive Residuals of US_best Model")
plot(y, pch=16, ylab= "Recursive Residuals",
     main = "Recursive Residuals of CH_best Model")
```

II.(g)

```
#Summary of Model
summary(US_best)
summary(CH_best)
```

II.(h)

```
#compute the respective 12-steps-ahead forecast for CH series and US series
plot(forecast(US_best, h=12), shadecols="oldstyle",
     main = "Forecast of US Economic Policy Uncertainty Index")
plot(forecast(CH_best, h=12), shadecols="oldstyle",
     main = "Forecast of CH Economic Policy Uncertainty Index")
```

II.(i)

```
a <- cbind(US, CH)
#Select Order of VAR & Construct VAR
VARselect(a, lag.max = 10, type = "both")

#Chose p = 5
y_model <- VAR(a, p=5, type = "both")

#Forecast Error Variance Decomposition
plot(fevd(y_model, n.ahead = 12))
```

II.(j)

```
#Impulse Response Functions
plot(irf(y_model, n.ahead=12))
```

II.(k)

```
#Granger-Causality Test
grangertest(US~CH, order=5)
grangertest(CH~US, order=5)
```

II.(l)

```
#12-steps Forecast
var.predict = predict(object=y_model, n.ahead=12,level=0.95)
plot(var.predict,xlab='Year', ylab='Index', lwd=2)
```