Civilian Unemployment Rate

ECON 5337
Fall 2018

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Series Overview

- The unemployment rate represents the number of unemployed as a percentage of the labor force.
- Labor force data are restricted to people 16 years of age and older, who currently reside in 1 of the 50 states or the District of Columbia, who do not reside in institutions (e.g., penal and mental facilities, homes for the aged), and who are not on active duty in the Armed Forces.
- Observation goes from January 1972 to October 2018.
- Predicting the unemployment rate is one of the most important applications for economists and policymakers.

Deterministic Variables

The variables we will be using are

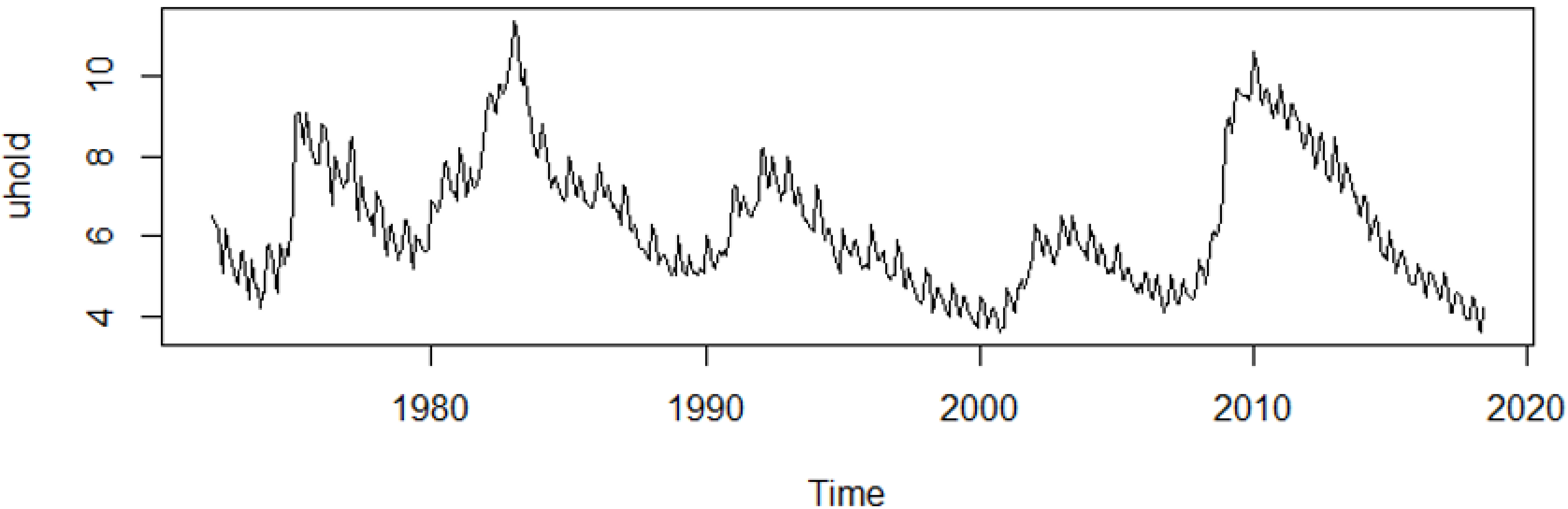
1) Civilian Unemployment Rate
2) Industrial Production Index
3) Federal Fund Rate
4) Consumer Price Index

Stationary Test

```
u=ts(temp[,2],start=c(1972,1),frequency=12)
uhold=ts(temp[,2],start = c(1972,1),end = c(2018,6), frequency = 12)
```

- Plot

```
plot(uhold)
```



- Should we take natural log of our restricted data?

Stationary Test

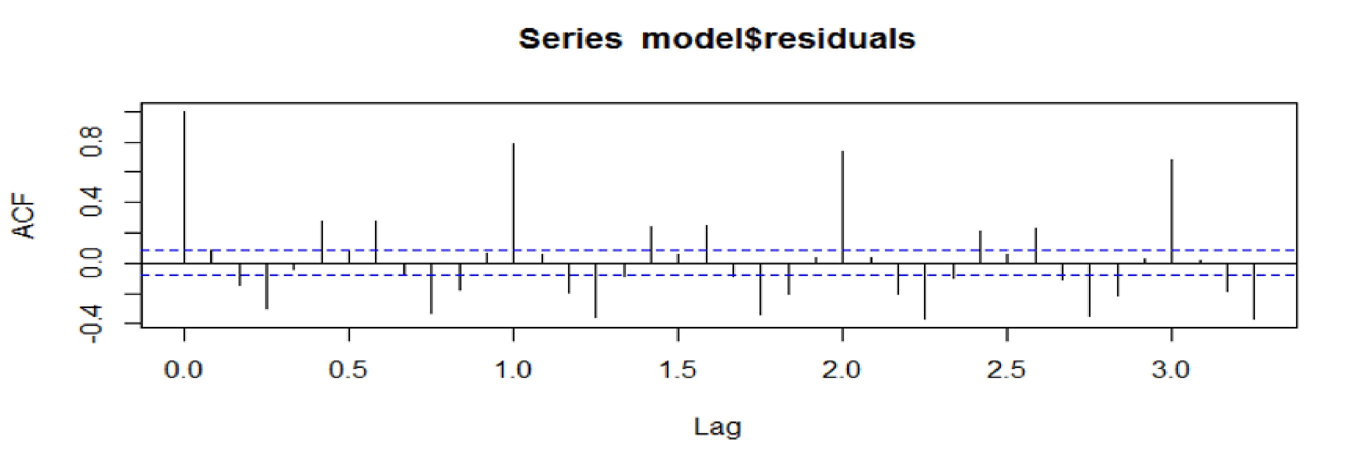
- Should we difference our restricted data?

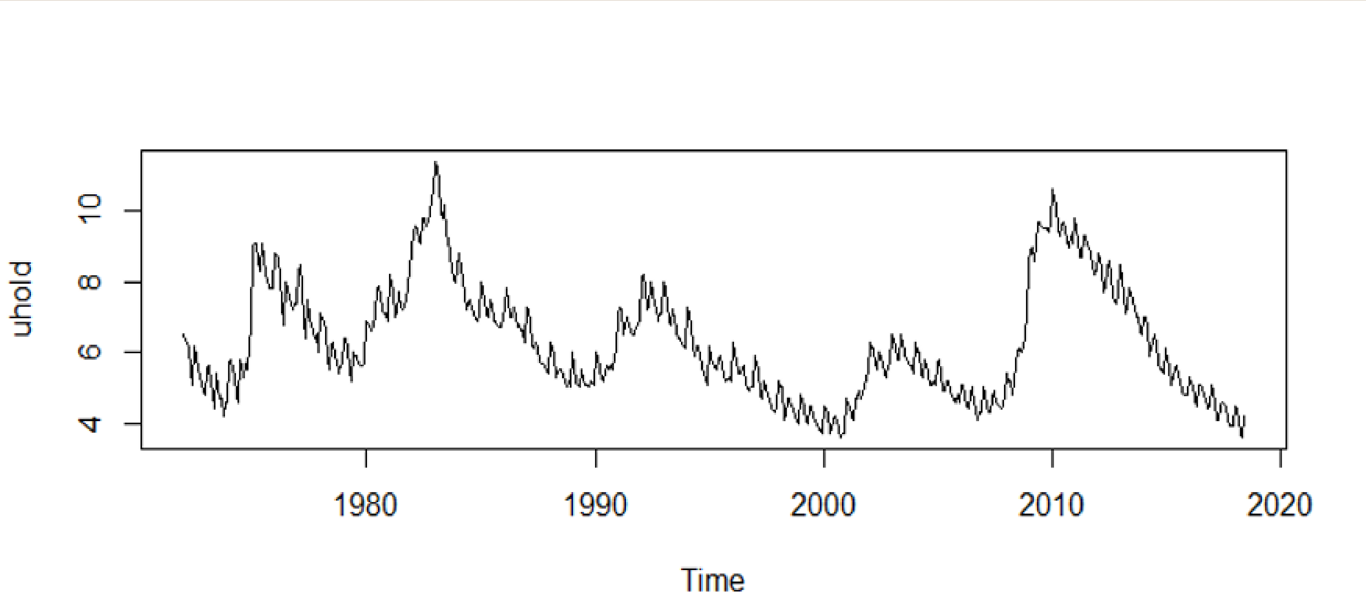
```
summary(ur.df(uhold,type="drift",lags=30,selectlags="AIC"))
```

```
Value of test-statistic is: -3.635 6.6252

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.43 -2.86 -2.57
phi1  6.43  4.59  3.78
```

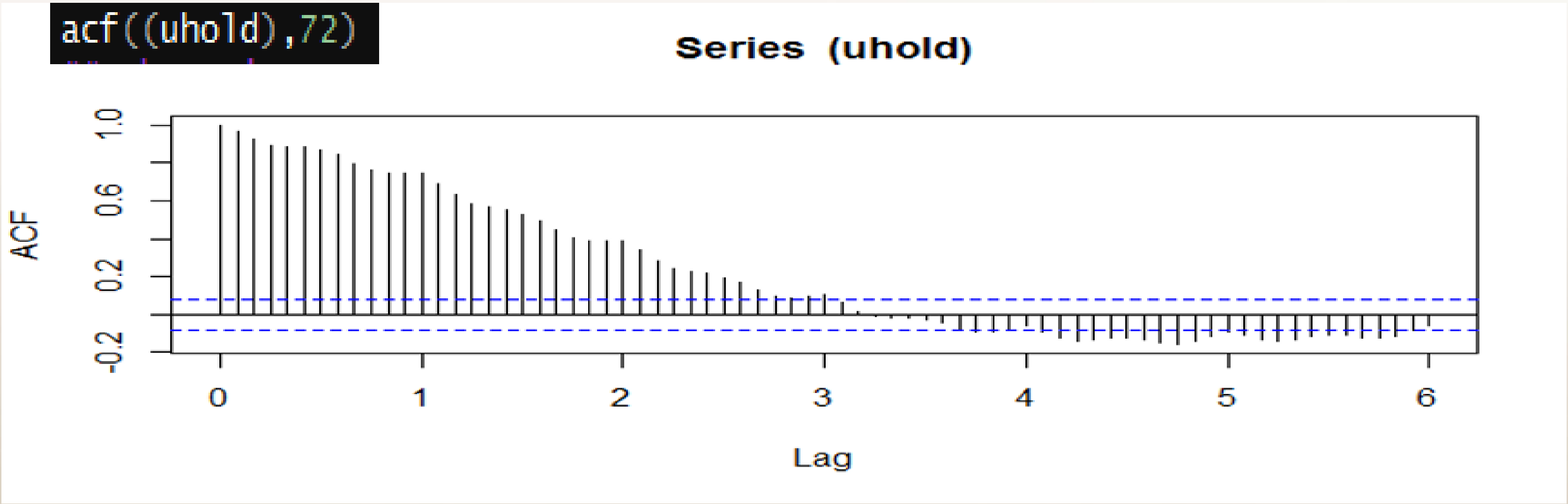
Seasonality/ Deterministic Trends/ Stochastic Variation

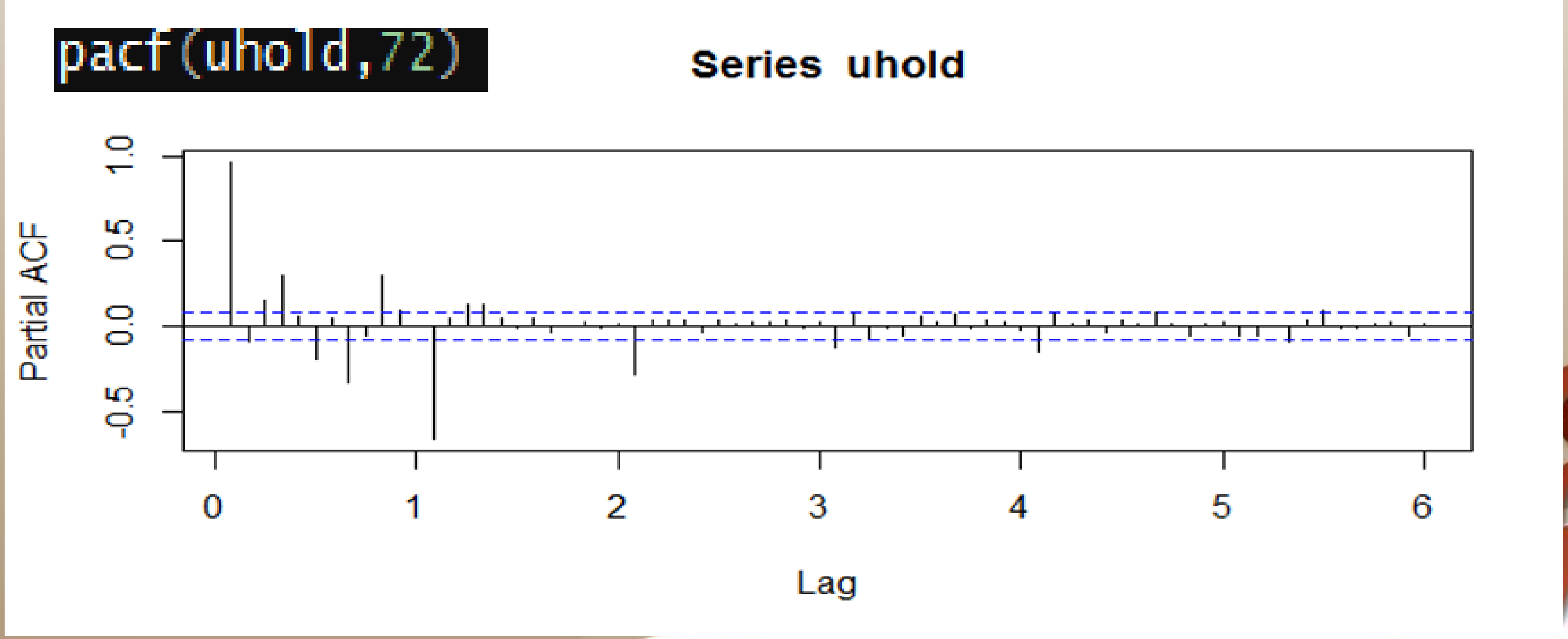
```
model=Arima(uhold,order=c(1,0,0))
acf(model$residuals,39)
```





SARIMA MODEL





SARIMA MODEL

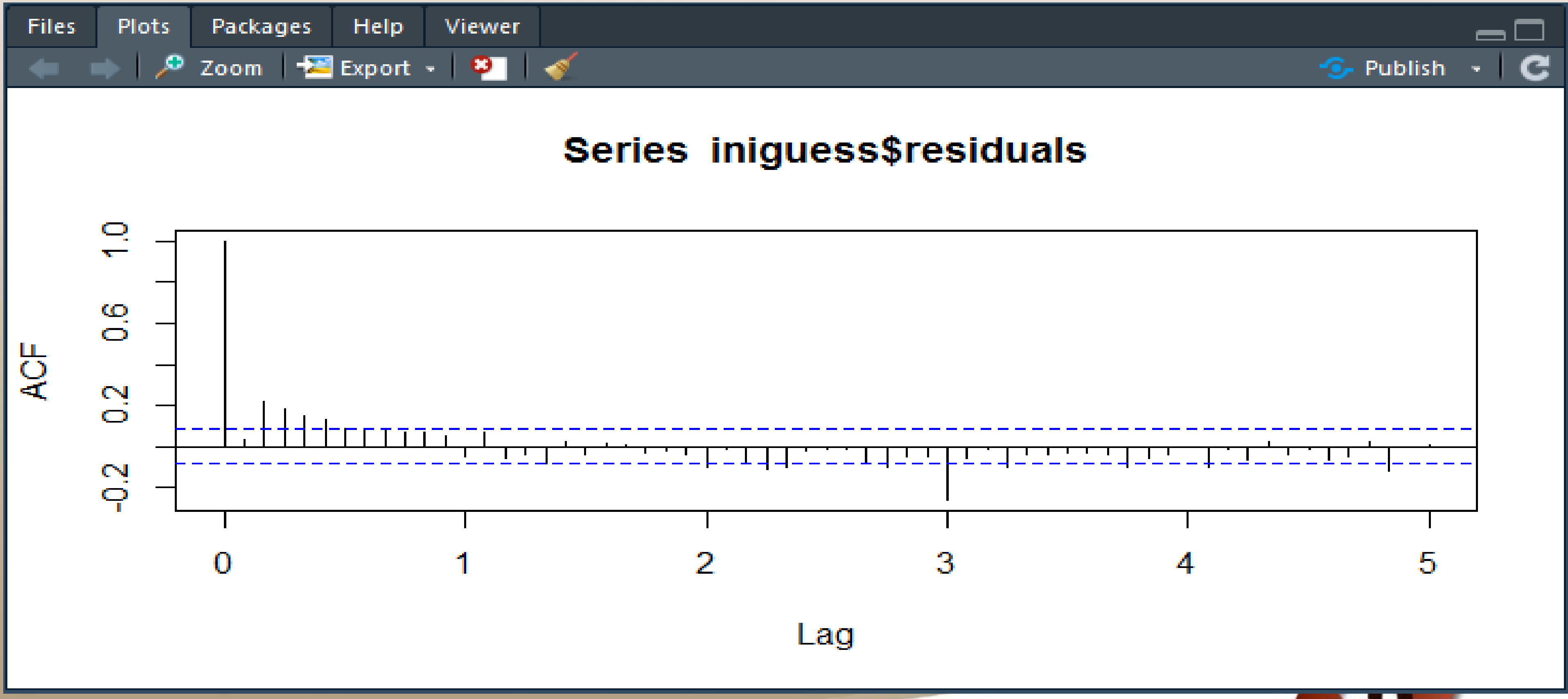
- INITIAL GUESS

```
iniguess= Arima(uhold,order=c(1,0,1),seasonal=c(3,0,0), include.drift = TRUE)
iniguess
```

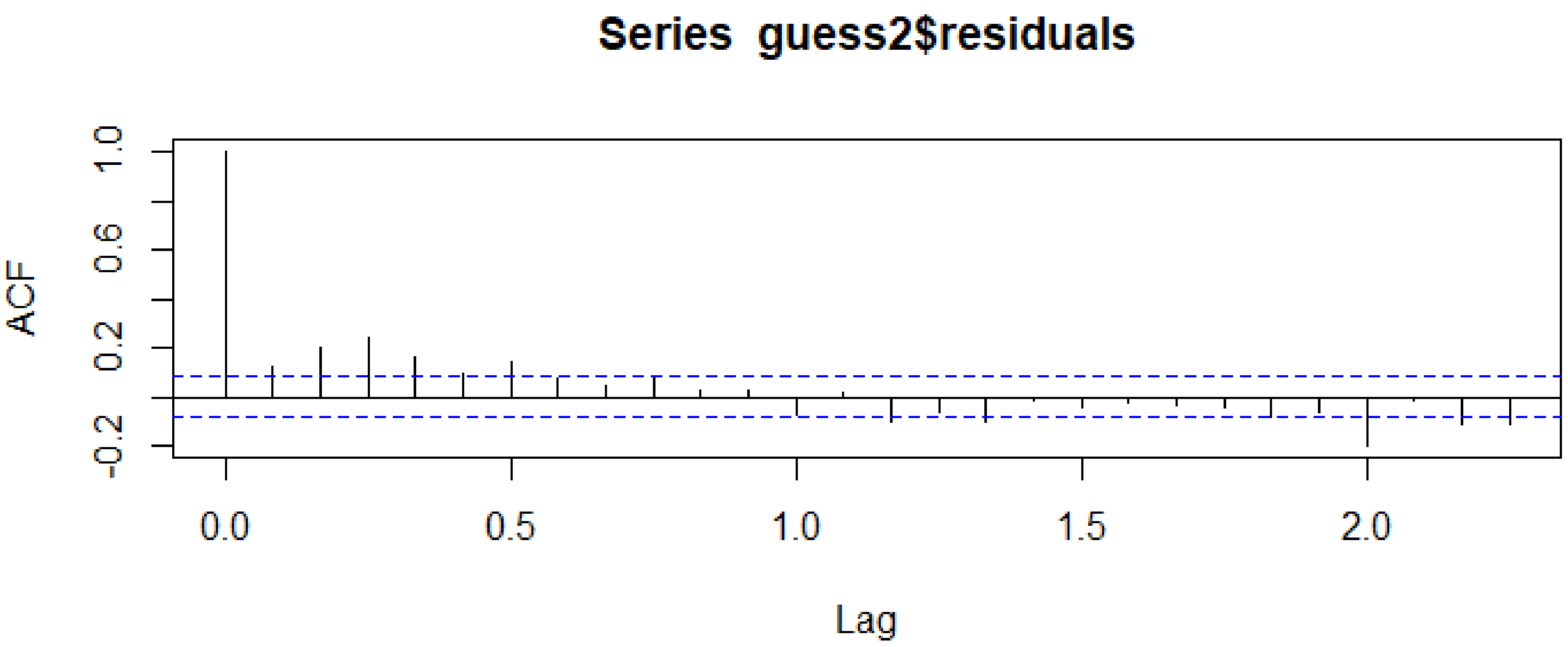
```
# sigma^2 estimated as 0.04951:  log likelihood=38.33
# AIC=-60.67   AICc=-60.41   BIC=-26.07
```

SARIMA Model

```
acf(iniguess$residuals,60)
```

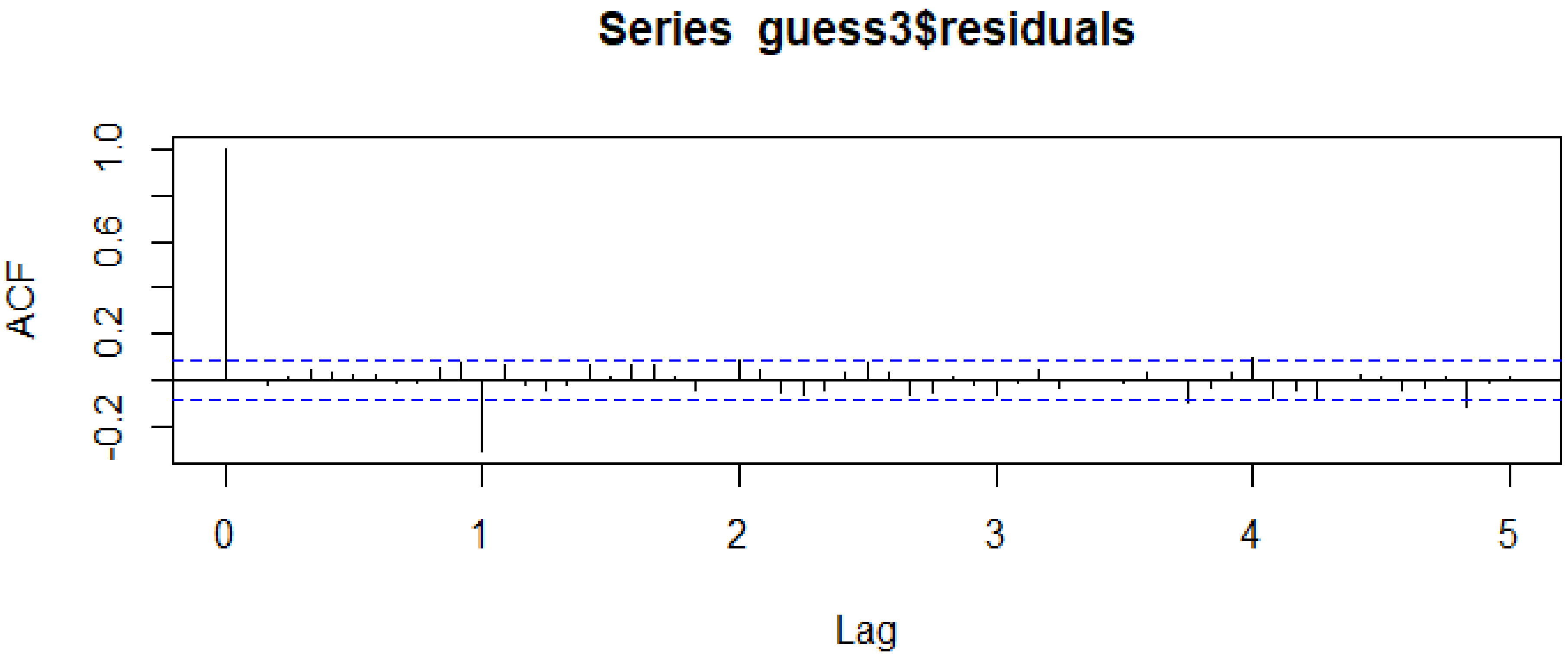


Different Models Estimation



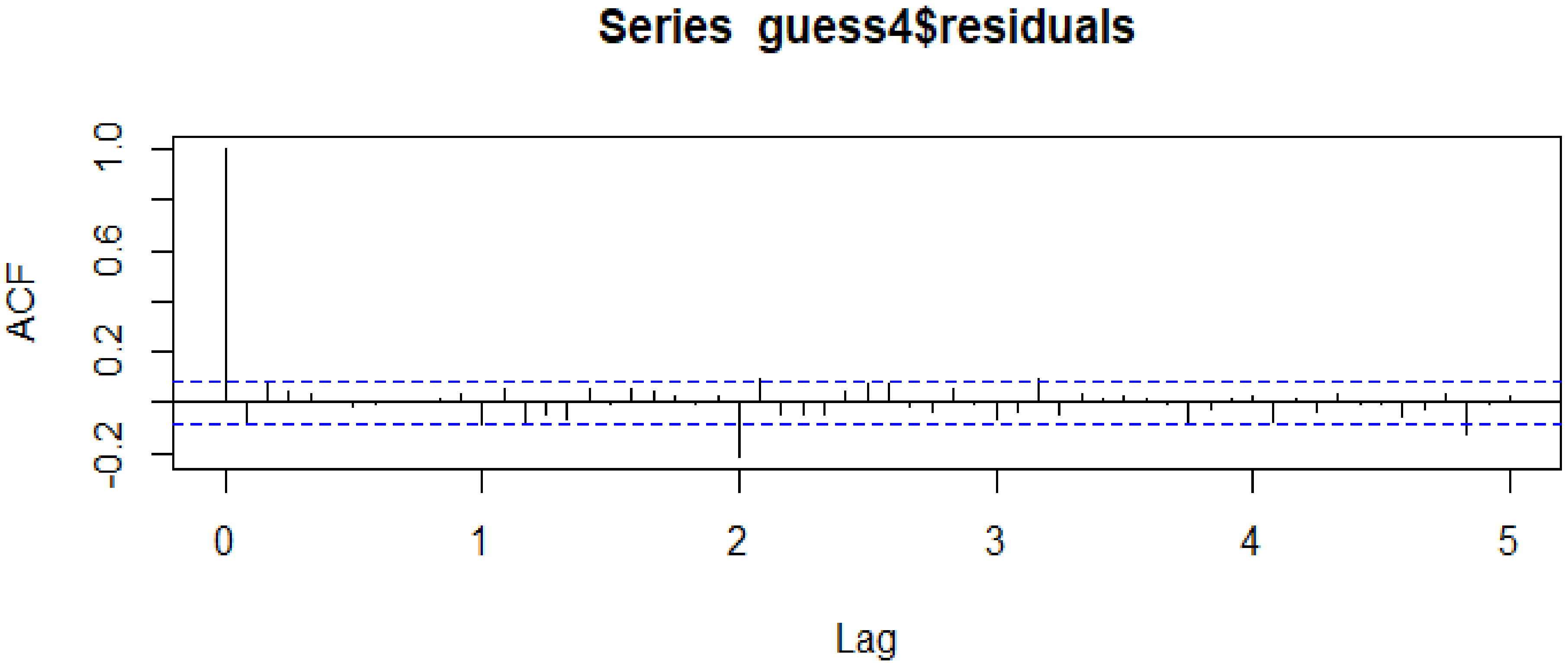
Guess2 = (3,0,2),(2,0,0)

Different Models Estimation



Guess3 = (3,0,1),(1,0,0)

Different Models Evaluation

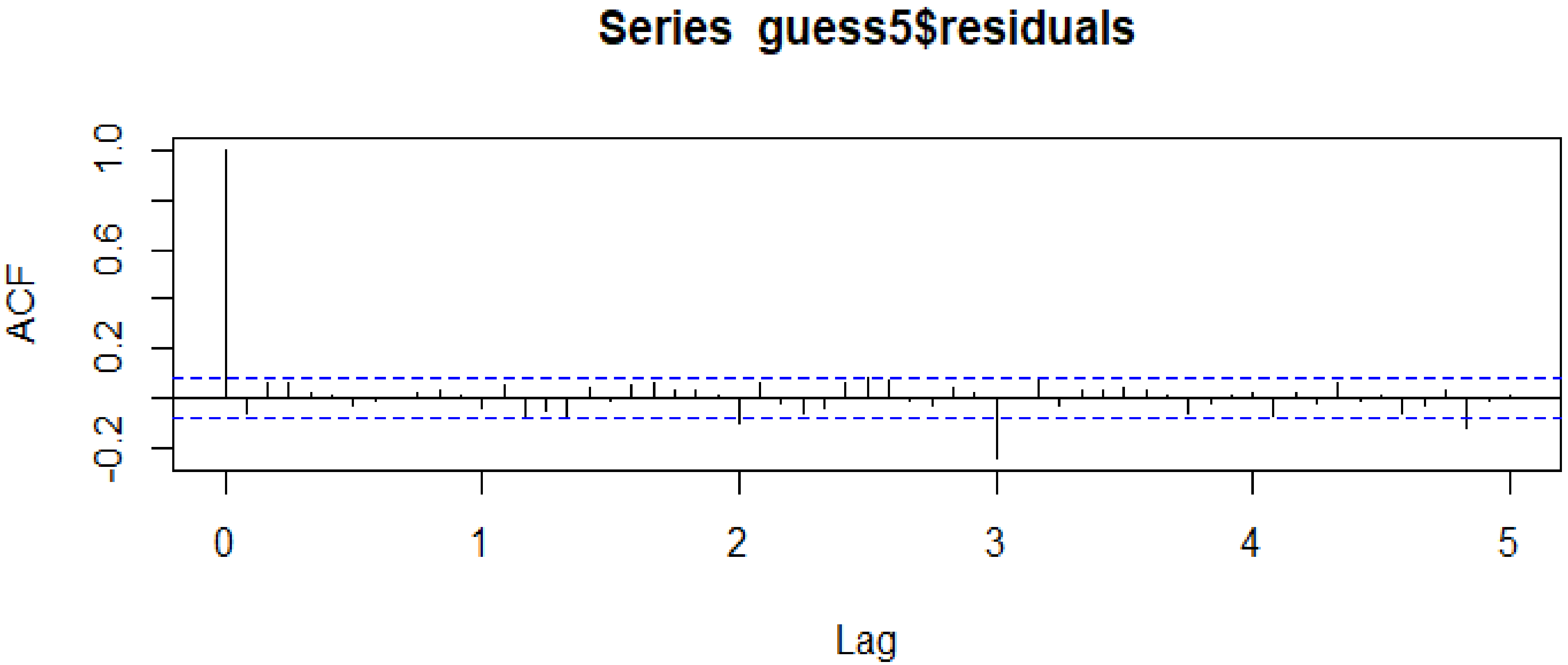


Guess4 = (2,0,1),(2,0,0)

Model selection

Models	AIC	BIC
1 <- (1,0,3),(1,0,0)	17.69	52.28
2 <- (3,0,2),(2,0,0)	-37.56	5.68
3 <- (3,0,1),(1,0,0)	-16.23	18.36
4 <- (2,0,1),(2,0,0)	-95.3	-60.71
5 <- (2,0,1),(3,0,0)	-122.44	-83.52

Selected Model ACF



Guess5 = (2,0,1),(3,0,0)

‘Box-Pierce’ Test

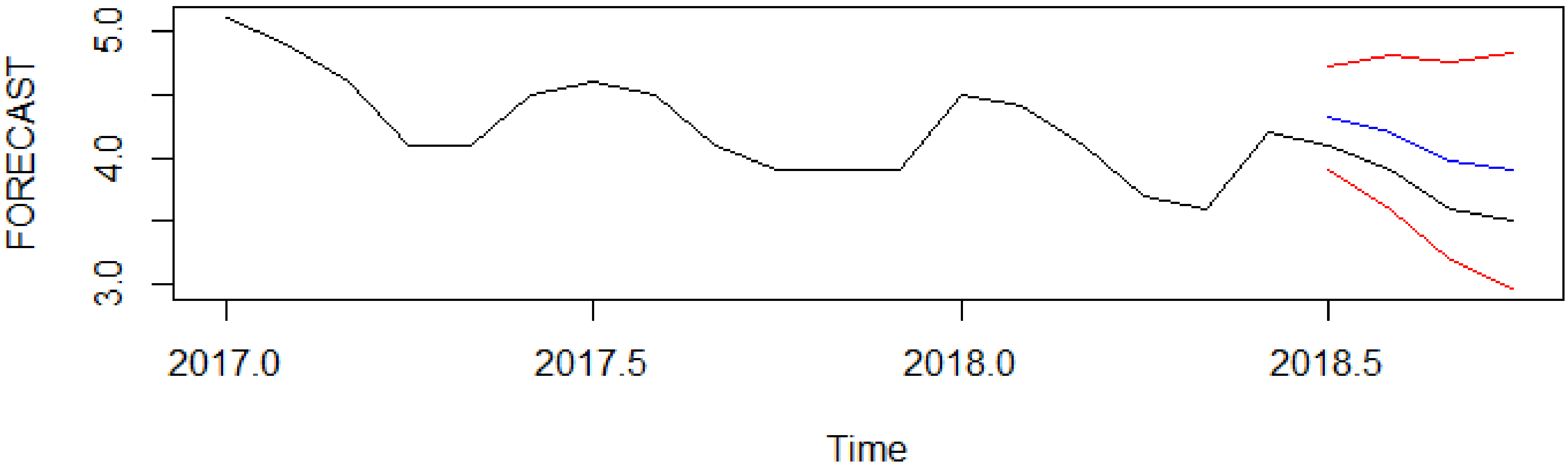
```
> Box.test(guess5$residuals,60,type="Box-Pierce")

        Box-Pierce test

data:  guess5$residuals
X-squared = 105.39, df = 60, p-value = 0.000268
```

The Forecast

```
> forecast = forecast(guess5,h=4,biasadj = TRUE)
> forecast
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
Jul 2018       4.316843 4.047666 4.586019 3.905173 4.728513
Aug 2018       4.205042 3.807162 4.602922 3.596537 4.813547
Sep 2018       3.974287 3.467508 4.481065 3.199235 4.749338
Oct 2018       3.899733 3.293999 4.505467 2.973343 4.826124
```

Time period	Actual values	Forecasted values
Jul 2018	4.1	4.316843
Aug 2018	3.9	4.205042
Sep 2018	3.6	3.974287
Oct 2018	3.5	3.899733

Plot of Forecasted values



VAR model

- Vector Auto regression model
- $Y_t = a + A_1Y_{t-1} + A_2Y_{t-2} + \dots + A_pY_{t-p} + \varepsilon$
- $Y_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$: an (nx1) vector of time series variables
- a: an (nx1) vector of intercepts
- A_i ($i=1, 2, \dots, p$): (nxn) coefficient matrices
- ε_t : an (nx1) vector of unobservable (white noise)

Variables

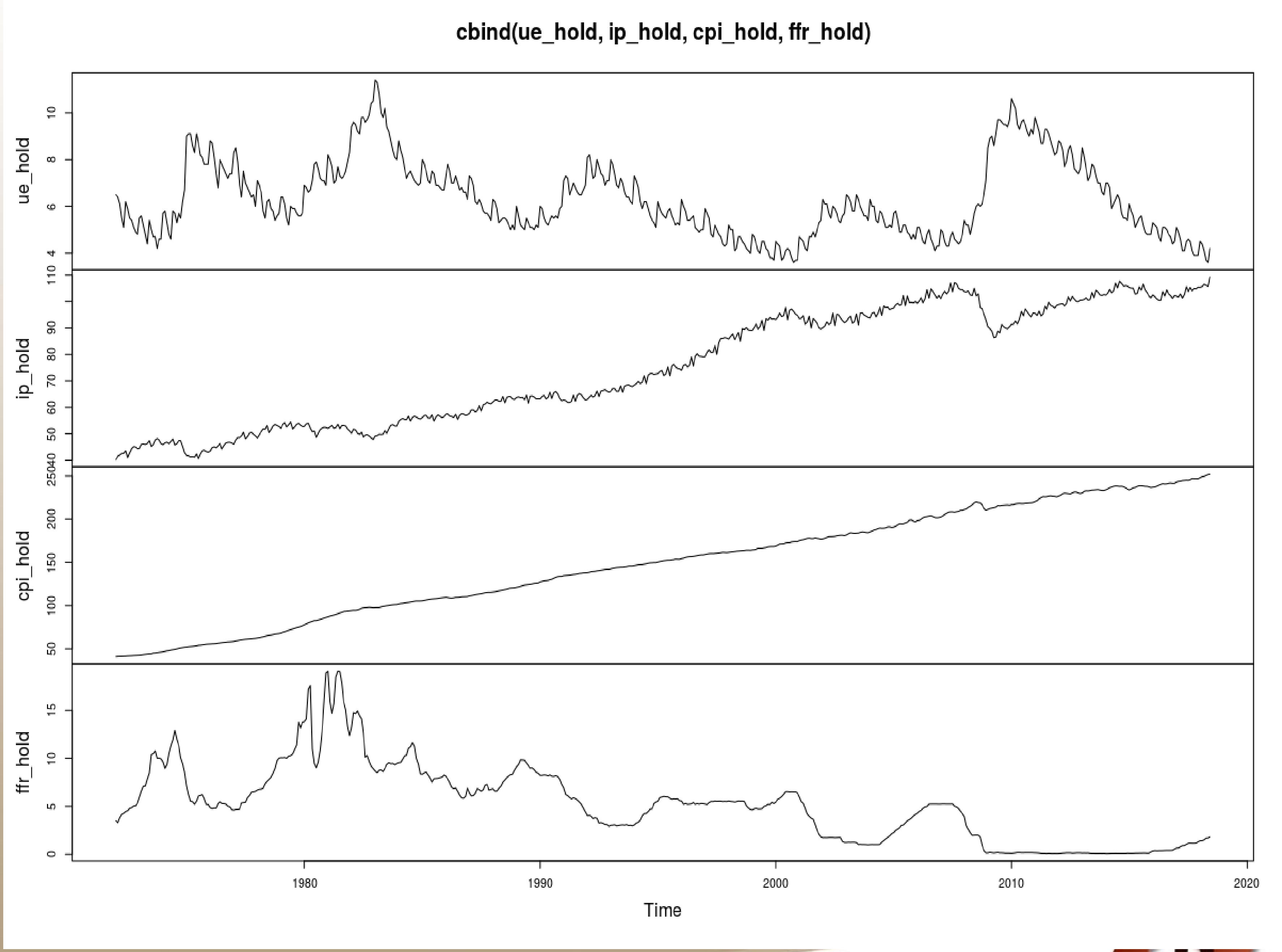
- Inflation: Discourages firms to invest, Inflation booms cause recessions
- Industrial production: Production requires workforce, negatively correlated
- Federal funds rate: High borrowing rates slows down/reduces economic activity relatively.
- bi-directional causality

Modelling

- Co-integrated: No elements data is not co-integrated
- ca.jo(full, type="eigen", K=2, ecdet="none", spec="longrun")
- values of test statistic and critical values of test:

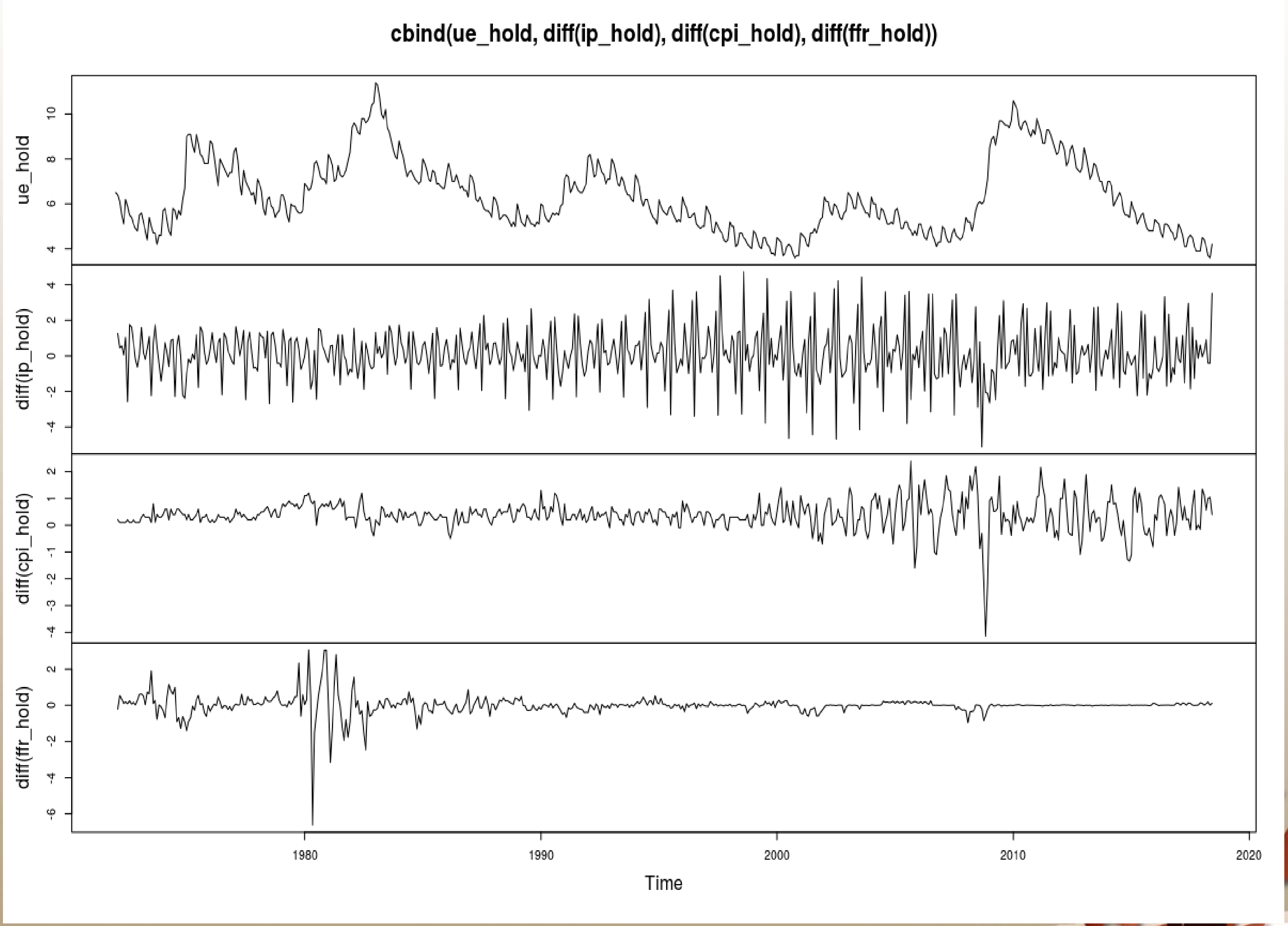
	test	10pct	5pct	1pct
r <= 1	20.24	18.90	21.07	25.75
r = 0	31.51	24.78	27.14	32.14

- No error term required in the model(VECM)

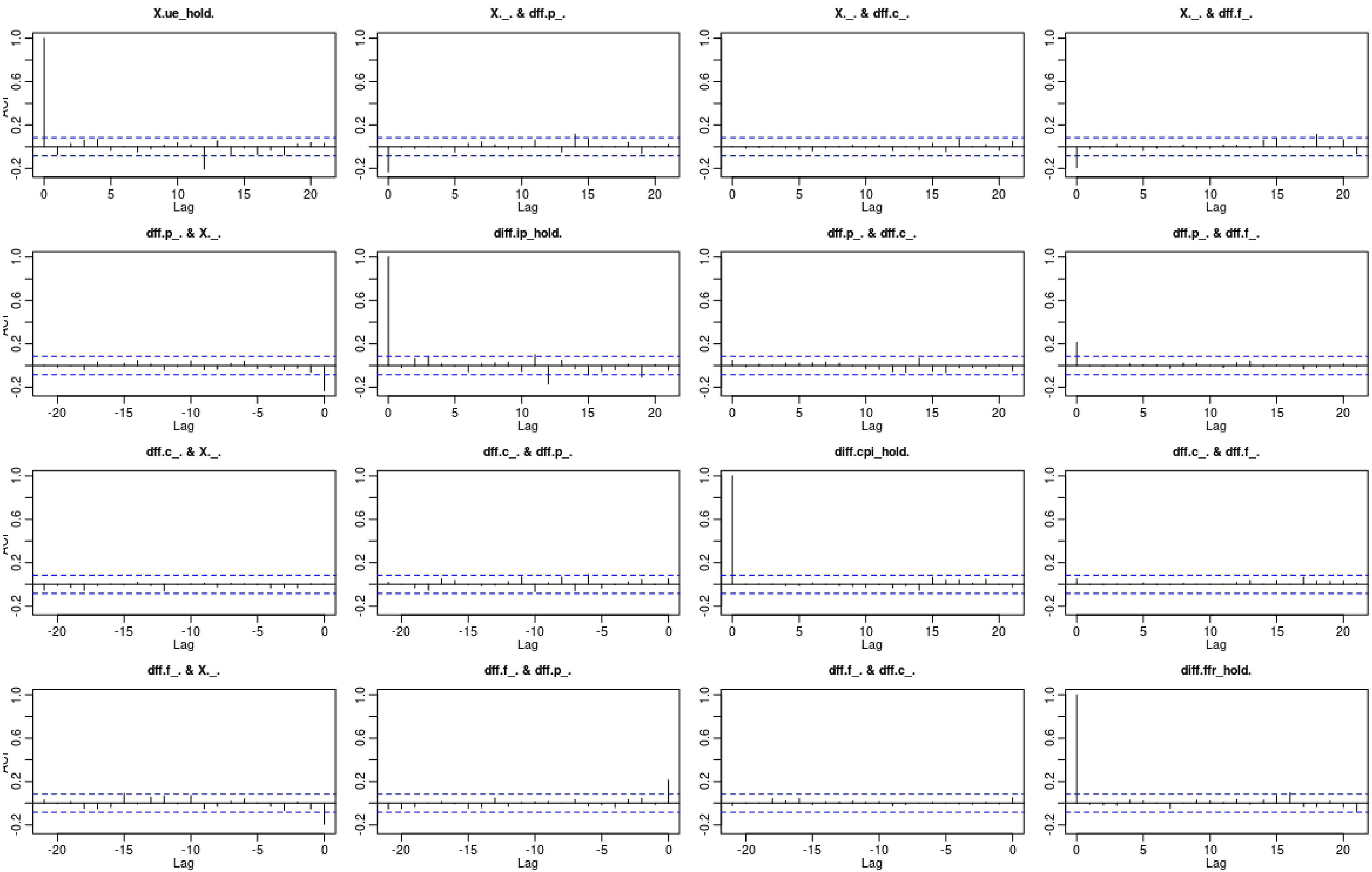

cbind(ue_hold, ip_hold, cpi_hold, ffr_hold)
ue_hold
ip_hold
cpi_hold
ffr_hold
Time
1980
1990
2000
2010
2020

Data transformation

	Unemployment	CPI	IPI	Fed rate
Unit root	rejected	Exists	Exists	Exists
differenced	No	First order	First order	First order
Seasonal/Non Seasonal		Non seasonal	Non seasonal	Non seasonal


cbind(ue_hold, diff(ip_hold), diff(cpi_hold), diff(ffr_hold))
ue_hold
diff(ip_hold)
diff(cpi_hold)
diff(ffr_hold)
1980
1990
2000
2010
2020
Time

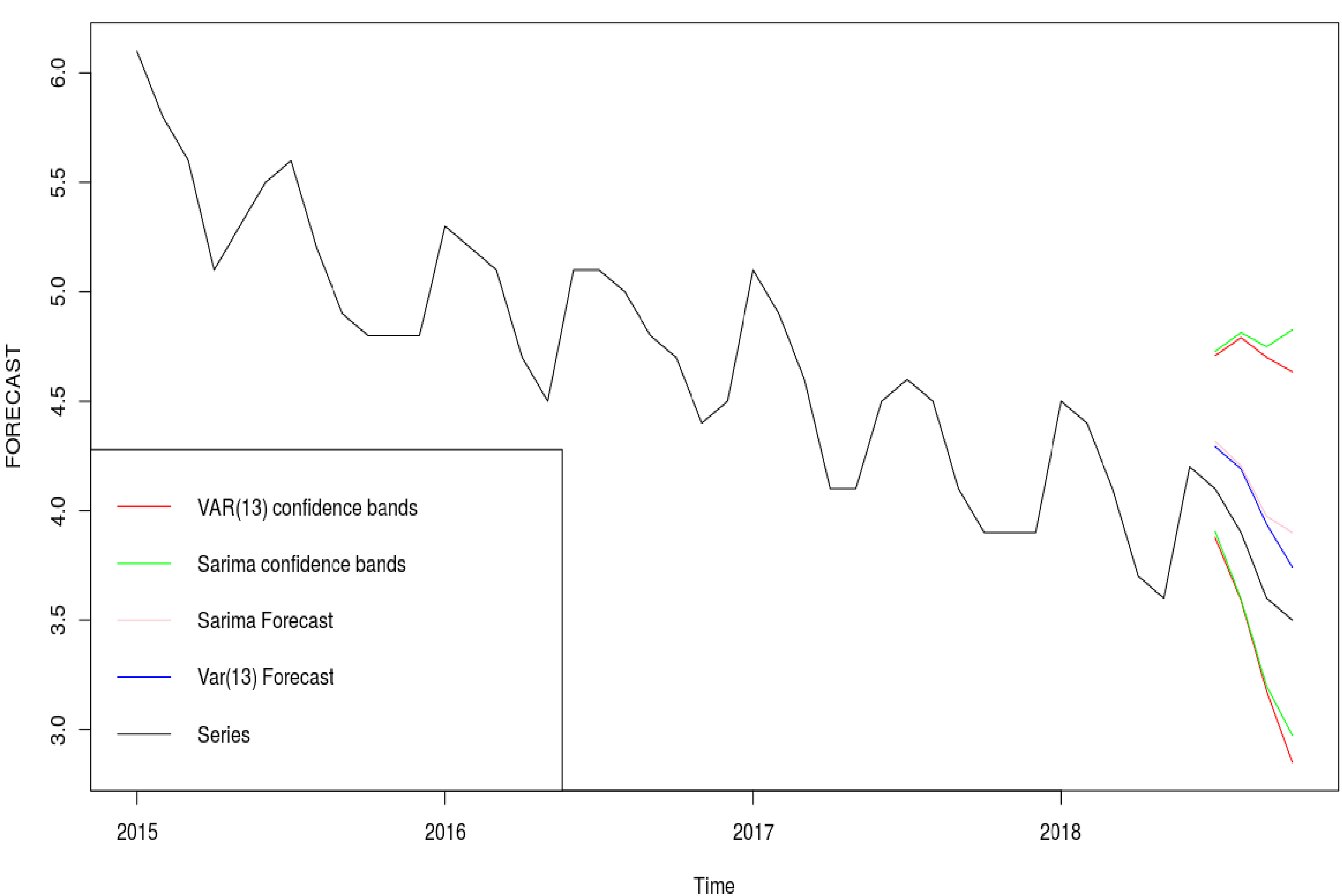
• VARselect(x,lag.max = 20,type = 'const')



SARIMA vs VAR

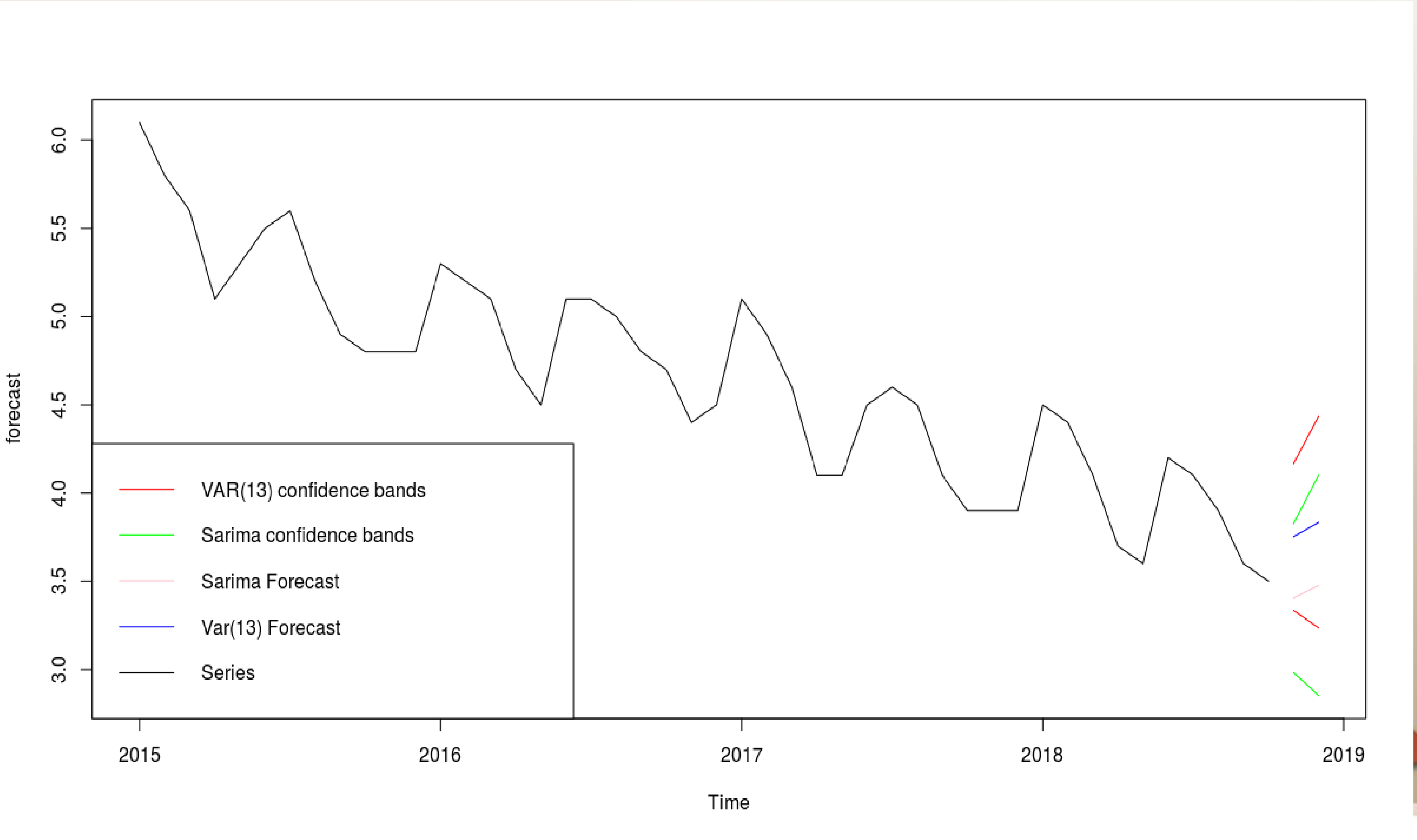
	Jul	Aug	Sep	Oct
Actual	4.1	3.9	3.6	3.5
SARIMA	4.31	4.20	3.97	3.89
VAR	4.29	4.19	3.93	3.74

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
VAR	-2.66E-01	0.271484	0.265943	-7.11706	7.117063	0.328213	-0.14863	1.372753
SARIMA	-.32398	0.331652	0.323984	-8.73228	8.732281	0.39967	0.2430	1.7279

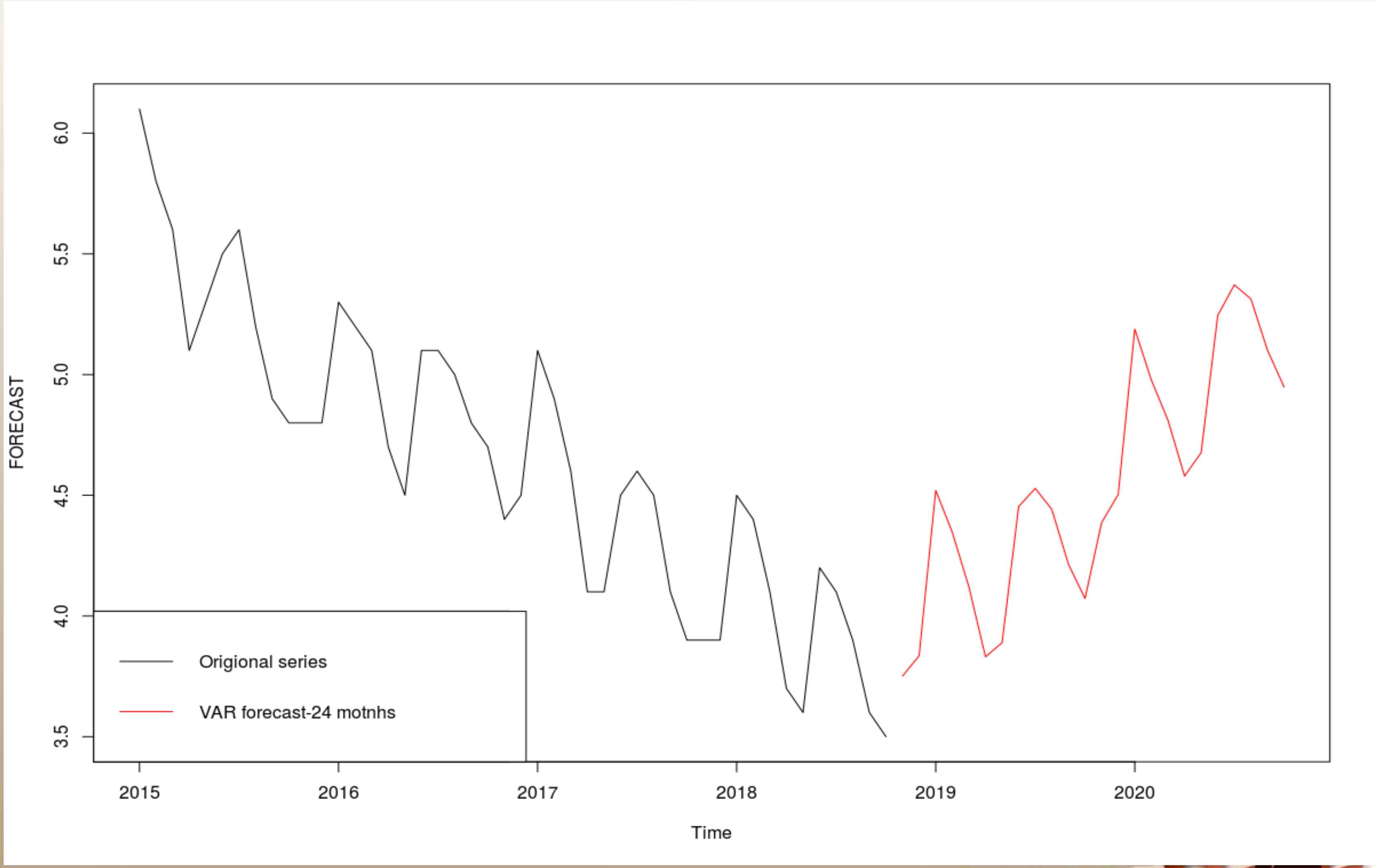


FORECAST
6.0
5.5
5.0
4.5
4.0
3.5
3.0
2015
2016
2017
2018
Time
VAR(13) confidence bands
Sarima confidence bands
Sarima Forecast
Var(13) Forecast
Series

Out of sample Forecast



Long Term Perspective



The Forecast For The Entire Series

- For Oct 2018,3.5

Forecast	Nov	Dec
SARIMA	3.40	3.47
VAR	3.75	3.83

VAR model is better suited because we have bidirectional causality in data, so it is better to include unemployment factor in other variables and other variables in unemployment.
We expect unemployment to increase as Fed started increasing interest rates .Unemployment being a lagging indicator and we are yet to see the effects.


QUESTIONS?