Homework 2

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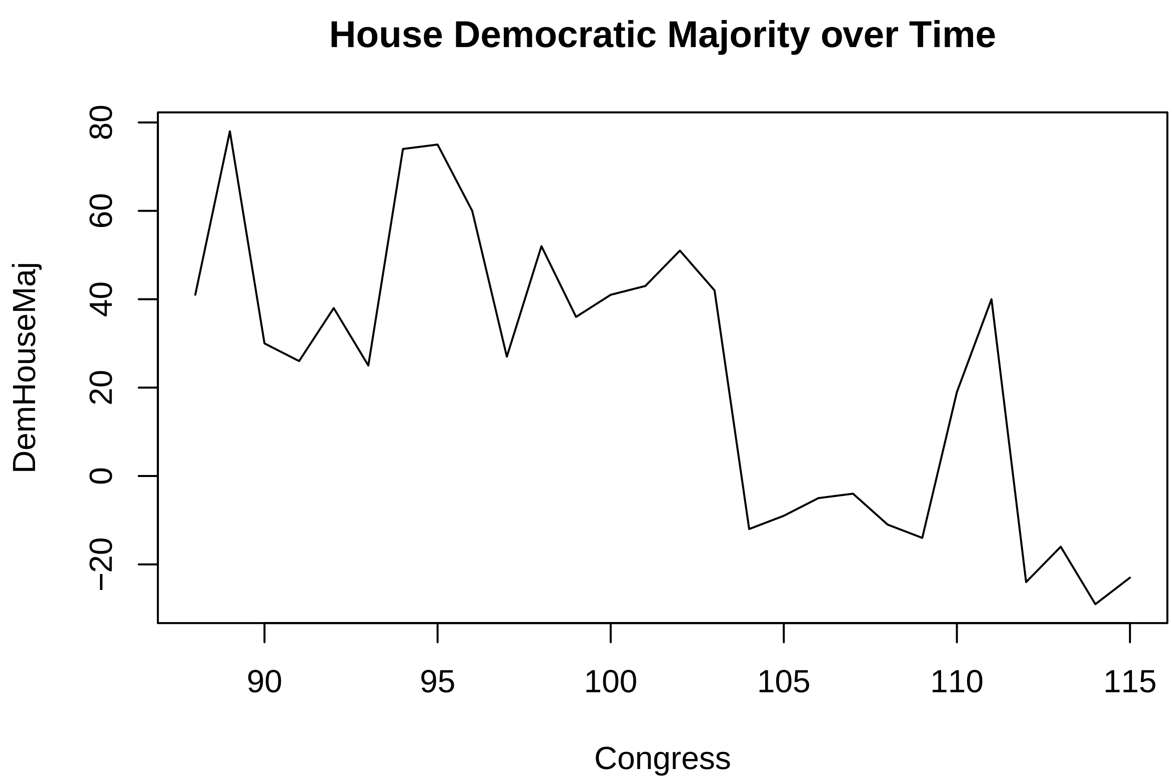
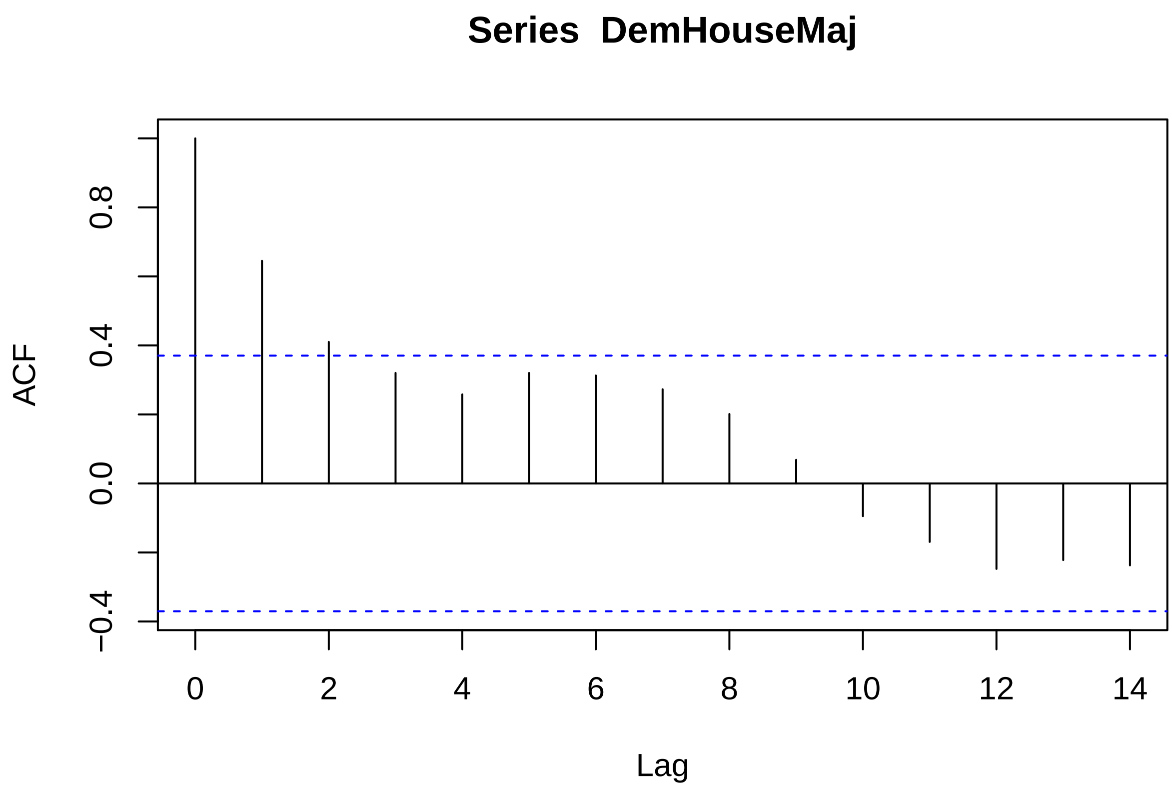
```
## Loading required package: grid
```

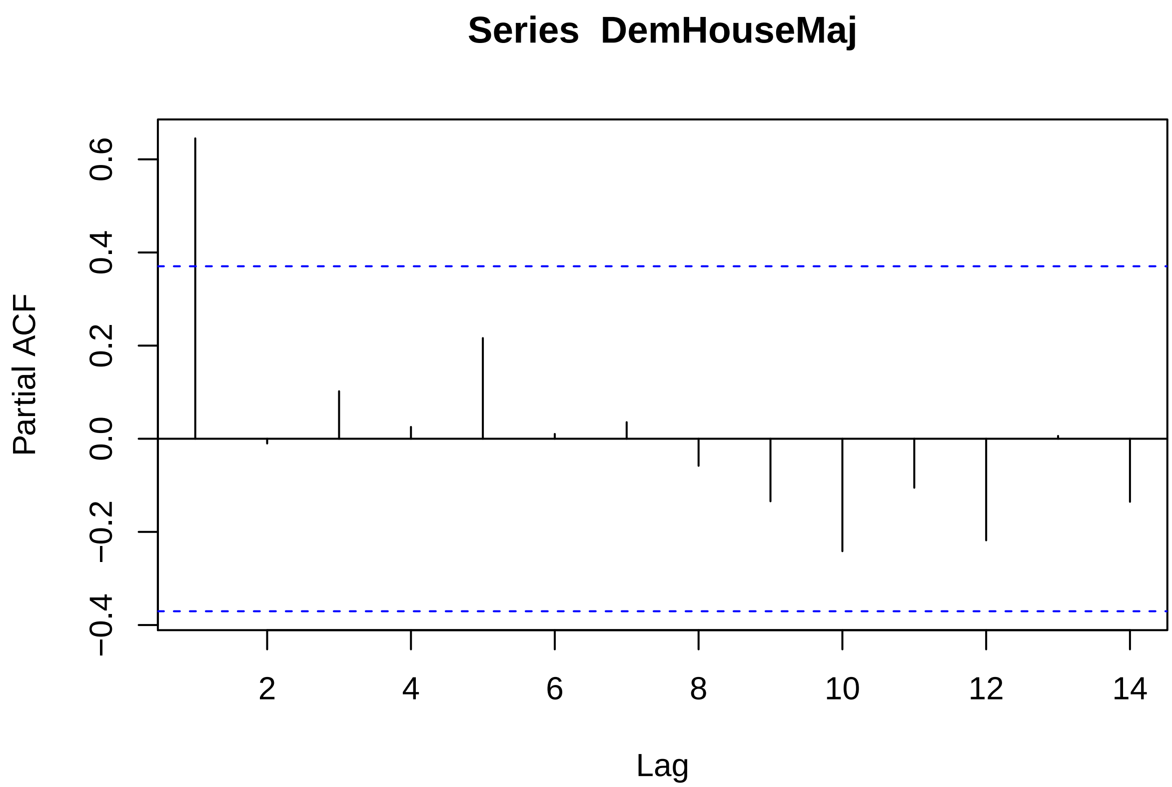
Question 1

Part A

I begin by plotting the time series for the Democratic House Majority as well as its ACF and PACF. I also run the augmented Dickey-Fuller and Phillips-Perron tests for unit roots. The correlograms below indicate the possibility of a first order autoregressive process. The unit root tests disagree in their findings; the ADF cannot reject the hypothesis of nonstationarity, while the Phillips-Perron can.




Series DemHouseMaj
ACF
0.8
0.4
0.0
−0.4
0
2
4
6
8
10
12
14
Lag

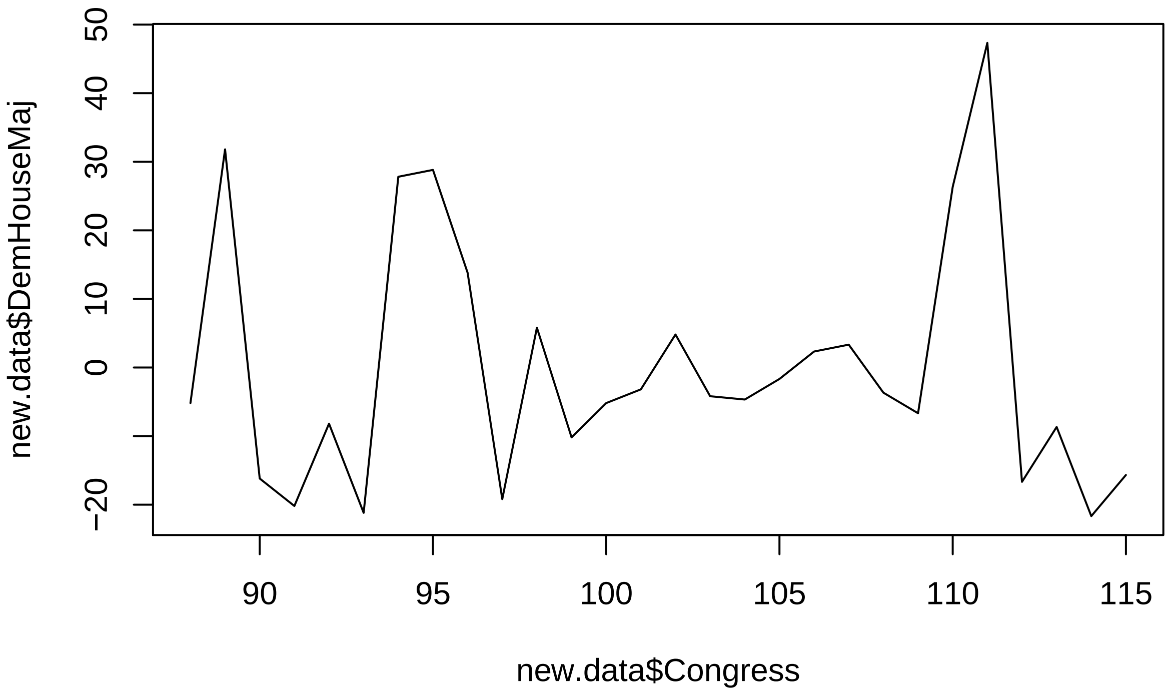



```
##
##  Augmented Dickey-Fuller Test
##
## data:  DemHouseMaj
## Dickey-Fuller = -3, Lag order = 3, p-value = 0.3
## alternative hypothesis: stationary
```

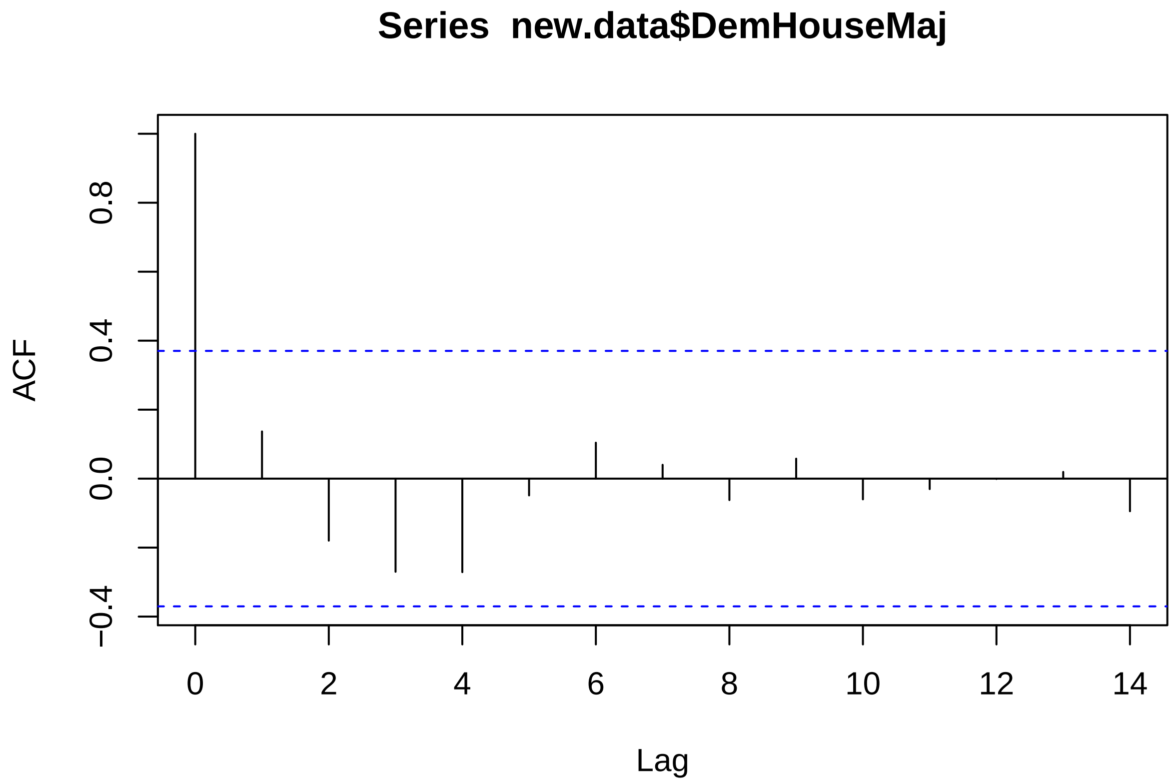
```
##
##  Phillips-Perron Unit Root Test
##
## data:  DemHouseMaj
## Dickey-Fuller = -4, Truncation lag parameter = 2, p-value = 0.04
```

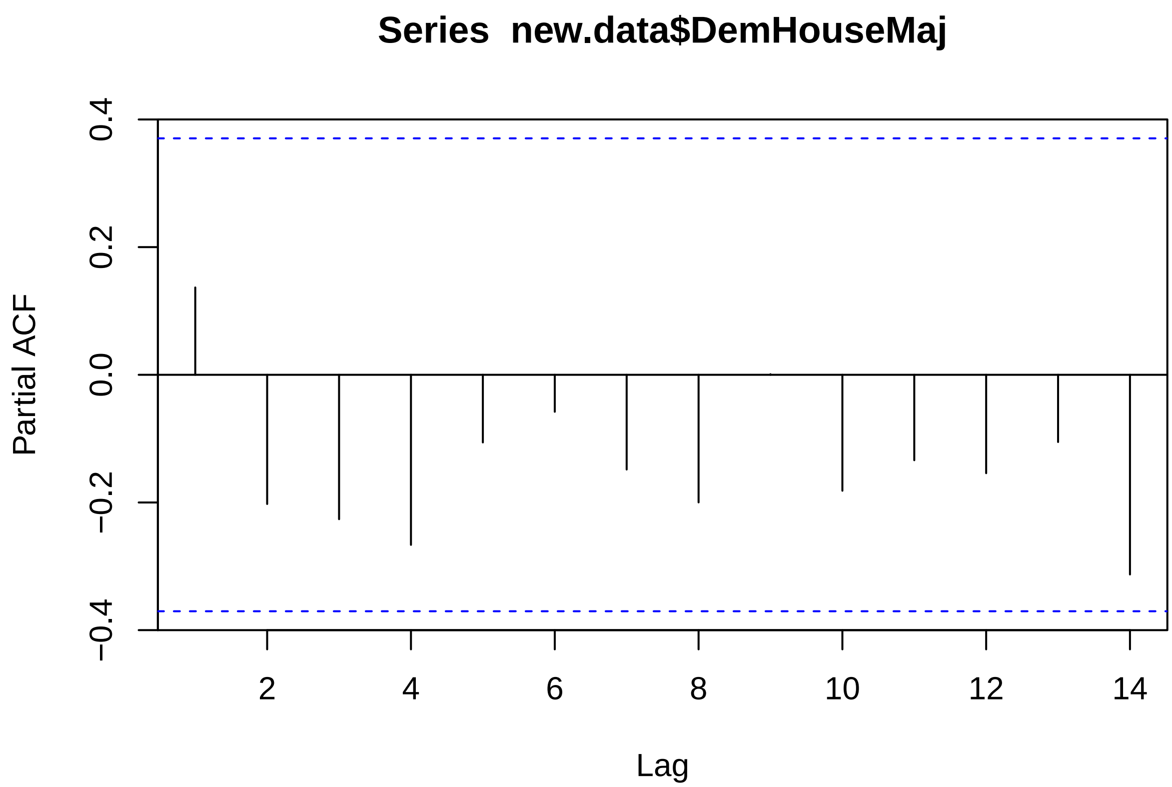
I continue by examining the possibility of a structural break in the model at the year 1994. I demeaned the data by period, both before and after 1994, constructing a new dataset. The modified time series and ACF/PACF plots are below. After accounting for the structural break, there does not seem to be evidence of a AR or MA process. Any analysis of this time series should include a control for this break.

```
pre1994 <- data[StartYear<1994,]
post1994 <- data[StartYear>1994,]
pre1994$DemHouseMaj <- pre1994$DemHouseMaj - mean(pre1994$DemHouseMaj)
post1994$DemHouseMaj <- post1994$DemHouseMaj - mean(post1994$DemHouseMaj)
new.data <- rbind(pre1994, post1994)
```



new.data$DemHouseMaj
50
40
30
20
10
0
−20
90
95
100
105
110
115
new.data$Congress


Series new.data$DemHouseMaj
ACF
0.8
0.4
0.0
−0.4
0
2
4
6
8
10
12
14
Lag



Part B

I fit an AR(0) regression by defining the relevant covariates and estimating the model with arima. Notably, OLS would give the same coefficient estimates for this model (but different standard errors). Relevant model information is displayed in Table 1.

```
xcovariates <- cbind(PartisanMidterm, PartisanUnem, Coattails, Pre1994)

ar0 <- arima(DemHouseMaj, order = c(0,0,0),
             xreg = xcovariates, include.mean = TRUE)
```

Table 1: Model Evaluation

Model Components	AIC	$\hat{\sigma}^2$	N	$\hat{\beta}_{PM}$	$\hat{\beta}_{PU}$	$\hat{\beta}_{CT}$	$\hat{\beta}_{1994}$
AR(0)	239.243	195.964	28	-7.27	-2.053	18.396	47.994
				(3.823)	(1.733)	(5.331)	(5.703)

The AR(0) model suggests that the House Democratic majority decreases by NA after midterms with a Democratic presidency, compared to non-midterm elections. The effect is in the opposite direction when there is a Republican president.

Part C

```
ar1 <- arima(DemHouseMaj, order = c(1,0,0),
             xreg = xcovariates, include.mean = TRUE)

ar2 <- arima(DemHouseMaj, order = c(2,0,0),
             xreg = xcovariates, include.mean = TRUE)

ma1 <- arima(DemHouseMaj, order = c(0,0,1),
             xreg = xcovariates, include.mean = TRUE)

arma11 <- arima(DemHouseMaj, order = c(1,0,1),
             xreg = xcovariates, include.mean = TRUE)
```

Table 2: Model Comparison

Model Components	AIC	$\hat{\sigma}^2$	N	$\hat{\beta}_{PM}$	$\hat{\beta}_{PU}$	$\hat{\beta}_{CT}$	$\hat{\beta}_{1994}$
AR(0)	239.243	195.964	28	-7.27	-2.053	18.396	47.994
				(3.823)	(1.733)	(5.331)	(5.703)
AR(1)	240.221	188.565	28	-8.848	-2.42	15.364	46.656
				(3.86)	(1.75)	(5.828)	(7.023)
AR(2)	239.243	169.879	28	-10.726	-2.858	10.279	44.729
				(3.158)	(1.744)	(5.862)	(6.038)
MA(1)	239.495	183.033	28	-9.866	-2.761	13.121	45.386
				(3.743)	(1.841)	(6.315)	(7.58)
ARMA(1,1)	238.096	148.58	28	-11.673	-2.758	14.522	42.887
				(3.204)	(1.484)	(6.058)	(6.623)

Part D

```
ar0.cv <- arimaCV(DemHouseMaj, order = c(0,0,0), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

ar1.cv <- arimaCV(DemHouseMaj, order = c(1,0,0), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

ar2.cv <- arimaCV(DemHouseMaj, order = c(2,0,0), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

ma1.cv <- arimaCV(DemHouseMaj, order = c(0,0,1), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

arma11.cv <- arimaCV(DemHouseMaj, order = c(1,0,1), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

allCV <- cbind(ar0.cv, ar1.cv, ar2.cv, ma1.cv, arma11.cv)
labs <- c("AR(0)", "AR(1)", "AR(2)", "MA(1)", "ARMA(1,1)")

col <- c(brewer.pal(7, "Reds")[3:7],
         brewer.pal(8, "Blues")[3:8])
```

```r
matplot(allCV, type="l", col=col, lty=1, ylab="Mean Absolute Error", xlab="Periods Forward",
        main="Cross-validation of House Democratic Majority models", xlim=c(0.75,3.75))
text(labs, x=rep(3.5,length(labs)), y=allCV[nrow(allCV),], col=col)
```

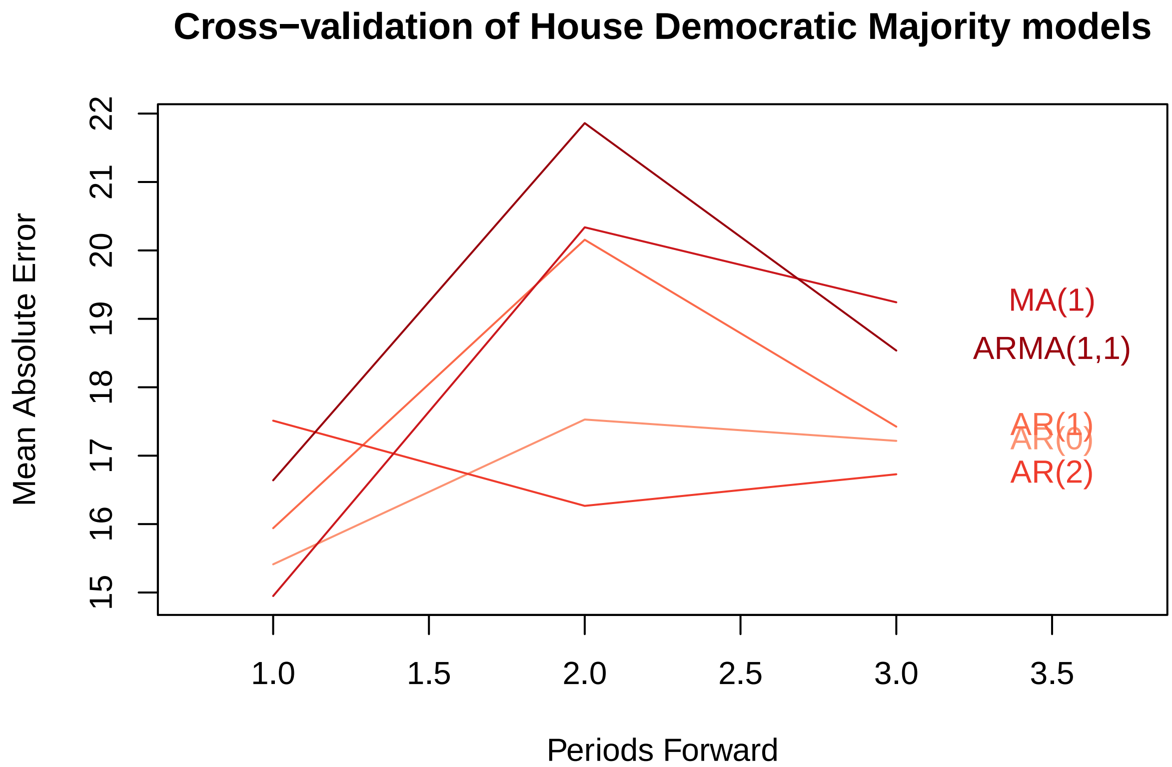


Table 3: Model Comparison

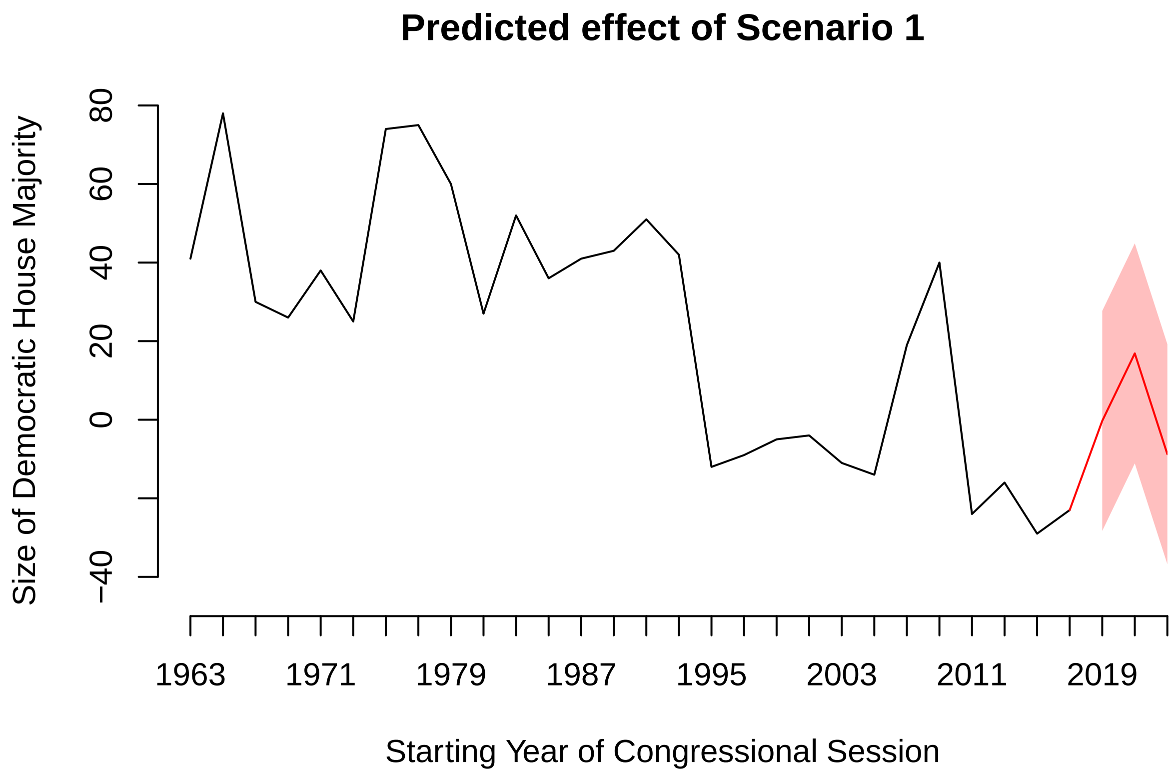
Model Components	AIC	RMSE	MAE_1	MAE_2	MAE_3	Average MAE
AR(0)	239.243	13.999	15.412	17.528	17.216	16.719
AR(1)	240.221	13.732	15.94	20.156	17.424	17.84
AR(2)	239.662	13.034	17.512	16.266	16.728	16.835
MA(1)	239.495	13.529	14.949	20.338	19.242	18.176
ARMA(1,1)	238.096	12.189	16.64	21.86	18.536	19.012

AR(0) is best model

Part E

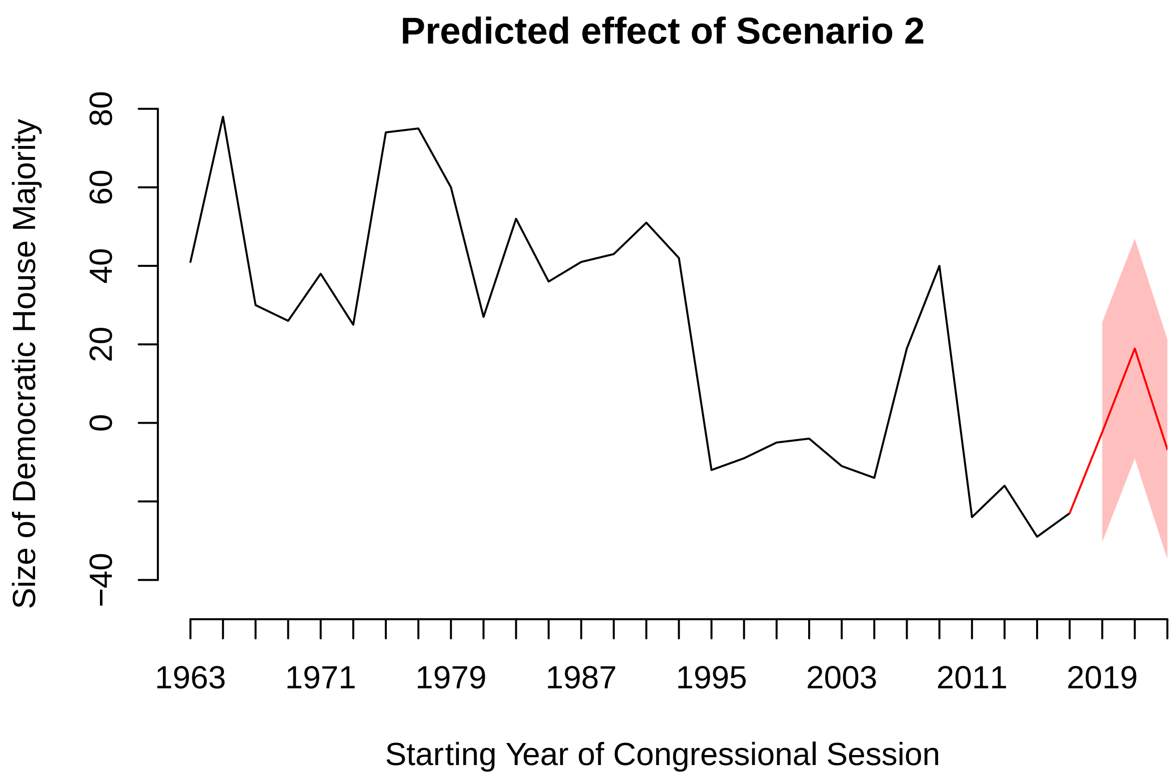
```r
n.ahead <- 3
PartisanMidterm.cf <- c(-1,0,1)
UnemDeviation.cf1 <- rep(4.6, n.ahead) - 6.075
UnemDeviation.cf2 <- rep(3.6, n.ahead) - 6.075
UnemDeviation.cf3 <- rep(5.6, n.ahead) - 6.075
PartisanUnem.cf1 <- c(-1,1,1)*UnemDeviation.cf1
```

```r
PartisanUnem.cf2 <- c(-1,1,1)*UnemDeviation.cf2
PartisanUnem.cf3 <- c(-1,1,1)*UnemDeviation.cf3
Coattails.cf <- c(0,1,0)
Pre1994.cf <- rep(0, n.ahead)

cf1.cov <- as.data.frame(cbind(PartisanMidterm.cf, PartisanUnem.cf1, Coattails.cf, Pre1994.cf))
cf2.cov <- as.data.frame(cbind(PartisanMidterm.cf, PartisanUnem.cf2, Coattails.cf, Pre1994.cf))
cf3.cov <- as.data.frame(cbind(PartisanMidterm.cf, PartisanUnem.cf3, Coattails.cf, Pre1994.cf))

names(cf1.cov) <- c("PartisanMidterm", "PartisanUnem", "Coattails", "Pre1994")
names(cf2.cov) <- c("PartisanMidterm", "PartisanUnem", "Coattails", "Pre1994")
names(cf3.cov) <- c("PartisanMidterm", "PartisanUnem", "Coattails", "Pre1994")

ypred1 <- predict(ar0, n.ahead=n.ahead, newxreg = cf1.cov)
ypred2 <- predict(ar0, n.ahead=n.ahead, newxreg = cf2.cov)
ypred3 <- predict(ar0, n.ahead=n.ahead, newxreg = cf3.cov)

# Make a plot
plot.new()
par(usr = c(0, length(DemHouseMaj) + n.ahead, -50, 80) )
# make the x-axis
axis(1,
     at = seq(from = 1, to = 31, by = 1),
     labels = seq(from = 1963, to = 2023, by = 2)
)
axis(2)

title(xlab = "Starting Year of Congressional Session",
      ylab = "Size of Democratic House Majority",
      main="Predicted effect of Scenario 1")


# Polygon of predictive interval for no law (optional)
x0 <- (length(DemHouseMaj)+1):(length(DemHouseMaj) + n.ahead)
y0 <- c(ypred1$pred - 2*ypred1$se, rev(ypred1$pred + 2*ypred1$se), (ypred1$pred - 2*ypred1$se)[1] )
polygon(x = c(x0, rev(x0), x0[1]),
        y = y0,
        border=NA,
        col="#FFBFBFFF"
)

# Plot the actual data
lines(x = 1:length(DemHouseMaj),
      y = DemHouseMaj
)

# Add the predictions for no law
lines(x = length(DemHouseMaj):(length(DemHouseMaj)+n.ahead),
      y = c(DemHouseMaj[length(DemHouseMaj)],ypred1$pred),  # link up the actual data to the prediction
      col = "red"
)
```




```
# Make a plot 2
plot.new()
par(usr = c(0, length(DemHouseMaj) + n.ahead, -50, 80) )
# make the x-axis
axis(1,
     at = seq(from = 1, to = 31, by = 1),
     labels = seq(from = 1963, to = 2023, by = 2)
)
axis(2)

title(xlab = "Starting Year of Congressional Session",
      ylab = "Size of Democratic House Majority",
      main="Predicted effect of Scenario 2")


# Polygon of predictive interval for no law (optional)
x0 <- (length(DemHouseMaj)+1):(length(DemHouseMaj) + n.ahead)
y0 <- c(ypred2$pred - 2*ypred2$se, rev(ypred2$pred + 2*ypred2$se), (ypred2$pred - 2*ypred2$se)[1] )
polygon(x = c(x0, rev(x0), x0[1]),
        y = y0,
        border=NA,
        col="#FFBFBFFF"
)

# Plot the actual data
lines(x = 1:length(DemHouseMaj),
```

```
      y = DemHouseMaj
)

# Add the predictions for no law
lines(x = length(DemHouseMaj):(length(DemHouseMaj)+n.ahead),
      y = c(DemHouseMaj[length(DemHouseMaj)],ypred2$pred),  # link up the actual data to the prediction
      col = "red"
)
```




```
# Make a plot 3
plot.new()
par(usr = c(0, length(DemHouseMaj) + n.ahead, -50, 80) )
# make the x-axis
axis(1,
     at = seq(from = 1, to = 31, by = 1),
     labels = seq(from = 1963, to = 2023, by = 2)
)
axis(2)

title(xlab = "Starting Year of Congressional Session",
      ylab = "Size of Democratic House Majority",
      main="Predicted effect of Scenario 3")


# Polygon of predictive interval for no law (optional)
x0 <- (length(DemHouseMaj)+1):(length(DemHouseMaj) + n.ahead)
```

```r
y0 <- c(ypred3$pred - 2*ypred3$se, rev(ypred3$pred + 2*ypred3$se), (ypred3$pred - 2*ypred3$se)[1] )
polygon(x = c(x0, rev(x0), x0[1]),
        y = y0,
        border=NA,
        col="#FFBFBFFF"
)

# Plot the actual data
lines(x = 1:length(DemHouseMaj),
      y = DemHouseMaj
)

# Add the predictions for no law
lines(x = length(DemHouseMaj):(length(DemHouseMaj)+n.ahead),
      y = c(DemHouseMaj[length(DemHouseMaj)],ypred3$pred),  # link up the actual data to the prediction
      col = "red"
)
```

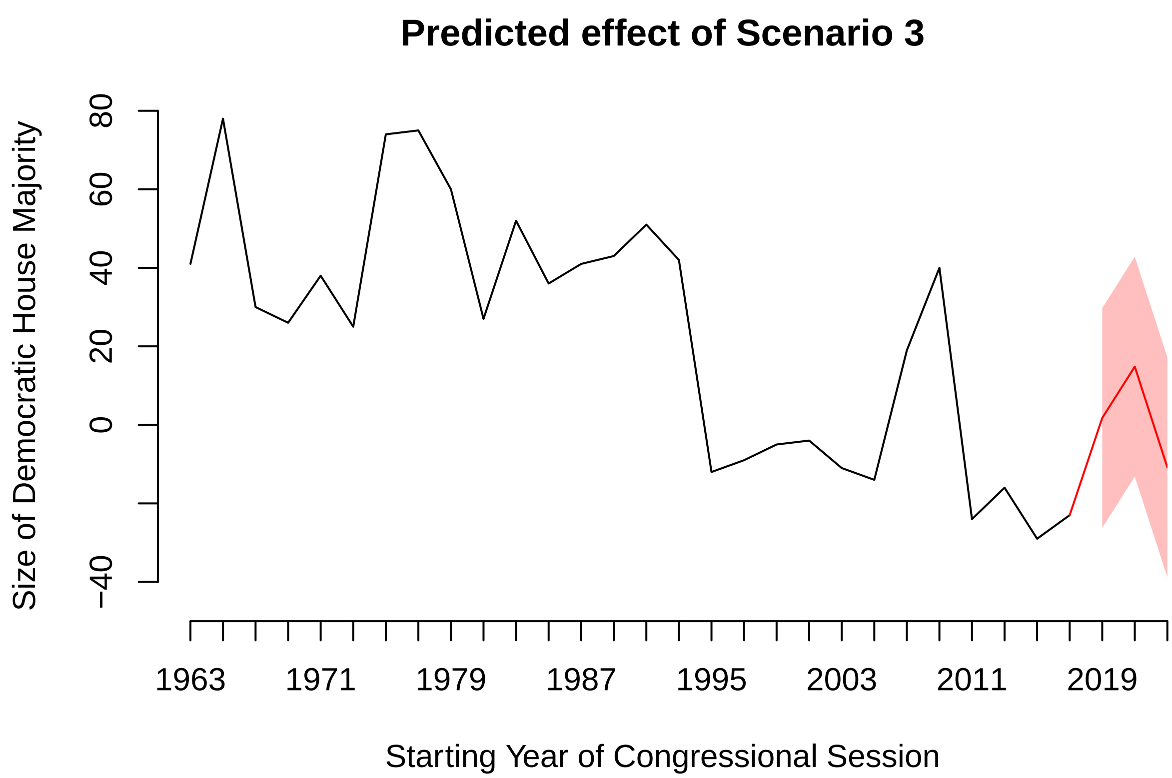


Table 4: Counterfactual Values

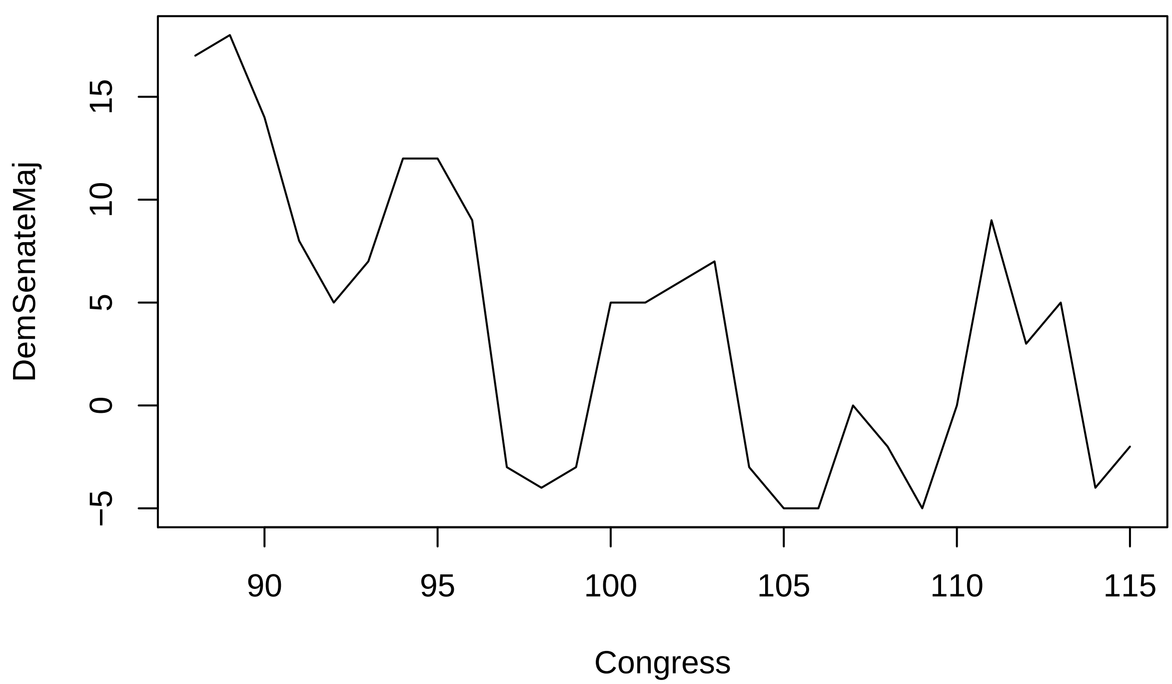
Variable	2018	2020	2022
Scenario 1			
Partisan Midterm	-1	0	1
Partisan Unemployment	1.475	-1.475	-1.475
Coattails	0	1	0
Pre-1994	0	0	0

Variable	2018	2020	2022
Scenario 2			
Partisan Midterm	-1	0	1
Partisan Unemployment	2.475	-2.475	-2.475
Coattails	0	1	0
Pre-1994	0	0	0
Scenario 3			
Partisan Midterm	-1	0	1
Partisan Unemployment	0.475	-0.475	-0.475
Coattails	0	1	0
Pre-1994	0	0	0

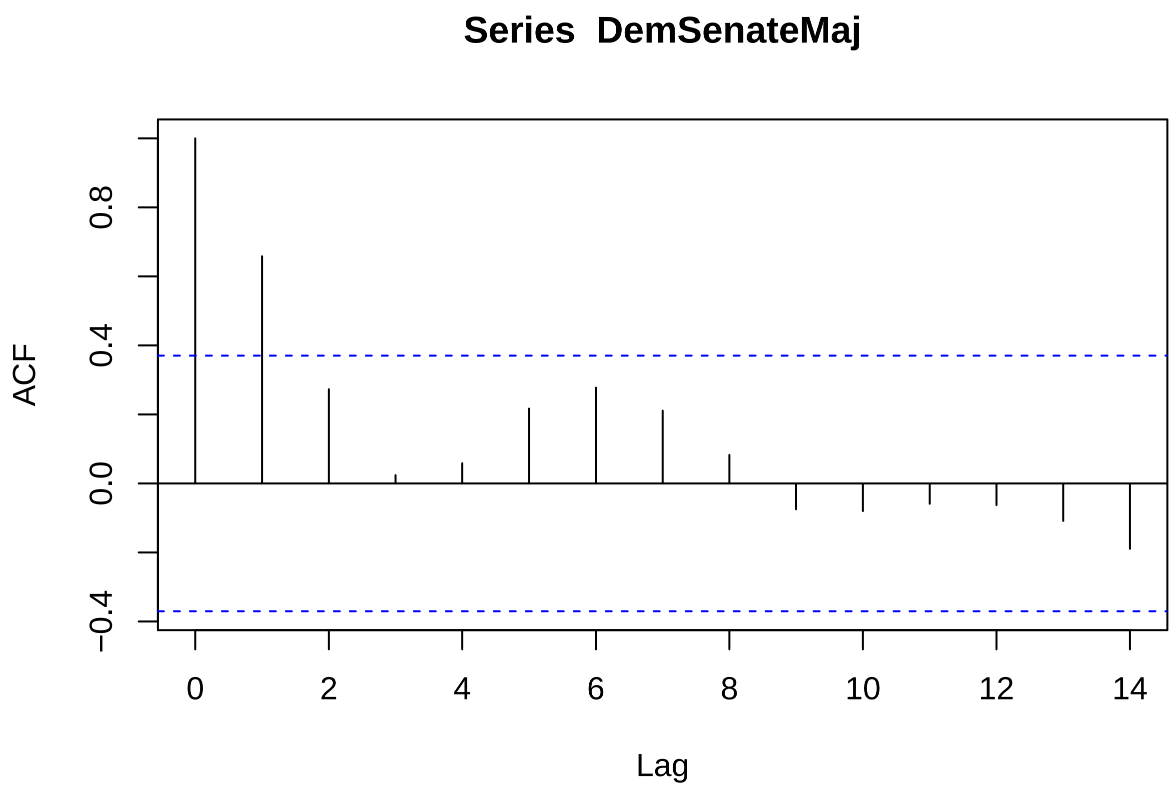
Question 2

Part A

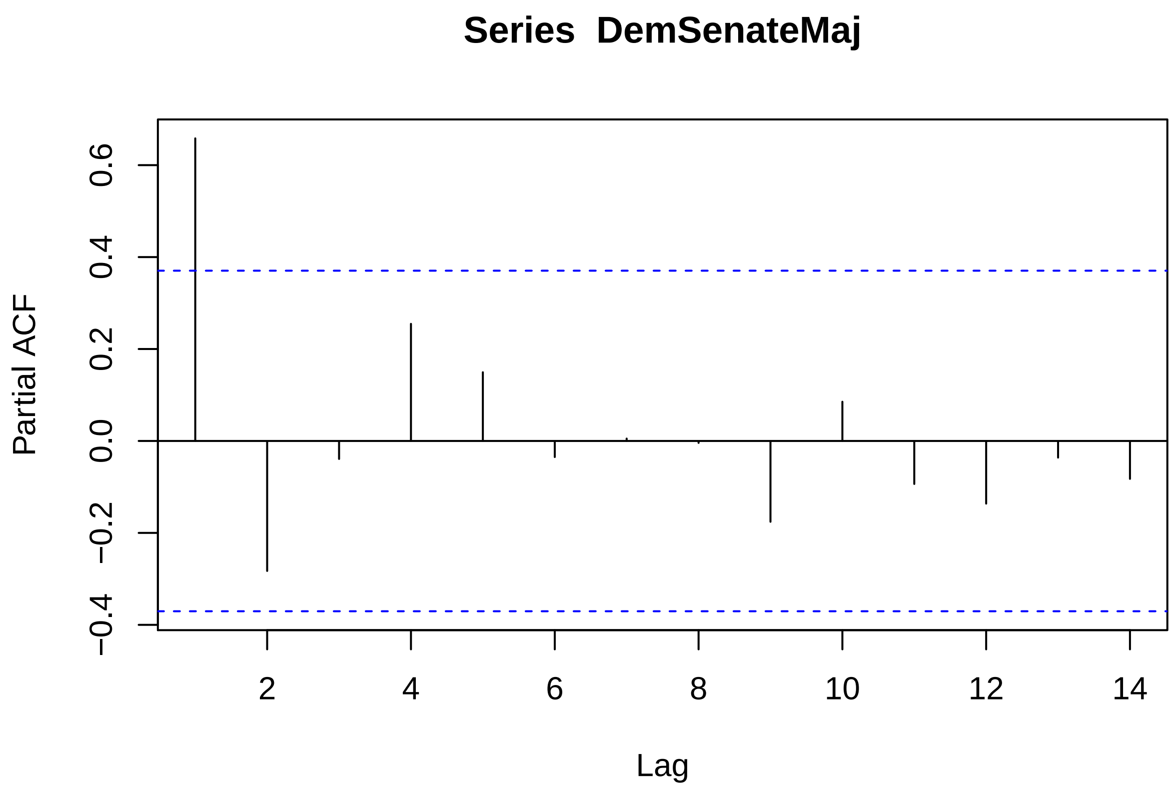
```r
plot(Congress, DemSenateMaj, type="l")
```




```r
acf(DemSenateMaj)
```




```r
pacf(DemSenateMaj)
```



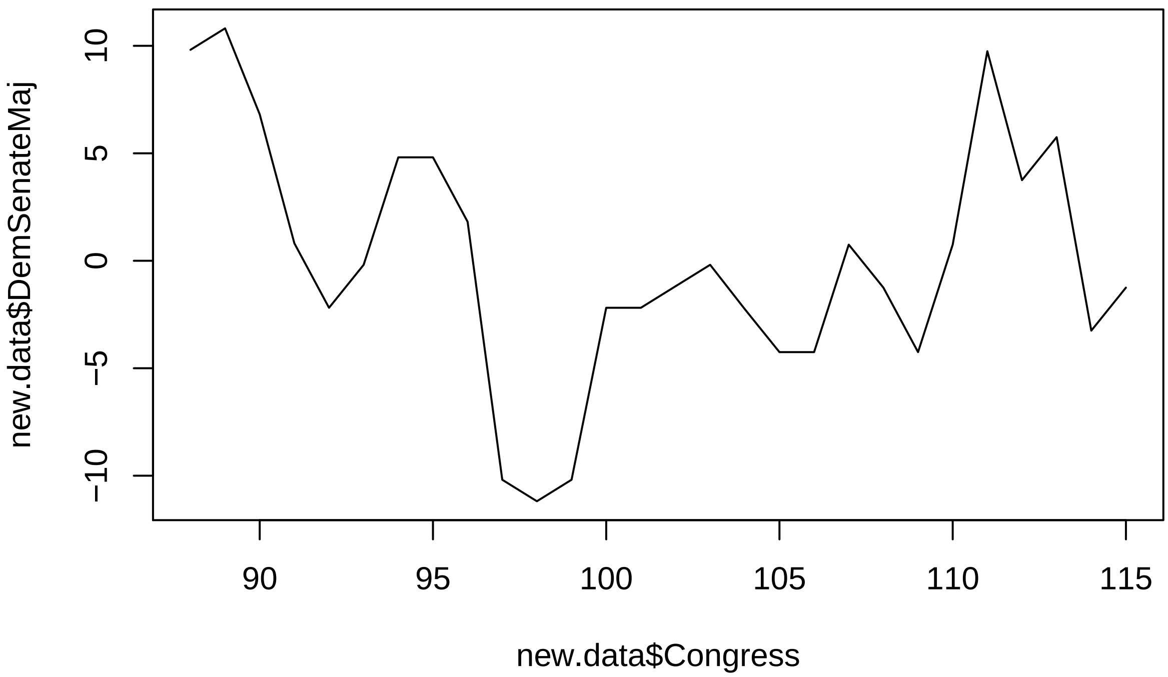

```
adf.test(DemSenateMaj)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  DemSenateMaj
## Dickey-Fuller = -2, Lag order = 3, p-value = 0.5
## alternative hypothesis: stationary
```

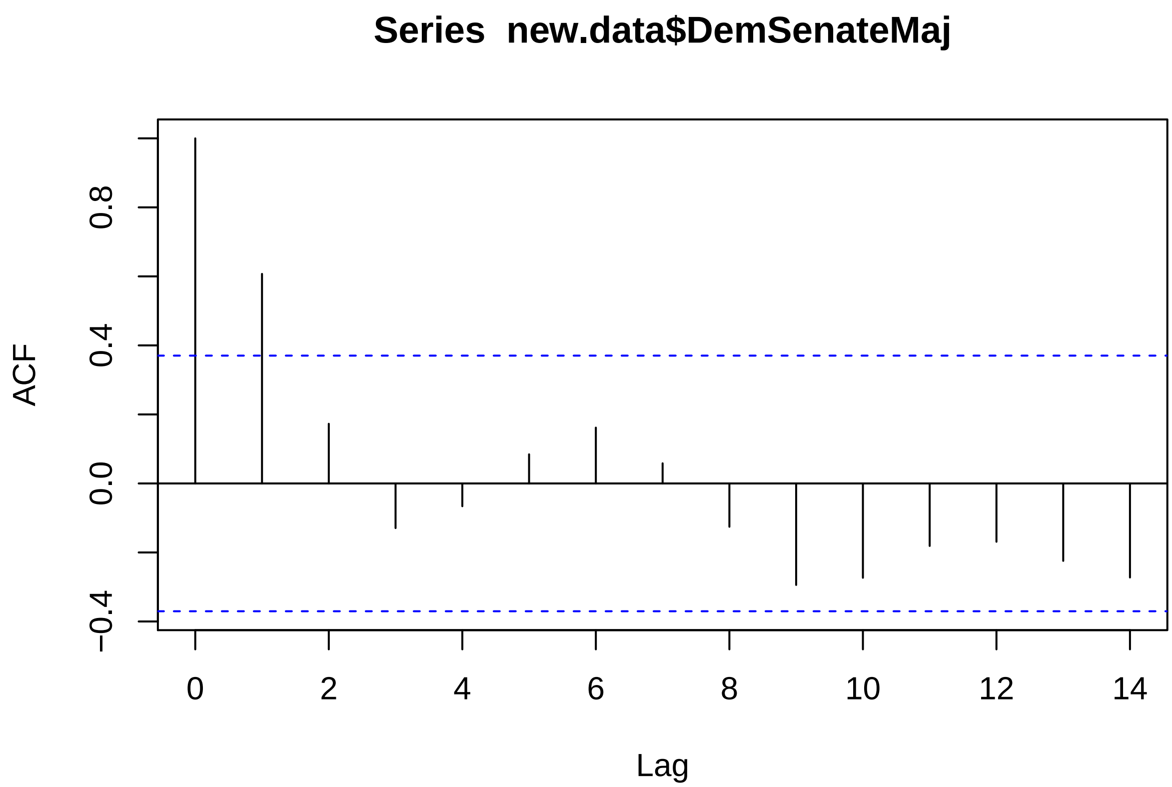
```
PP.test(DemSenateMaj)
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  DemSenateMaj
## Dickey-Fuller = -3, Truncation lag parameter = 2, p-value = 0.3
```

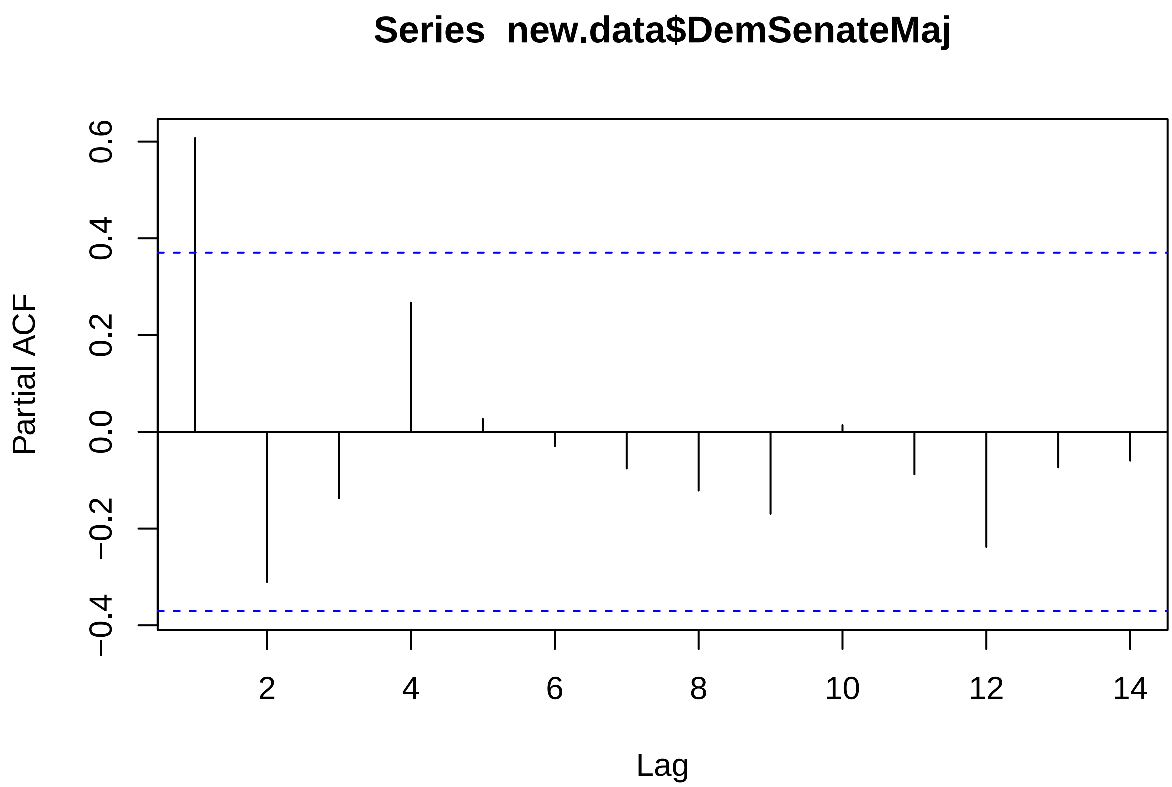
```
pre1994 <- data[StartYear<1994,]
post1994 <- data[StartYear>1994,]
pre1994$DemSenateMaj <- pre1994$DemSenateMaj - mean(pre1994$DemSenateMaj)
post1994$DemSenateMaj <- post1994$DemSenateMaj - mean(post1994$DemSenateMaj)
new.data <- rbind(pre1994, post1994)


plot(new.data$Congress, new.data$DemSenateMaj, type="l")
```




```r
acf(new.data$DemSenateMaj)
```




```r
pacf(new.data$DemSenateMaj)
```



Part B

```
xcovariates <- cbind(PartisanMidterm, PartisanUnem, Coattails, Pre1994)
ar0 <- arima(DemSenateMaj, order = c(0,0,0),
             xreg = xcovariates, include.mean = TRUE)

ar1 <- arima(DemSenateMaj, order = c(1,0,0),
             xreg = xcovariates, include.mean = TRUE)

ar2 <- arima(DemSenateMaj, order = c(2,0,0),
             xreg = xcovariates, include.mean = TRUE)

ma1 <- arima(DemSenateMaj, order = c(0,0,1),
             xreg = xcovariates, include.mean = TRUE)

arma11 <- arima(DemSenateMaj, order = c(1,0,1),
             xreg = xcovariates, include.mean = TRUE)
```

Table 5: Model Comparison

Model Components	AIC	$\hat{\sigma}^2$	N	$\hat{\beta}_{PM}$	$\hat{\beta}_{PU}$	$\hat{\beta}_{CT}$	$\hat{\beta}_{1994}$
AR(0)	183.044	26.333	28	1.792	0.358	3.403	8.503
				(1.402)	(0.635)	(1.954)	(2.091)
AR(1)	172.3	16.315	28	-0.341	-0.268	1.892	8.151

Model Components	AIC	$\hat{\sigma}^2$	N	$\hat{\beta}_{PM}$	$\hat{\beta}_{PU}$	$\hat{\beta}_{CT}$	$\hat{\beta}_{1994}$
				(0.945)	(0.459)	(1.392)	(3.507)
AR(2)	183.044	12.698	28	-0.806	-0.884	0.103	6.611
				(0.635)	(0.367)	(1.091)	(2.581)
MA(1)	170.826	14.053	28	-0.464	-1.224	1.784	7.377
				(0.767)	(0.339)	(1.467)	(2.204)
ARMA(1,1)	168.501	11.651	28	-0.72	-1.309	0.807	9.131
				(0.576)	(0.24)	(1.134)	(2.171)

```r
ar0.cv <- arimaCV(DemSenateMaj, order = c(0,0,0), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

ar1.cv <- arimaCV(DemSenateMaj, order = c(1,0,0), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

ar2.cv <- arimaCV(DemSenateMaj, order = c(2,0,0), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

ma1.cv <- arimaCV(DemSenateMaj, order = c(0,0,1), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

arma11.cv <- arimaCV(DemSenateMaj, order = c(1,0,1), forward=3,
                  xreg=xcovariates, include.mean = TRUE, minper = 20)

allCV <- cbind(ar0.cv, ar1.cv, ar2.cv, ma1.cv, arma11.cv)
labs <- c("AR(0)", "AR(1)", "AR(2)", "MA(1)", "ARMA(1,1)")

col <- c(brewer.pal(7, "Reds")[3:7],
         brewer.pal(8, "Blues")[3:8])

matplot(allCV, type="l", col=col, lty=1, ylab="Mean Absolute Error", xlab="Periods Forward",
        main="Cross-validation of Senate Democratic Majority models", xlim=c(0.75,3.75))
text(labs, x=rep(3.5,length(labs)), y=allCV[nrow(allCV),], col=col)
```

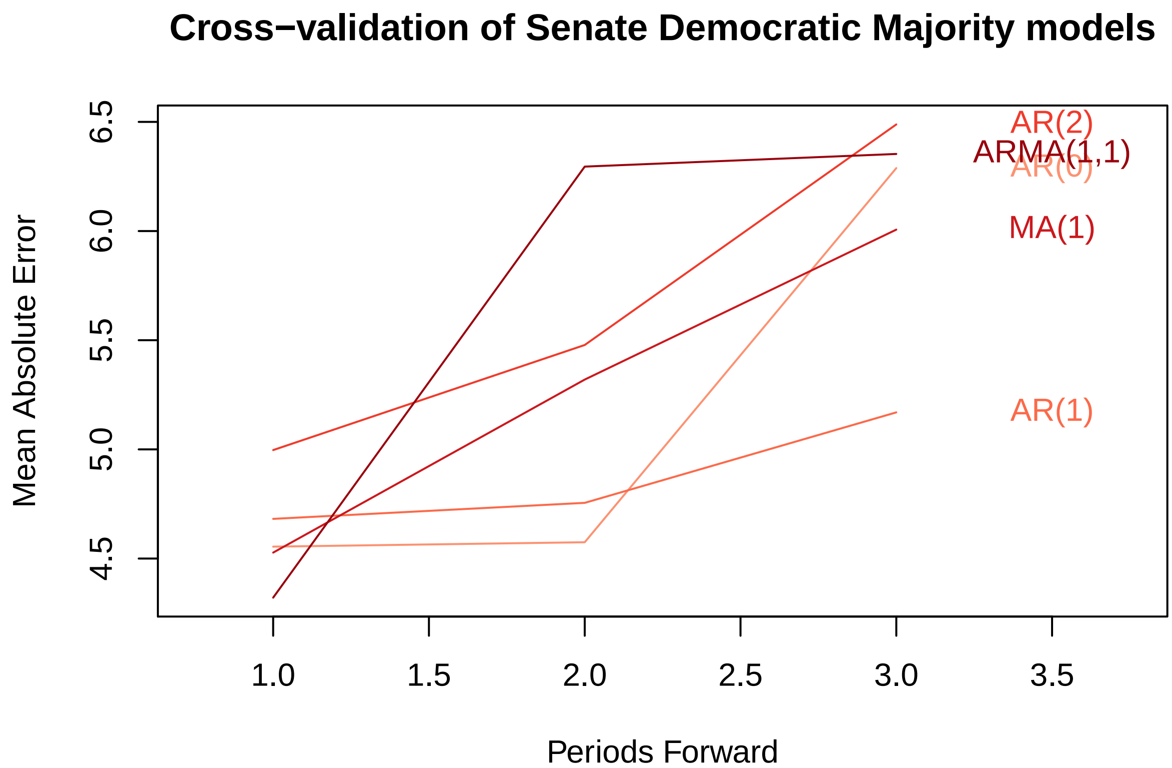


Table 6: Model Comparison

Model Components	AIC	RMSE	MAE_1	MAE_2	MAE_3	Average MAE
AR(0)	183.044	5.132	4.555	4.575	6.288	5.139
AR(1)	172.3	4.039	4.682	4.755	5.169	4.869
AR(2)	168.047	3.563	4.997	5.478	6.488	5.654
MA(1)	170.826	3.749	4.527	5.32	6.006	5.284
ARMA(1,1)	168.501	3.413	4.321	6.295	6.353	5.656

Part C

```
ar1ar1.3 <- arima(DemSenateMaj, order = c(1,0,0),
                  seasonal = list(order = c(1,0,0), period = 3),
                  xreg = xcovariates, include.mean = TRUE)

ar1ar1.3.cv <- arimaCV(DemSenateMaj, order = c(1,0,0), forward=3,
                       seasonal = list(order= c(1,0,0), period=3),
                  xreg=xcovariates, include.mean = TRUE, minper = 20)
```

Table 7: Model Comparison

Model Components	AIC	$\hat{\sigma}^2$	N	$\hat{\beta}_{PM}$	$\hat{\beta}_{PU}$	$\hat{\beta}_{CT}$	$\hat{\beta}_{1994}$
AR(0)	183.044	26.333	28	1.792	0.358	3.403	8.503

Model Components	AIC	$\hat{\sigma}^2$	N	$\hat{\beta}_{PM}$	$\hat{\beta}_{PU}$	$\hat{\beta}_{CT}$	$\hat{\beta}_{1994}$
				(1.402)	(0.635)	(1.954)	(2.091)
AR(1)	172.3	16.315	28	-0.341	-0.268	1.892	8.151
				(0.945)	(0.459)	(1.392)	(3.507)
AR(2)	183.044	12.698	28	-0.806	-0.884	0.103	6.611
				(0.635)	(0.367)	(1.091)	(2.581)
MA(1)	170.826	14.053	28	-0.464	-1.224	1.784	7.377
				(0.767)	(0.339)	(1.467)	(2.204)
ARMA(1,1)	168.501	11.651	28	-0.72	-1.309	0.807	9.131
				(0.576)	(0.24)	(1.134)	(2.171)
$AR(1)AR(1)_3$	169.047	13.117	28	-0.494	-0.301	0.728	6.887
				(0.641)	(0.388)	(1.029)	(3.045)

Table 8: Model Comparison

Model Components	AIC	RMSE	MAE_1	MAE_2	MAE_3	Average MAE
AR(0)	183.044	26.333	4.555	4.575	6.288	5.139
AR(1)	172.3	16.315	4.682	4.755	5.169	4.869
AR(2)	168.047	12.698	4.997	5.478	6.488	5.654
MA(1)	170.826	14.053	4.527	5.32	6.006	5.284
ARMA(1,1)	168.501	11.651	4.321	6.295	6.353	5.656
$AR(1)AR(1)_3$	169.047	13.117	4.802	5.482	5.659	5.314