Statistical Methods for Discrete Response, Time Series, and Panel Data (W271): Lab 3

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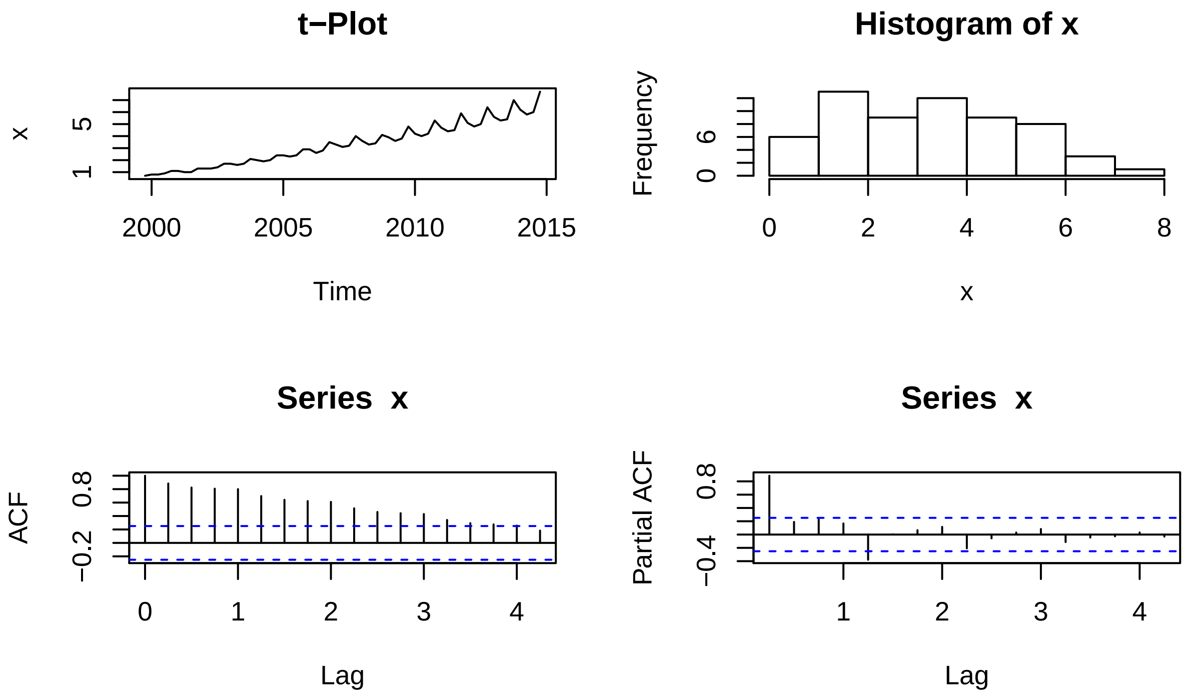
Question 1: Forecasting using a SARIMA model

Note: Custom function ts_plots() [plot time series], ts_resid() [plot residuals], forecast_exp() [exponentiate all values in forecasts objects] and arimatable() [summarizes arima table] are not included in the R pdf but is in the R-markdown file.

In the following report, we analyze and model quarterly data of E-Commerce Retail Sales as the Percent of Total Sales. Our goal is to use the data, ranging from Q4 1999 to Q4 2016, to forecast predictions for each quarter in 2017. First we explore the data and determine what models to further pursue. We select two models to test in depth, including diagnostic tests and with in- and out-of-model sampling. We use our final model to make a 2017 prediction.

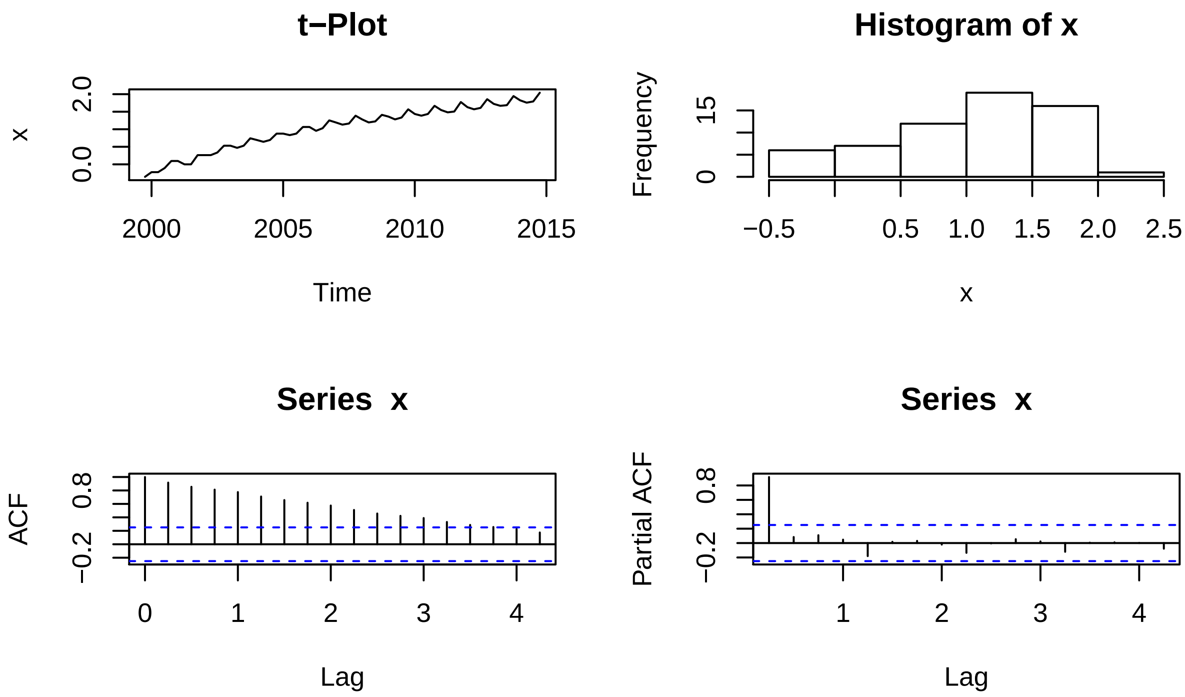
We bgein by examining a timeseries plot, a histogram of the time series and the ACF and PACF plots.

```r
df=read.csv('ECOMPCTNSA.csv')
head(df)
# exclude 2015 & 2016
dfts=ts(df$ECOMPCTNSA,start=c(1999,4),end=c(2014,4),freq=4)
ts_plots(dfts)
```



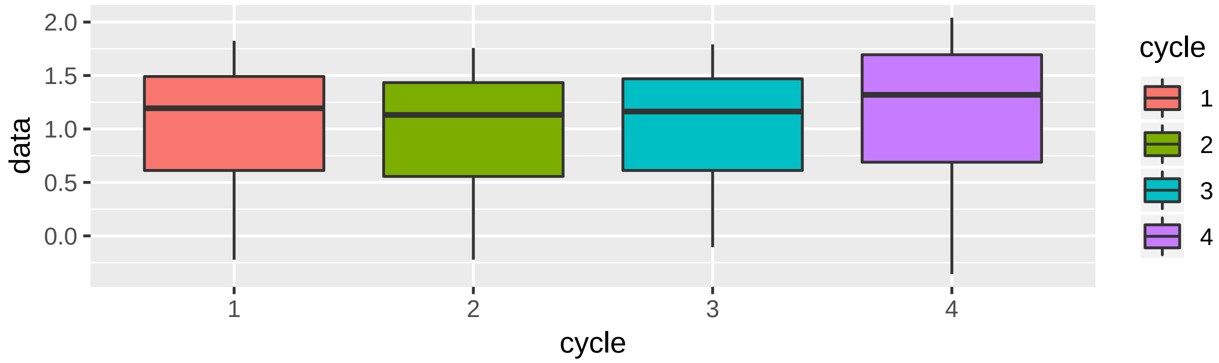
There is clearly a seaonsonal component based on the plot. Additionally, the plot seems to be potentially heteroskedastic. We will perform a `log` transformation on the time series to decrease the heteroskedasticity and re-analyze the time series from the starting point.

```
dfts_log=log(dfts)
ts_plots(dfts_log)
```



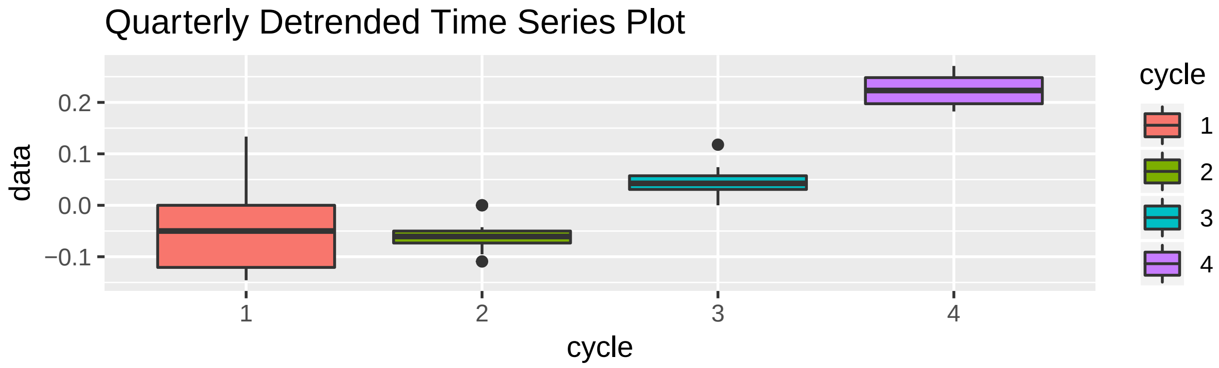
From the logged time series plots, there is a trend and seasonal component. The seasonality is likely to be quarterly from the t-plot. We will look at a box plot of the data by season.

```
ggplot(data.frame(cycle=factor(cycle(dfts_log)),data=as.numeric(dfts_log)),aes(x=cycle,y=data,
```



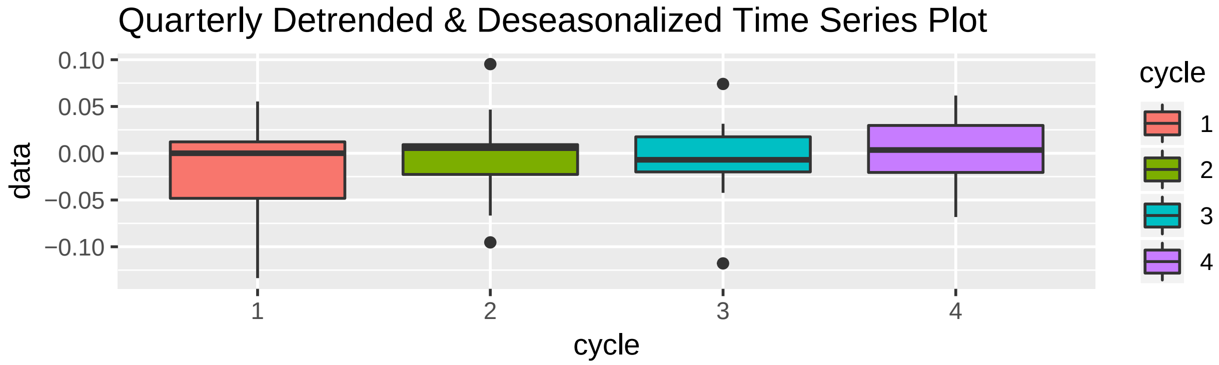
The seasonal boxplot does not show significant differences in each of the quarters. However, this is possibly due to the trend component affecting the cycles. We will detrend the series first and re-examine the quarterly plots.

```
tmp=diff(dfts_log,lag=1)
ggplot(data.frame(cycle=factor(cycle(tmp)),data=as.numeric(tmp)),aes(x=cycle,y=data,group=cycl
```



The detrended series shows a strong quarterly seasonality. The time series will be deseasonalized using a quarterly cycle.

```
df_ds=diff(diff(dfts_log,lag=1),lag=4)
ggplot(data.frame(cycle=factor(cycle(df_ds)),data=as.numeric(df_ds)),aes(x=cycle,y=data,group=
```



```
adf.test(df_ds)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  df_ds
## Dickey-Fuller = -7.2107, Lag order = 3, p-value = 0.01
## alternative hypothesis: stationary
```

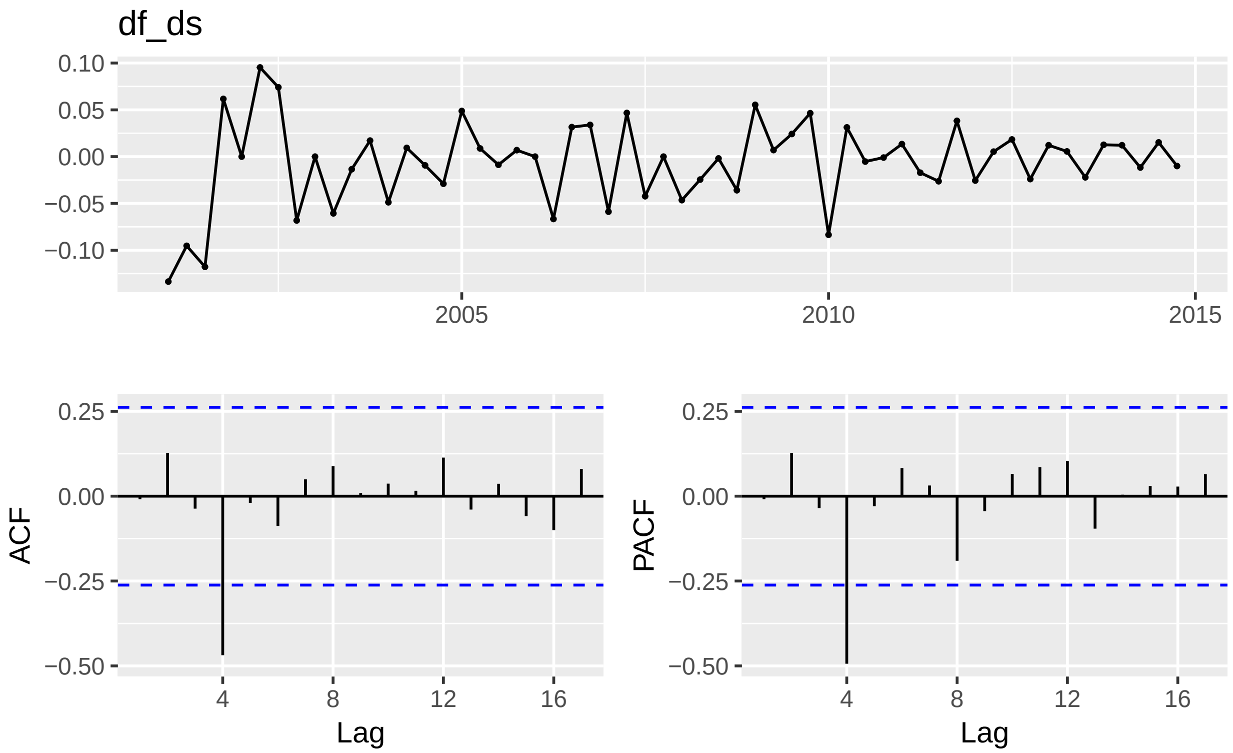
```
pp.test(df_ds)
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  df_ds
## Dickey-Fuller Z(alpha) = -52.65, Truncation lag parameter = 3,
## p-value = 0.01
## alternative hypothesis: stationary
```

The plot of the detrended and deseasonalized data shows the quarterly mean and variance is now similar across the quarters, indicating a deseasonalized time series. Augmented Dickey-Fuller and Phillips-Perron tests are performed on deseasonalized, detrended time series. Both tests reject the non-stationary hypothesis.

With a stationary time series, we can use an ARMA model to model the detrended, deseasonalized time series. Since the there are $I(1)$ and $I(1)_4$ components in the time series, we will use the SARIMA model to model the original log-transformed time series rather than modeling the detrended and deseasonalized logged data, thus combining the steps.

```r
ggtsdisplay(df_ds)
```



Reviewing the plots of the data we detrended and deseasonalized, we confirm the the time series to have been detrended and deseasonalized. On the PACF plot, there appears to strong serial correlation quarterly as it oscillates towards zero. The ACF plot has high serial correlation at the 4th lag. The strong ACF at lag 4 and cycling towards 0 in pact suggest there is a SMA(1) component.

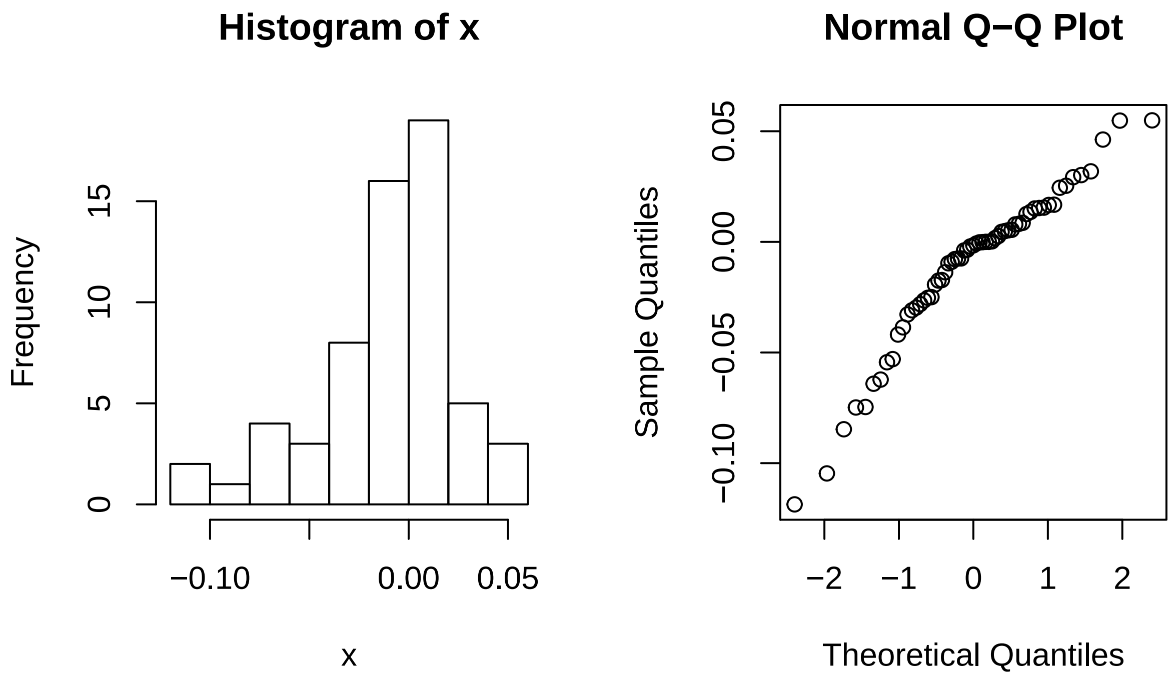
Based on our exploration, we know our model will have a seasonal period $s = 4$, that we will need differencing of $d = 1, D = 1$. Our intial model will be $SARIMA(0,1,0)(0,1,1)_4$.

```r
m = arima(dfts_log,order=c(0,1,0),seasonal=list(order=c(0,1,1),period=4))
xtable(arimatable(m,dfts_log))
```

	beta	SE	Sigma2	AIC	BIC	LogLik	ME	RMSE	MAE
sma1	-0.52	0.10	0.00	-201.54	-197.49	102.77	-0.01	0.04	0.03

The SMA1 β at -0.5167 with $SE = 0.0975$ suggesting signficance. The β_{sma1} does not cross zero.

```
ts_resid(m$residuals)
```



	PhillipsPerron	AugmentedDickeyFuller	LjungBox
p-Value	0.01	0.01	0.35

```
shapiro.test(m$residuals)
```

```
Shapiro-Wilk normality test
```

data: m$residuals W = 0.93609, p-value = 0.00331

The t-plot of the residuals appears to be white noise with heteroskedasticity. We will not further attempt to fit the variance of the residuals with GARCH/ARCH models. The t-plot shows no trend or seasonality. The residuals appear to be a stationary white noise process from the augmented Dickey Fuller and Phillips-Perron Test. However, the Shaprio-Wilks tests indicates that the residsuals of the model are non-normal. Finally, the Ljung-box test almost shows the residuals to be uncorrelated with a p-Value of 0.35 as confirmed by the visual inspection.

We will examine other $SARIMA(p,1,q)(P,1,Q)_4$ up to $p = q = P = Q = 2$ to aid in choosing our final model.

```
results=data.frame(matrix(ncol=9,nrow=0))
for (p in 0:2){ for (q in 0:2) { for (PS in 0:2) { for (QS in 0:2) {
        m.tmp=arima(dfts_log,order=c(p,1,q),seasonal = list(order=c(PS,1,QS),period=4))
        results=rbind(results,c(p=p,d=1, q=q,P=PS,D=1,Q=QS,AIC=AIC(m.tmp),BIC=BIC(m.tmp),Log_Li
colnames(results) = c('p','d','q','P','D','Q','AIC','BIC','Log_Likelihood')
xtable(head(results[order(results$AIC,results$BIC),],5))
```

	p	d	q	P	D	Q	AIC	BIC	Log_Likelihood
3	0.00	1.00	0.00	0.00	1.00	2.00	-207.22	-201.14	106.61
7	0.00	1.00	0.00	2.00	1.00	0.00	-206.50	-200.42	106.25
4	0.00	1.00	0.00	1.00	1.00	0.00	-206.22	-202.17	105.11
30	1.00	1.00	0.00	0.00	1.00	2.00	-205.53	-197.42	106.76
5	0.00	1.00	0.00	1.00	1.00	1.00	-205.50	-199.42	105.75

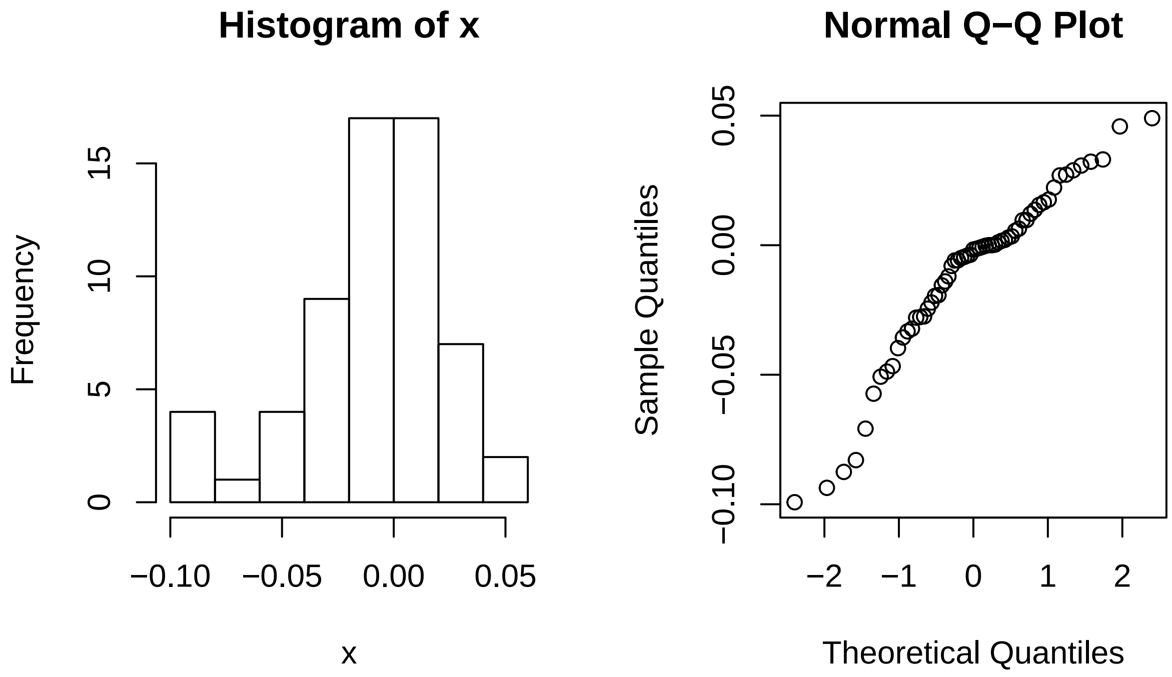
	beta	SE	Sigma2	AIC	BIC	LogLik	ME	RMSE	MAE
sar1	-0.80	0.15	0.00	-206.50	-200.42	106.25	-0.01	0.03	0.02
sar2	-0.25	0.16	0.00	-206.50	-200.42	106.25	-0.01	0.03	0.02

Auto.arima() selected $SARIMA(0,1,0)(2,1,0)_4$. From the manual iterations and auto.arima(), $SARIMA(0,1,0)(0,1,2)_4$ and $SARIMA(0,1,0)(2,1,0)_4$ are chosen as the candidate models as they have the lowest AICs and BICs.

```r
m.010210=arima(dfts_log,order=c(0,1,0),seasonal = list(order=c(2,1,0),period=4))
xtable(arimatable(m.010210,dfts_log))
```

	beta	SE	Sigma2	AIC	BIC	LogLik	ME	RMSE	MAE
sar1	-0.80	0.15	0.00	-206.50	-200.42	106.25	-0.01	0.03	0.02
sar2	-0.25	0.16	0.00	-206.50	-200.42	106.25	-0.01	0.03	0.02

```r
ts_resid(m.010210$residuals)
```



	PhillipsPerron	AugmentedDickeyFuller	LjungBox
p-Value	0.01	0.01	0.09

```r
shapiro.test(m.010210$residuals)
```

```
Shapiro-Wilk normality test
```

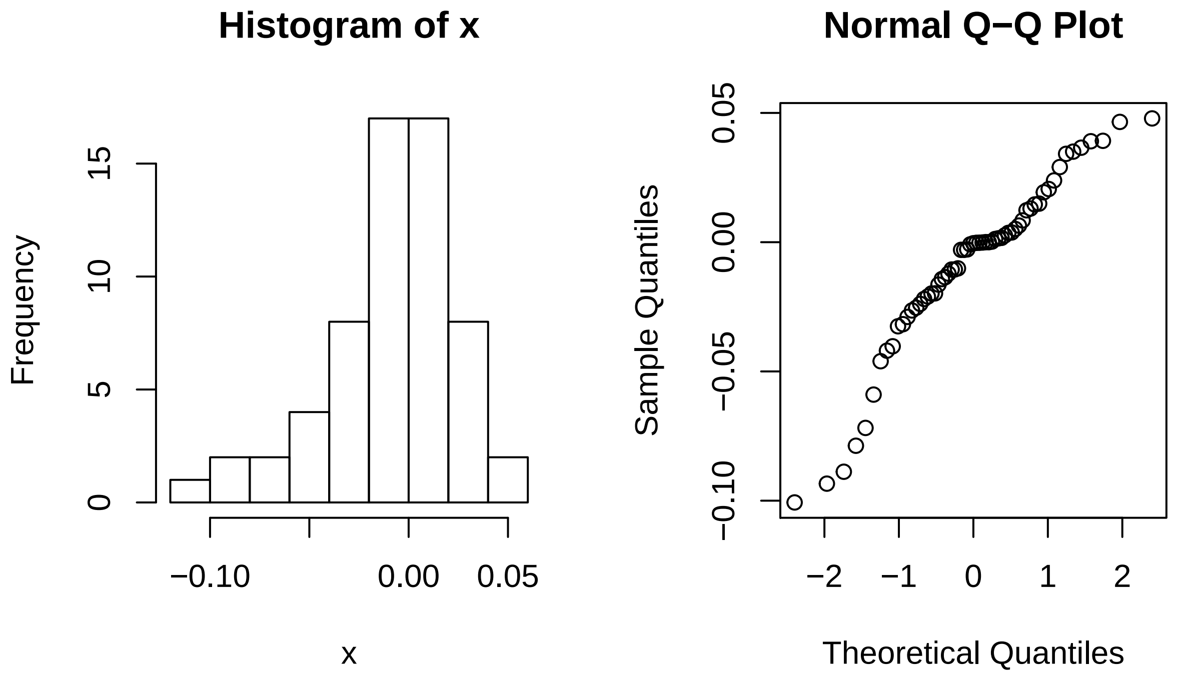
data: m.010210$residuals W = 0.93616, p-value = 0.003334

In the $SARIMA(0,1,0)(2,1,0)_4$, the βs do not include zero up to the 95% confidence interval and the residual appear to be stationary and white noise. The Ljung-Box p-Value is .13 and the heterskedasticity of the residuals is not evident. The Shaprio-Wilks test on the model residuals gives a significant p-value, indicating a non-normal distribution.

```r
m.010012=arima(dfts_log,order=c(0,1,0),seasonal = list(order=c(0,1,2),period=4))
xtable(arimatable(m.010012,dfts_log))
```

	beta	SE	Sigma2	AIC	BIC	LogLik	ME	RMSE	MAE
sma1	-0.77	0.16	0.00	-207.22	-201.14	106.61	-0.01	0.03	0.02
sma2	0.40	0.13	0.00	-207.22	-201.14	106.61	-0.01	0.03	0.02

```r
ts_resid(m.010012$residuals)
```



	PhillipsPerron	AugmentedDickeyFuller	LjungBox
p-Value	0.01	0.01	0.13

```
shapiro.test(m.010012$residuals)
```

```
Shapiro-Wilk normality test
```

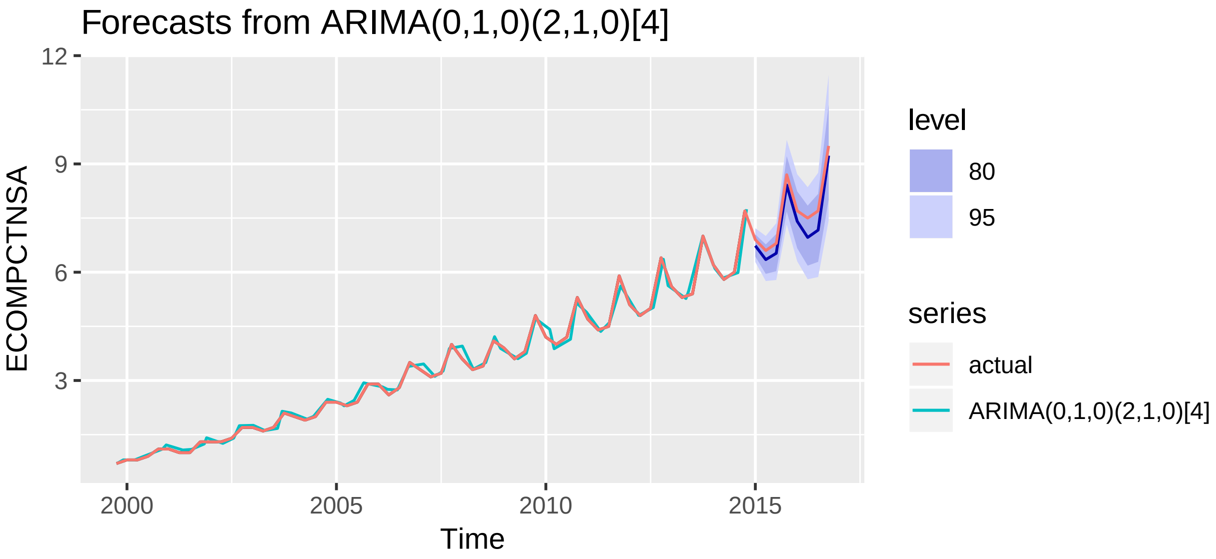
data: m.010012$residuals W = 0.93323, p-value = 0.002479

In the $SARIMA(0,1,0)(0,1,2)_4$, βs appear to be statistically siginficant and the residuals do appear to be white noise with stationarity and no autocorrelation. The Ljung-Box p-Value is higher than the $SARIMA(0,1,0)(0,1,1)_4$ model. Note that the heteroskedasticity in residuals no longer appear. Here, the Shaprio-Wilks test also gives $p > 0.05$, indicating the distribution is non-normal.

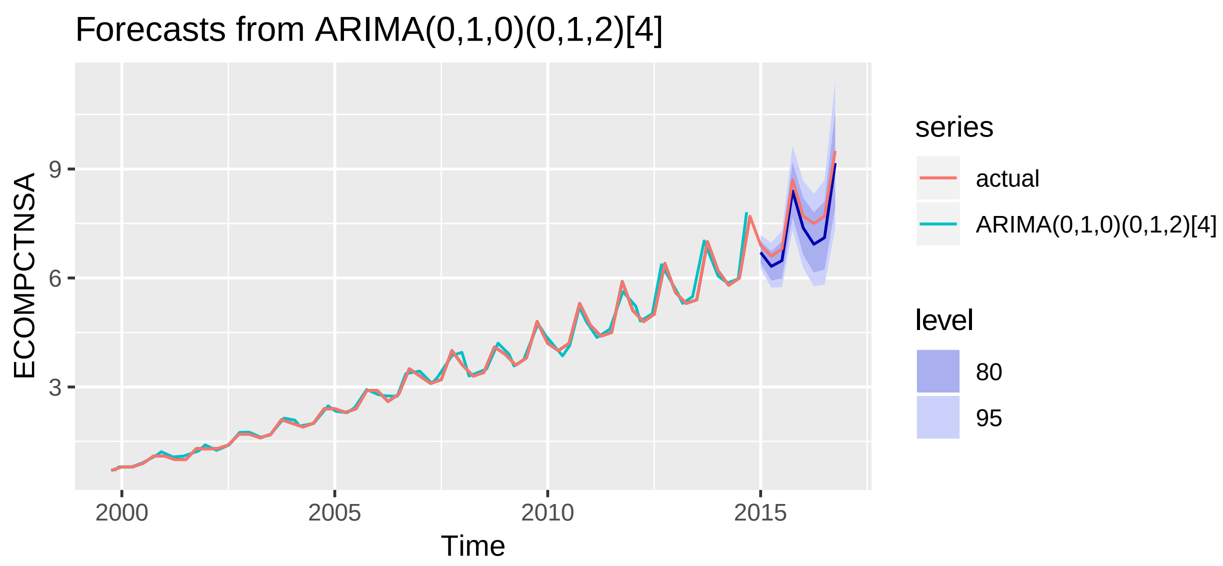
We first note that these series seem comparable as a MA model can be inverted to become an AR model. An $SARIMA(0,1,0)(0,1,2)_4$ is very similar to $SARIMA(0,1,0)(2,1,0)_4$ from invertibility of MA models.

The 2 models will be chosen as potential candidates. We will examine both in-sample and out-of-sample fits to chose the final model.

```
actual=ts(df$ECOMPCTNSA,start=c(1999,4),freq=4)
forecast_sar=forecast_exp_func(forecast(m.010210))
forecast_sma=forecast_exp_func(forecast(m.010012))
autoplot(forecast_sar) +autolayer(exp(fitted(m.010210)),series='ARIMA(0,1,0)(2,1,0)[4]',positi
```



```
autoplot(forecast_sma) +autolayer(exp(fitted(m.010012)),series='ARIMA(0,1,0)(0,1,2)[4]',positi
```



The in-sample fits for both models are extremely close to the historical fit. The predictions for both models are extremely similar. We will select the models based on accuracy of the time series. The time series is logged to avoid overweighting the larger values on the time series due to the trend.

```
pred_test=window(log(actual),start=c(2015,1))
xtable(accuracy(forecast(m.010210),pred_test),caption='$ARIMA(0,1,0)(2,1,0)_4$')
```

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
Training set	-0.01	0.03	0.02	-Inf	Inf	0.16	-0.21	
Test set	0.04	0.05	0.04	2.17	2.17	0.30	0.18	0.37

Table 1: $ARIMA(0,1,0)(2,1,0)_4$

```
xtable(accuracy(forecast(m.010012),pred_test),caption='$ARIMA(0,1,0)(0,1,2)_4$')
```

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
Training set	-0.01	0.03	0.02	-Inf	Inf	0.16	-0.19	
Test set	0.05	0.05	0.05	2.44	2.44	0.34	0.20	0.41

Table 2: $ARIMA(0,1,0)(0,1,2)_4$

Every accuracy measure tested showed a lower error with $SARIMA(0,1,0)(2,1,0)_4$ model. The final model chosen is # CHECK BELOW

$$SARIMA(0,1,0)(2,1,0)_4$$

$$(1-0.7851B-0.23651B^2)_4(1-B)_4(1-B)x_t=\epsilon_t$$

$$y_t=y_{t-1}+y_{t-4}+-0.7851y_{t-4}+-0.23651y_{t-5}+\epsilon_t$$

```
df_full_log=ts(log(df$ECOMPCTNSA),start=c(1999,4),freq=4)
m=arima(df_full_log,order=c(0,1,0),seasonal = list(order=c(2,1,0),period=4))
xtable(arimatable(m,df_full_log))
```

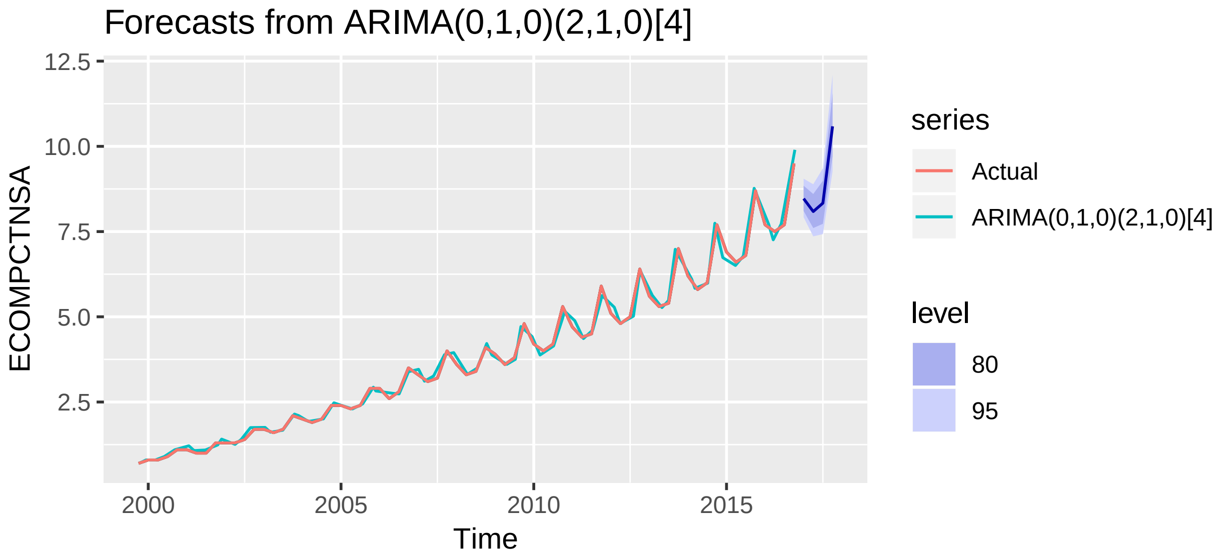
The forecast for 2017 using $SARIMA(0,1,0)(2,1,0)_4$ is

	beta	SE	Sigma2	AIC	BIC	LogLik	ME	RMSE	MAE
sar1	-0.79	0.14	0.00	-242.53	-236.05	124.27	-0.01	0.03	0.02
sar2	-0.24	0.16	0.00	-242.53	-236.05	124.27	-0.01	0.03	0.02

```
forecast_sar=forecast_exp_func(forecast(m,h = 4))
xtable(data.frame(forecast_sar))
```

	Point.Forecast	Lo.80	Hi.80	Lo.95	Hi.95
2017 Q1	8.47	8.11	8.84	7.92	9.05
2017 Q2	8.09	7.60	8.60	7.36	8.89
2017 Q3	8.33	7.73	8.99	7.43	9.36
2017 Q4	10.59	9.70	11.55	9.27	12.10

```
autoplot(forecast_sar,'Model') +autolayer(exp(fitted(m)),series='ARIMA(0,1,0)(2,1,0)[4]',posit
```



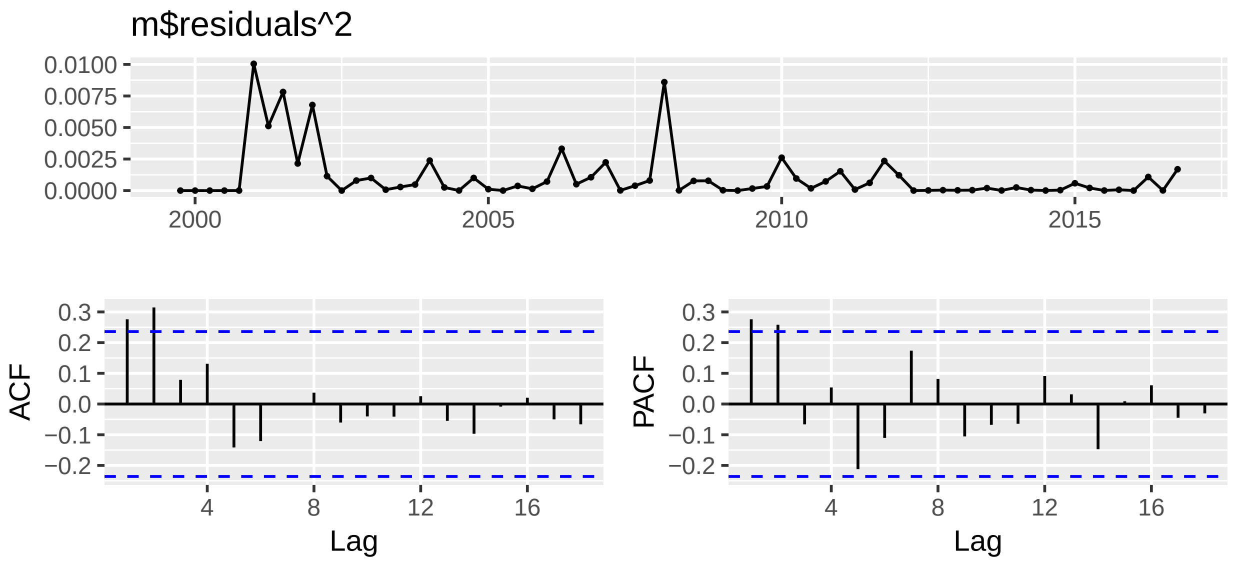
The forecast closely follows what we would expect of the trend going forward in 2017.

KYLE - OWN TEST

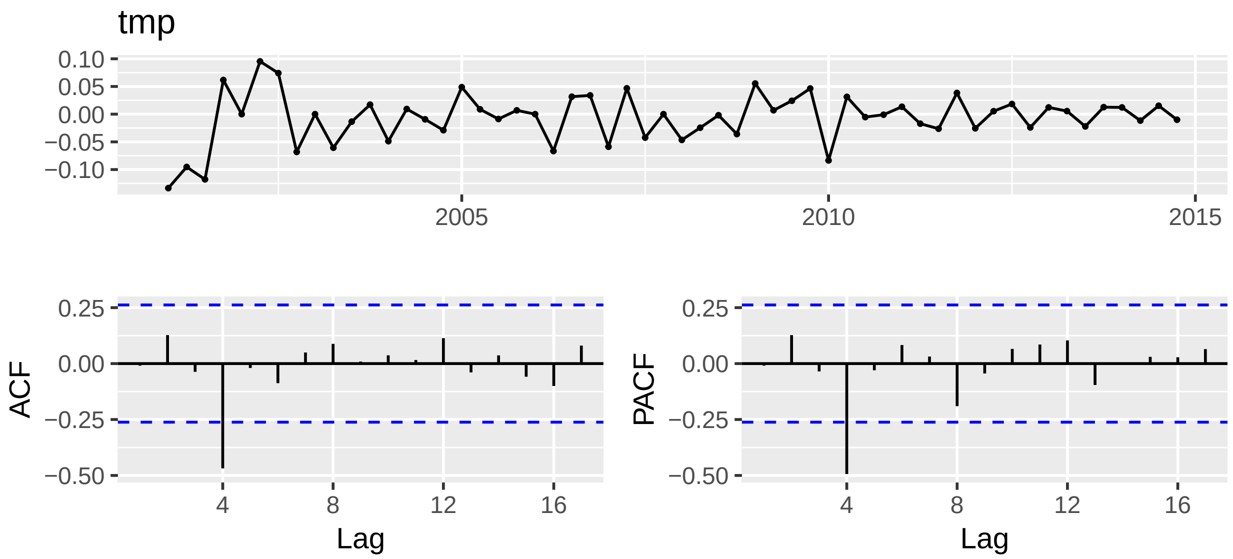
Furthermore, the residuals appear to be heteroskedastic. From the $residuals^2$ act and pacf plots, There appears to be an AR component in the volatility suggesting a GARCH(1,0) model.

```
#library(fGarch)
#m.garch=garchFit(~garch(1,0),m$residuals,trace=FALSE)
#summary(m.garch)
```

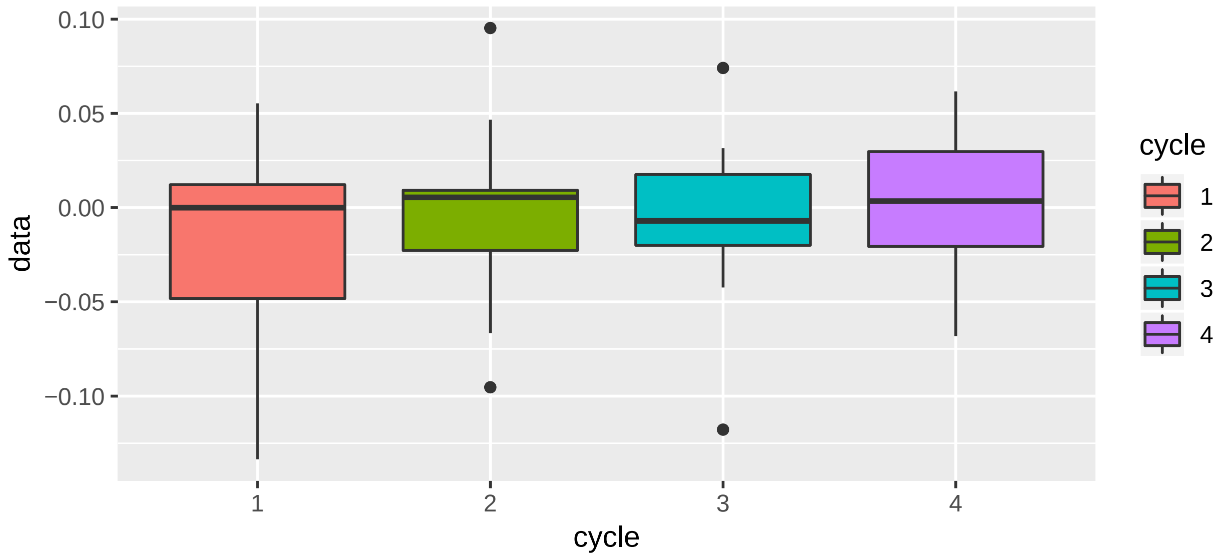
```
ggtsdisplay(m$residuals^2)
```



```
tmp=diff(diff(dfts_log,lag=1),lag=4)
ggtsdisplay(tmp)
```



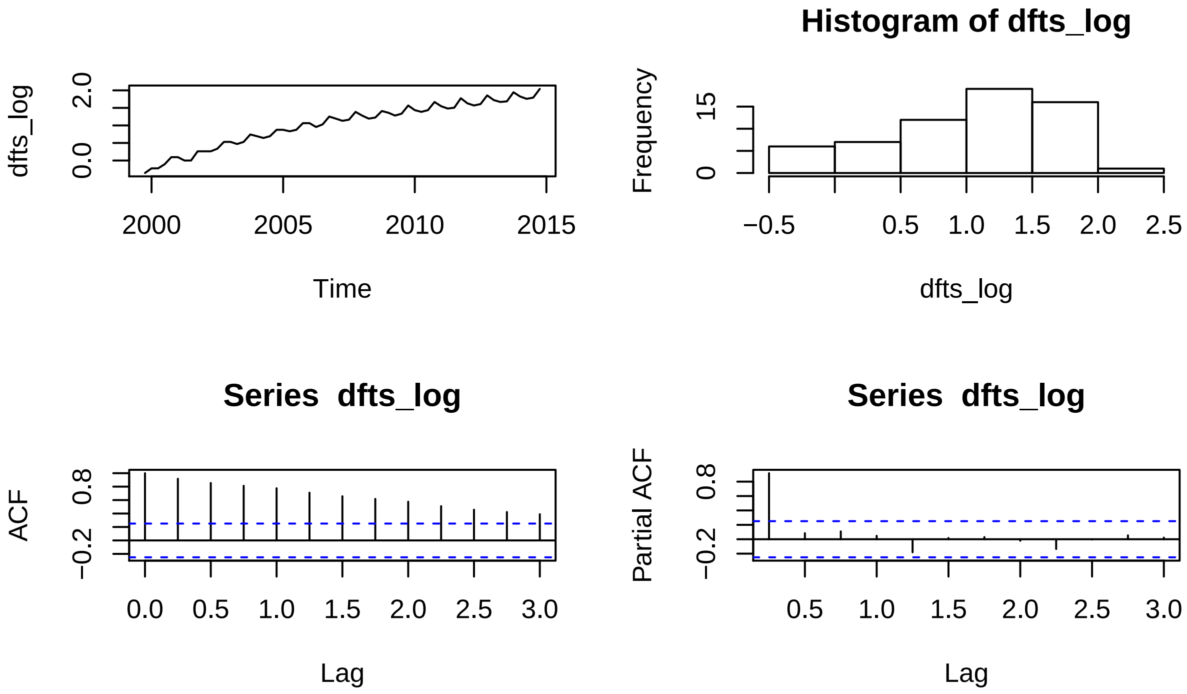
```
ggplot(data.frame(cycle=factor(cycle(tmp)),data=as.numeric(tmp)),aes(x=cycle,y=data,group=cycl
```



```r
#ggplot(data.frame(r=residuals(m.garch)),aes(sample=r))+geom_qq()+geom_qq_line(col='red')
#hist(residuals(m.garch))
#predict(m.garch)
```

The series appear to be detrended and deseaonalized. From the ACF gaph

```r
par(mfrow=c(2,2))
plot(dfts_log)
hist(dfts_log)
acf(dfts_log,lag=12)
pacf(dfts_log,lag=12)
```



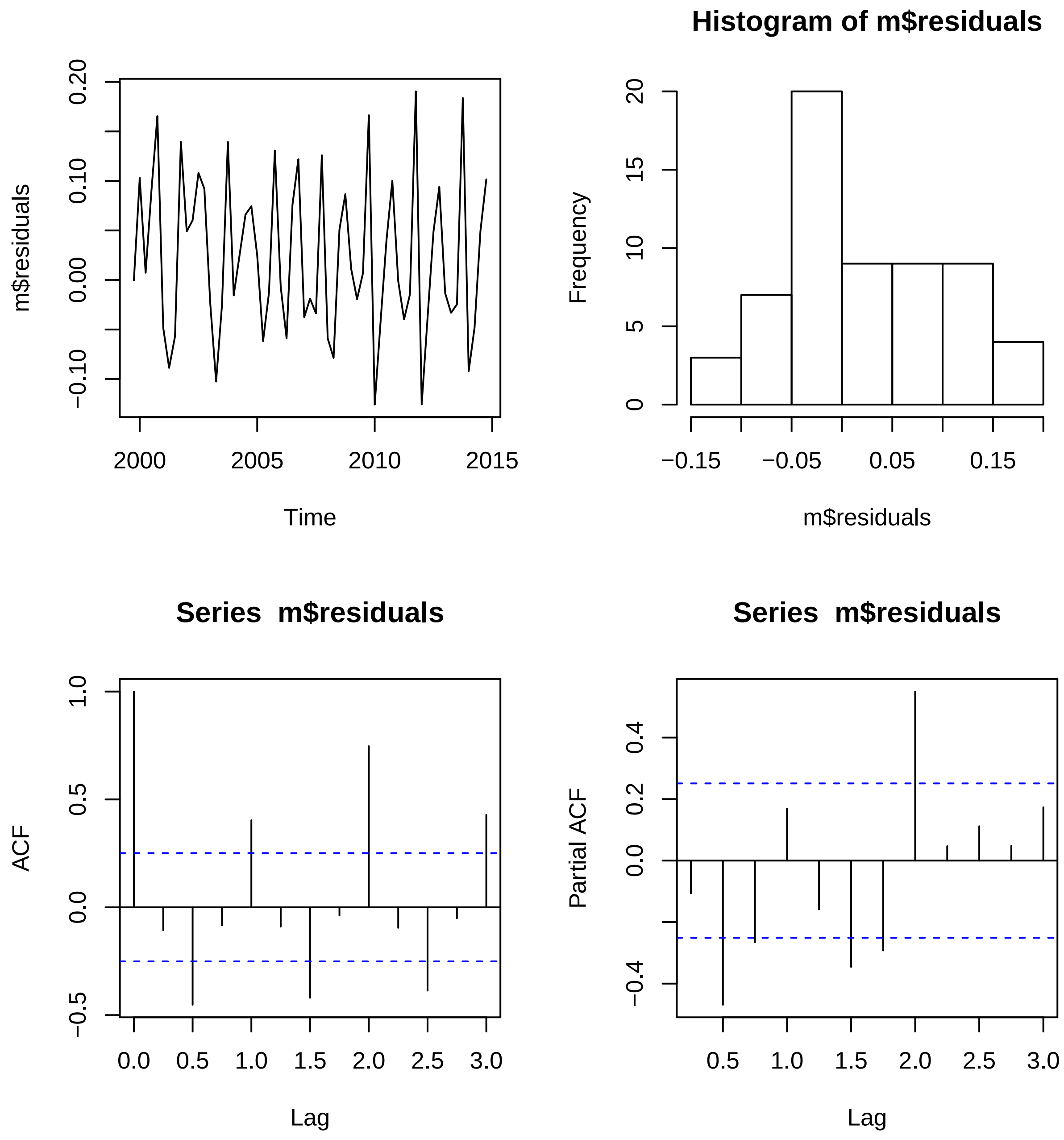
The initial model proposed is a $SARIMA(1,1,0)(0,0,1)_4$ model.

```
m=arima(dfts_log,order=c(1,1,0),seasonal=list(order=c(0,0,1),period=4))
```

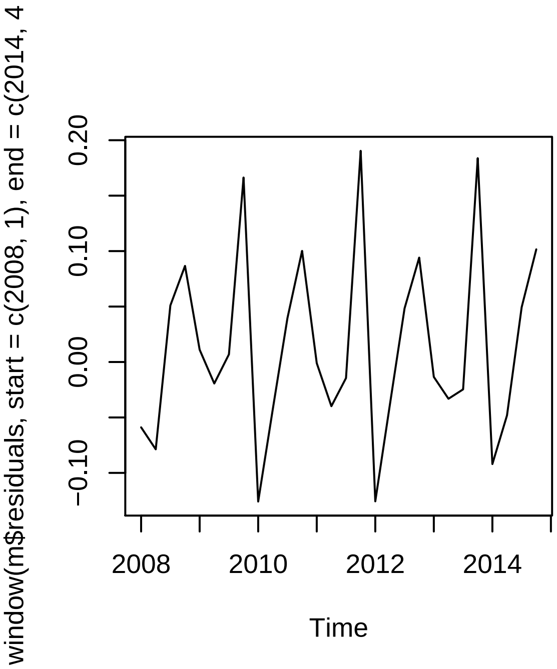
The AR(1) component is likely to be 0 given the -0.0705 β and s.e. of 0.1347. The SMA(1) β appears siginificant. We will examine the residuals to see if the I(1) has removed the trend.

From the t-plot, the I(1) appears to have removed the trend. The seasonality does not seem to be removed but m

```
par(mfrow=c(2,2))
plot(m$residuals)
hist(m$residuals)
acf(m$residuals,lag=12)
pacf(m$residuals,lag=12)
```



```r
plot(window(m$residuals,start=c(2008,1),end=c(2014,4)))
```


window(m$residuals, start = c(2008, 1), end = c(2014, 4
0.20
0.10
0.00
−0.10
2008
2010
2012
2014
Time

```r
library(ggplot2)
```

Question 2: Learning how to use the xts library

Only Task 5 is left for brevity.

Task 5:

1. Read AMAZ.csv and UMCSENT.csv into R as R DataFrames

```r
library(xts)
amaz <- read.csv('AMAZ.csv')
umcsent <- read.csv('UMCSENT.csv')
xtable(head(amaz))
```

	Index	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume
1	2007-01-03	20.00	20.00	16.00	16.00	650
2	2007-01-04	20.00	20.00	20.00	20.00	67
3	2007-01-08	19.20	22.00	19.20	22.00	1801
4	2007-01-09	22.00	22.00	20.80	20.80	356
5	2007-01-10	20.80	20.80	20.80	20.80	438
6	2007-01-11	20.80	21.60	20.80	21.60	2318

```r
xtable(tail(amaz))
```

	Index	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume
1174	2013-01-04	0.88	0.88	0.80	0.80	3850
1175	2013-01-07	0.80	1.00	0.80	1.00	2715
1176	2013-01-08	0.80	0.80	0.68	0.68	4668
1177	2013-01-09	0.88	0.88	0.80	0.80	2750
1178	2013-01-11	0.80	0.80	0.80	0.80	3000
1179	2013-01-15	0.68	0.68	0.68	0.68	1000

```r
length(amaz$Index)
```

```
[1] 1179
```

```r
xtable(head(umcsent))
```

	Index	UMCSENT
1	1978-01-01	83.70
2	1978-02-01	84.30
3	1978-03-01	78.80
4	1978-04-01	81.60
5	1978-05-01	82.90
6	1978-06-01	80.00

```
xtable(tail(umcsent))
```

	Index	UMCSENT
472	2017-04-01	97.00
473	2017-05-01	97.10
474	2017-06-01	95.10
475	2017-07-01	93.40
476	2017-08-01	96.80
477	2017-09-01	95.10

```
length(umcsent$Index)
```

[1] 477

2. Convert them to xts objects

```
amaz.xts <- as.xts(amaz[,2:6],order.by=as.Date(amaz$Index,format="%Y-%m-%d"))
xtable(head(amaz.xts))
```

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume
1	20.00	20.00	16.00	16.00	650.00
2	20.00	20.00	20.00	20.00	67.00
3	19.20	22.00	19.20	22.00	1801.00
4	22.00	22.00	20.80	20.80	356.00
5	20.80	20.80	20.80	20.80	438.00
6	20.80	21.60	20.80	21.60	2318.00

```
xtable(tail(amaz.xts))
```

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume
1	0.88	0.88	0.80	0.80	3850.00
2	0.80	1.00	0.80	1.00	2715.00
3	0.80	0.80	0.68	0.68	4668.00
4	0.88	0.88	0.80	0.80	2750.00
5	0.80	0.80	0.80	0.80	3000.00
6	0.68	0.68	0.68	0.68	1000.00

```
umcsent.xts <- as.xts(umcsent[,2], order.by=as.Date(umcsent$Index, format="%Y-%d-%m"))
colnames(umcsent.xts)=c('umcsent')
xtable(head(umcsent.xts))
```

```
xtable(tail(umcsent.xts))
```

It is important to note here that the `amaz.xts` has a shorter duration and span than the `umcscent.xts` series. However, the `amaz.xts` series has more observations than `umcsent.xts`.

3. Merge the two set of series together, perserving all of the observations in both set of series

```
merged <- merge(amaz.xts, umcsent.xts, join="outer")
xtable(head(merged))
```

	Value
1	83.70
2	84.30
3	78.80
4	81.60
5	82.90
6	80.00

	Value
1	97.00
2	97.10
3	95.10
4	93.40
5	96.80
6	95.10

```
xtable(tail(merged))
```

```
dim(merged)
```

[1] 1610 6

```
a. fill all of the missing values of the UMCSENT series with -9999
```

```
umcsent01=merged
xtable(head(umcsent01))
```

```
umcsent01=na.fill(umcsent01,-9999)
xtable(head(umcsent01))
```

b. then create a new series, named UMCSENT02, from the original UMCSENT series replace all of the -9999 with NAs

```
umcsent02 <- umcsent01
xtable(head(umcsent02))
```

```
umcsent02[umcsent02 <= -9999 ] <- NA
xtable(head(umcsent02))
```

c. then create a new series, named UMCSENT03, and replace the NAs with the last observation

```
umcsent03=umcsent02
xtable(head(umcsent03))
```

```
umcsent03 <- na.locf(umcsent02, na.rm = TRUE, fromLast = TRUE)
xtable(head(umcsent03))
```

d. then create a new series, named UMCSENT04, and replace the NAs using linear interpolation.

```
umcsent04=umcsent02
xtable(head(umcsent04))
```

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1						83.70
2						84.30
3						78.80
4						81.60
5						82.90
6						80.00

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1						97.00
2						97.10
3						95.10
4						93.40
5						96.80
6						95.10

```
xtable(head(umcsent04['2007-01',],15))
```

```
umcsent04=na.approx(umcsent04,maxgap=10000)
# Note amazon has N/As in 1/1/17 and 1/2/17 because there is no data before 1/1/03 so there is
xtable(head(umcsent04['2007-01',],15))
```

e. Print out some observations to ensure that your merge as well as the missing value imputation are done correctly. I leave it up to you to decide exactly how many observations to print; do something that makes sense. (Hint: Do not print out the entire dataset!)

Observations to check the merge and imputation are printed in the above sections.

4. Calculate the daily return of the Amazon closing price (AMAZ.close), where daily return is defined as $(x(t) - x(t-1))/x(t-1)$. Plot the daily return series.

```
amaz.xts.close=amaz.xts$AMAZ.Close
xtable(head(amaz.xts.close))
```

```
xtable(head(diff(amaz.xts.close,lag=1,differences=1,log=FALSE,na.pad=FALSE)))
```

```
xtable(head(diff(amaz.xts.close,lag=1,differences=1,log=FALSE,na.pad=FALSE)/amaz.xts.close))
```

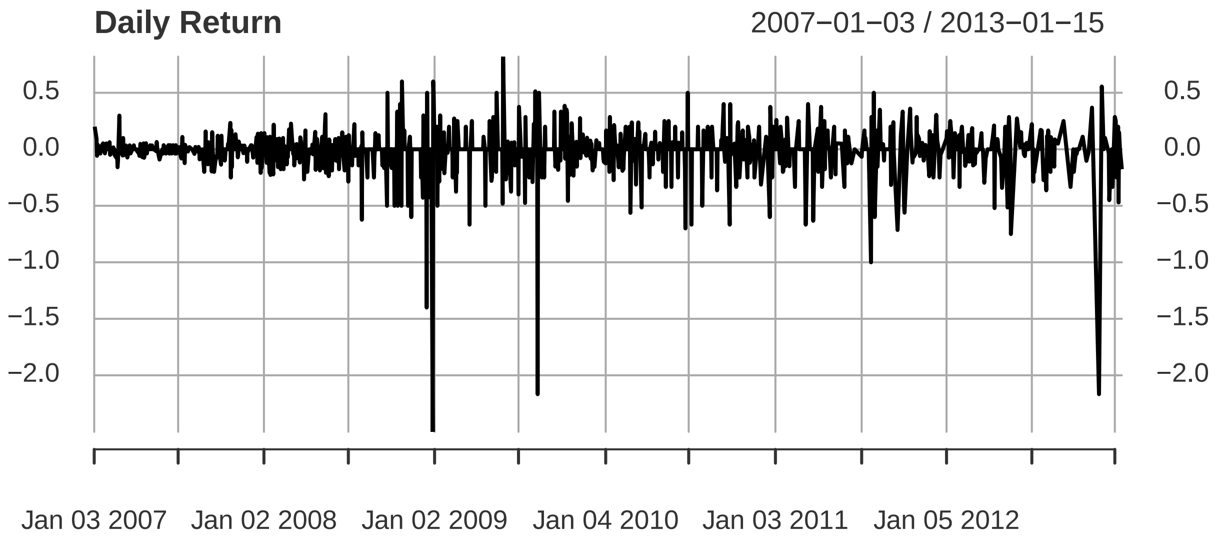
```
xtable(head(cbind(amaz.xts.close,diff(amaz.xts.close,lag=1,differences=1,log=FALSE,na.pad=TRUE
```

```
# another way to do it in 1 long line...
#head(diff(amaz.xts$AMAZ.Close,lag=1,differences=1,log=F,na.pad=F)/amaz.xts$AMAZ.Close)
```

```
plot(diff(amaz.xts.close,lag=1,differences=1,log=FALSE,na.pad=TRUE)/amaz.xts.close, main="Daily
```

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1						83.70
2						84.30
3						78.80
4						81.60
5						82.90
6						80.00

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	83.70
2	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	84.30
3	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	78.80
4	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	81.60
5	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	82.90
6	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	80.00



5. Create a 20-day and a 50-day rolling mean series from the AMAZ.close series.

```
xtable(tail(cbind(amaz.xts.close,rollapply(amaz.xts.close,20,FUN=mean,na.rm=TRUE)),15))
```

```
xtable(tail(cbind(amaz.xts.close,rollapply(amaz.xts.close,50,FUN=mean,na.rm=TRUE)),15))
```

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	83.70
2	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	84.30
3	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	78.80
4	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	81.60
5	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	82.90
6	-9999.00	-9999.00	-9999.00	-9999.00	-9999.00	80.00

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1						83.70
2						84.30
3						78.80
4						81.60
5						82.90
6						80.00

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1						83.70
2						84.30
3						78.80
4						81.60
5						82.90
6						80.00

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1	20.00	20.00	16.00	16.00	650.00	83.70
2	20.00	20.00	16.00	16.00	650.00	84.30
3	20.00	20.00	16.00	16.00	650.00	78.80
4	20.00	20.00	16.00	16.00	650.00	81.60
5	20.00	20.00	16.00	16.00	650.00	82.90
6	20.00	20.00	16.00	16.00	650.00	80.00

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1						83.70
2						84.30
3						78.80
4						81.60
5						82.90
6						80.00

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1						96.90
2						91.30
3	20.00	20.00	16.00	16.00	650.00	88.40
4	20.00	20.00	20.00	20.00	67.00	87.10
5						88.30
6						85.30
7						90.40
8	19.20	22.00	19.20	22.00	1801.00	83.40
9	22.00	22.00	20.80	20.80	356.00	83.40
10	20.80	20.80	20.80	20.80	438.00	80.90
11	20.80	21.60	20.80	21.60	2318.00	76.10
12	22.00	22.00	22.00	22.00	306.00	75.50
13	21.60	21.60	21.20	21.20	925.00	
14	22.00	22.00	21.60	21.60	2138.00	
15	23.20	23.20	22.80	22.80	527.00	

	AMAZ.Open	AMAZ.High	AMAZ.Low	AMAZ.Close	AMAZ.Volume	umcsent
1						96.90
2						91.30
3	20.00	20.00	16.00	16.00	650.00	88.40
4	20.00	20.00	20.00	20.00	67.00	87.10
5	19.80	20.50	19.80	20.50	500.50	88.30
6	19.60	21.00	19.60	21.00	934.00	85.30
7	19.40	21.50	19.40	21.50	1367.50	90.40
8	19.20	22.00	19.20	22.00	1801.00	83.40
9	22.00	22.00	20.80	20.80	356.00	83.40
10	20.80	20.80	20.80	20.80	438.00	80.90
11	20.80	21.60	20.80	21.60	2318.00	76.10
12	22.00	22.00	22.00	22.00	306.00	75.50
13	21.60	21.60	21.20	21.20	925.00	75.53
14	22.00	22.00	21.60	21.60	2138.00	75.54
15	23.20	23.20	22.80	22.80	527.00	75.58

	Value
1	16.00
2	20.00
3	22.00
4	20.80
5	20.80
6	21.60

	Value
1	4.00
2	2.00
3	-1.20
4	0.00
5	0.80
6	0.40

	Value
1	0.20
2	0.09
3	-0.06
4	0.00
5	0.04
6	0.02

	AMAZ.Close	AMAZ.Close.1	AMAZ.Close.2
1	16.00		
2	20.00	4.00	0.20
3	22.00	2.00	0.09
4	20.80	-1.20	-0.06
5	20.80	0.00	0.00
6	21.60	0.80	0.04

	AMAZ.Close	AMAZ.Close.1
1	1.08	1.09
2	1.20	1.09
3	1.16	1.09
4	0.80	1.08
5	0.80	1.06
6	0.60	1.03
7	0.84	0.99
8	1.12	0.99
9	1.00	0.98
10	0.80	0.97
11	1.00	0.97
12	0.68	0.95
13	0.80	0.95
14	0.80	0.94
15	0.68	0.92

	AMAZ.Close	AMAZ.Close.1
1	1.08	1.21
2	1.20	1.21
3	1.16	1.21
4	0.80	1.21
5	0.80	1.20
6	0.60	1.19
7	0.84	1.18
8	1.12	1.17
9	1.00	1.16
10	0.80	1.15
11	1.00	1.14
12	0.68	1.13
13	0.80	1.12
14	0.80	1.11
15	0.68	1.09