

Group 8 presentation

Stat 443 Forecasting
Dr. Reza Ramezan

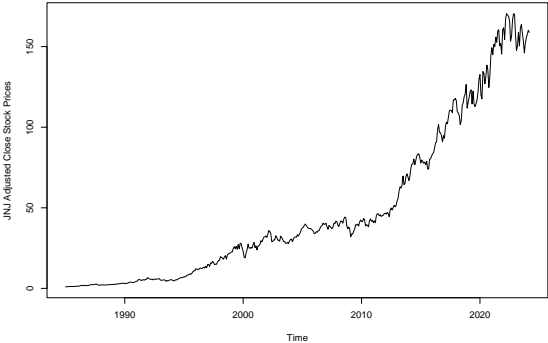
Shirley Yang (j584yang)
Claudia Chen (j867chen)
Xinyi Shen (x77shen)
Dominic Song (z85song)

Data Description

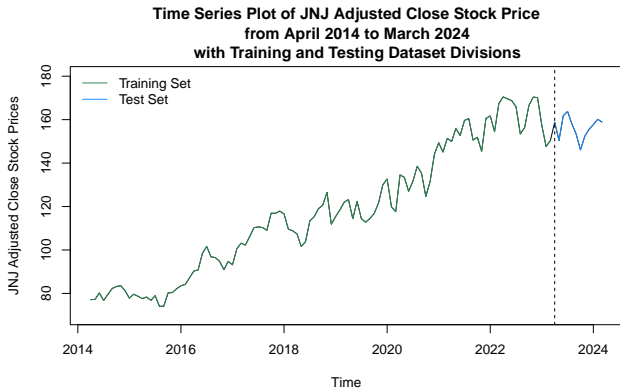
Table 1: First Five Rows of JNJ Historical Stock Prices

Date	Open	High	Low	Close	Adj.Close
1985-01-01	2.242188	2.453125	2.195313	2.437500	0.975024
1985-02-01	2.390625	2.507813	2.312500	2.460938	0.984401
1985-03-01	2.437500	2.632813	2.421875	2.625000	1.058037
1985-04-01	2.609375	2.796875	2.523438	2.742188	1.105271
1985-05-01	2.726563	2.960938	2.679688	2.937500	1.183994

Time Series Plot of JNJ Adjusted Close Stock Price
from January 1985 to March 2024



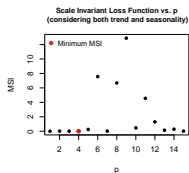
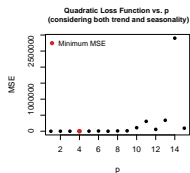
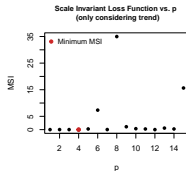
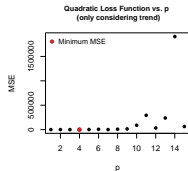
Training and Test Dataset



Possible Solutions

```
##  
## Fligner-Killeen test of homogeneity of variances  
##  
## data: JNJ.ts and seg  
## Fligner-Killeen:med chi-squared = 16.225, df = 9, p-value = 0.06233
```

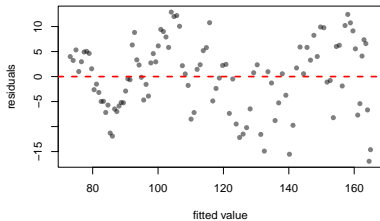
Regression Modelling



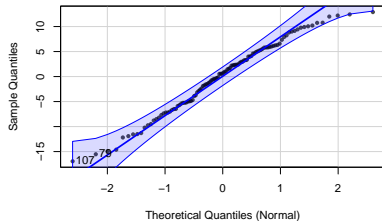
Regression	MSE	MSI
Only consider the trend	120.4273	0.0034556
Consider both the trend and seasonality	140.2979	0.0041335

Regression Modelling

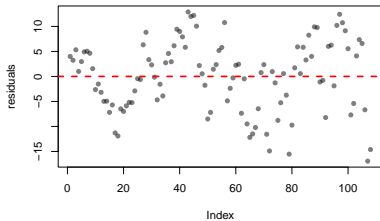
Residuals vs. Fitted Values



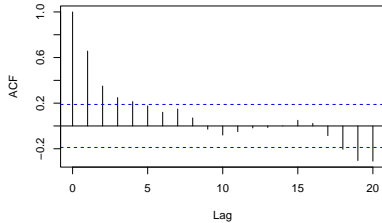
Normal QQ Plot



Residuals vs. Time



ACF Plot of Residuals



Regression Modelling

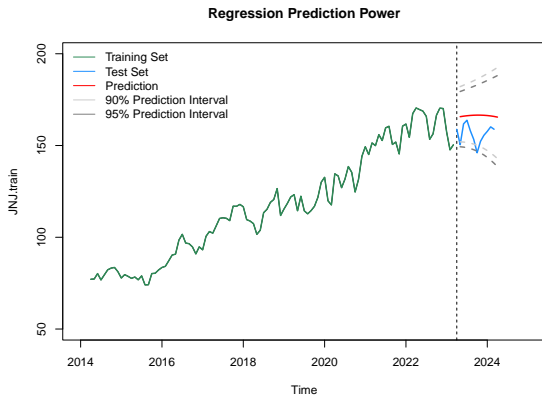
```
##
## Shapiro-Wilk normality test
##
## data: residuals(mod.regression)
## W = 0.98043, p-value = 0.1128

##
## Fligner-Killeen test of homogeneity of variances
##
## data: residuals(mod.regression) and segment
## Fligner-Killeen:med chi-squared = 20.584, df = 8, p-value = 0.008338

##
## Difference Sign Test
##
## data: residuals(mod.regression)
## statistic = 0.4977, n = 108, p-value = 0.6187
## alternative hypothesis: nonrandomness

##
## Runs Test
##
## data: residuals(mod.regression)
## statistic = -5.994, runs = 24, n1 = 54, n2 = 54, n = 108, p-value =
## 2.047e-09
## alternative hypothesis: nonrandomness
```

Regression Modelling



$$APSE = MSE_{pred.} = \frac{\sum_{y \in test} (y - \hat{y})^2}{n_{test}} = 120.5942$$

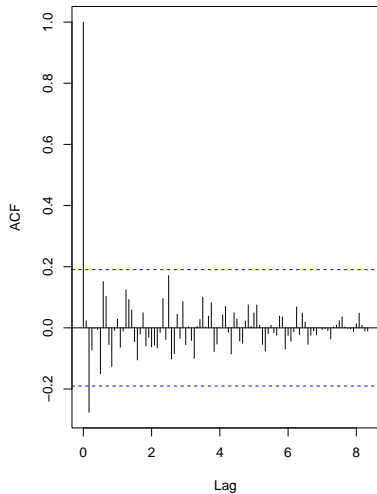
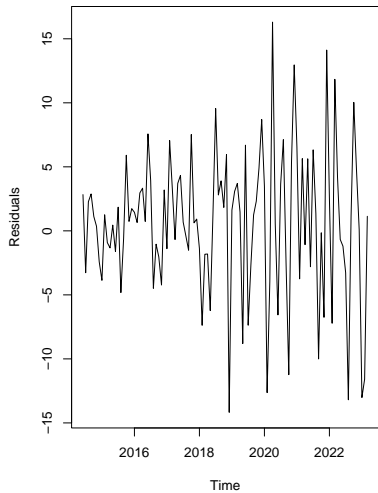
Smoothing Methods

SmoothingModel	APSE
simple exponential	61.92671
double exponential	45.57445
additive HW	62.05079
multiplicative HW	64.51194

```
## Holt-Winters exponential smoothing with trend and without seasonal component
##
## Call:
## HoltWinters(x = JNJ.train, gamma = FALSE)
##
## Smoothing parameters:
##   alpha: 0.8814822
##   beta  : 0.002122442
##   gamma: FALSE
##
## Coefficients:
##           [,1]
## a 150.2403648
## b   0.2402865
```

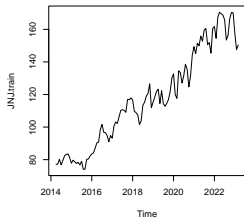
Smoothing Methods

Double exponential model

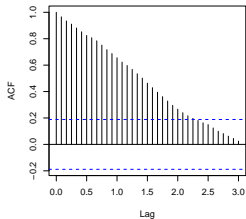


Box-Jenkins Modelling: Model Proposal

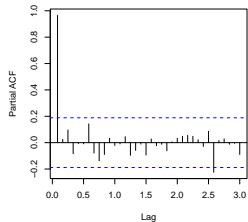
Time Series Plot of JNJ Training Data



ACF Plot of JNJ Training Data

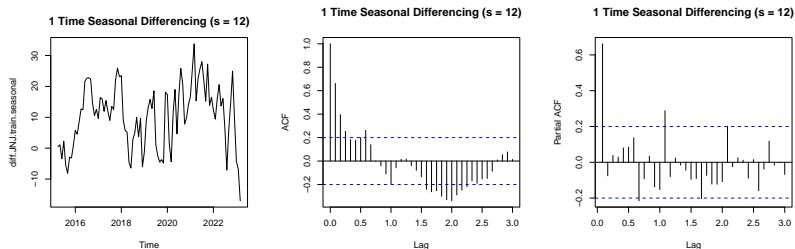


PACF Plot of JNJ Training Data



Box-Jenkins Modelling: Model Proposal

Case 1: start with seasonal differencing $\nabla_{12}X_t = (1 - B^{12})X_t$.



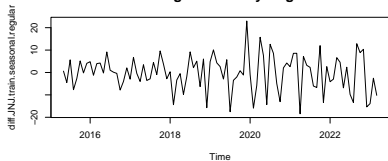
If it already achieves stationarity: $SARIMA(2, 0, 0) \times (0, 1, 0)_{12}$

Box-Jenkins Modelling: Model Proposal

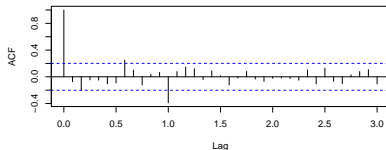
regular differencing following the seasonal differencing

$$\nabla \nabla_{12} X_t = (1 - B)(1 - B^{12})X_t$$

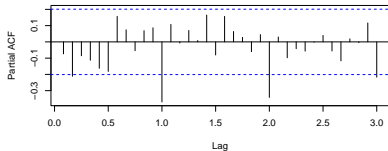
Seasonal Differencing followed by Regular Differencing



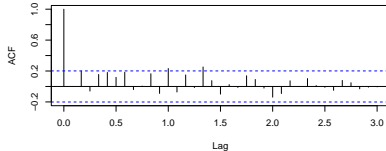
Seasonal Differencing followed by Regular Differencing



Seasonal Differencing followed by Regular Differencing



(Seasonal Differencing followed by Regular Differencing)^:



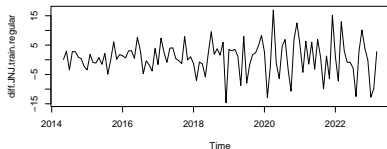
Box-Jenkins Modelling: Model Proposal

$SARIMA(0, 1, 1) \times (0, 1, 0)_{12}$, $SARIMA(1, 1, 1) \times (0, 1, 0)_{12}$, $SARIMA(2, 1, 1) \times (0, 1, 0)_{12}$,
 $SARIMA(0, 1, 1) \times (0, 1, 1)_{12}$, $SARIMA(1, 1, 1) \times (0, 1, 1)_{12}$, $SARIMA(2, 1, 1) \times (0, 1, 1)_{12}$,
 $SARIMA(0, 1, 1) \times (1, 1, 0)_{12}$, $SARIMA(1, 1, 1) \times (1, 1, 0)_{12}$, $SARIMA(2, 1, 1) \times (1, 1, 0)_{12}$,
 $SARIMA(0, 1, 1) \times (1, 1, 1)_{12}$, $SARIMA(1, 1, 1) \times (1, 1, 1)_{12}$, $SARIMA(2, 1, 1) \times (1, 1, 1)_{12}$,
 $SARIMA(0, 1, 2) \times (0, 1, 0)_{12}$, $SARIMA(1, 1, 2) \times (0, 1, 0)_{12}$, $SARIMA(2, 1, 2) \times (0, 1, 0)_{12}$,
 $SARIMA(0, 1, 2) \times (0, 1, 1)_{12}$, $SARIMA(1, 1, 2) \times (0, 1, 1)_{12}$, $SARIMA(2, 1, 2) \times (0, 1, 1)_{12}$,
 $SARIMA(0, 1, 2) \times (1, 1, 0)_{12}$, $SARIMA(1, 1, 2) \times (1, 1, 0)_{12}$, $SARIMA(2, 1, 2) \times (1, 1, 0)_{12}$,
 $SARIMA(0, 1, 2) \times (1, 1, 1)_{12}$, $SARIMA(1, 1, 2) \times (1, 1, 1)_{12}$, $SARIMA(2, 1, 2) \times (1, 1, 1)_{12}$.

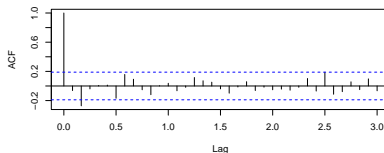
Box-Jenkins Modelling: Model Proposal

Case 2: Let us also try starting with a regular differencing $\nabla X_t = (1 - B)X_t$.

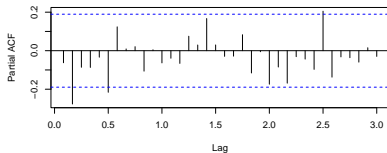
1 Time Regular Differencing



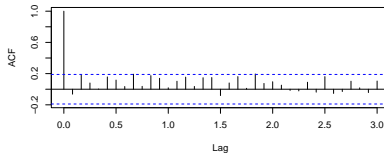
1 Time Regular Differencing



1 Time Regular Differencing



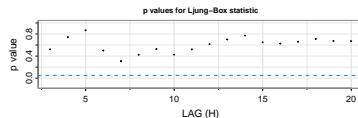
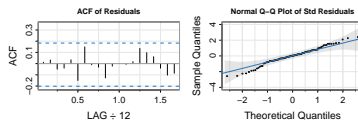
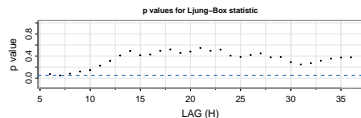
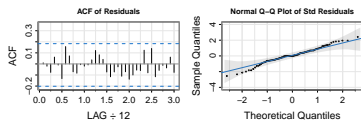
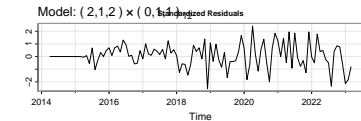
(1 Time Regular Differencing)²



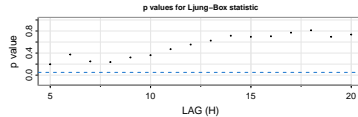
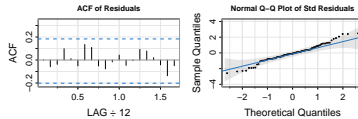
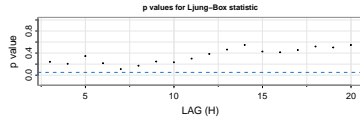
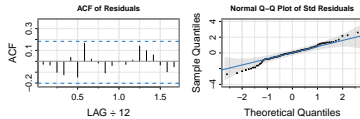
Box-Jenkins Modelling: Model Proposal

ARIMA(0, 1, 0), *ARIMA*(0, 1, 1), *ARIMA*(0, 1, 2),
ARIMA(1, 1, 0), *ARIMA*(1, 1, 1), *ARIMA*(1, 1, 2),
ARIMA(2, 1, 0), *ARIMA*(2, 1, 1), *ARIMA*(2, 1, 2).

Box-Jenkins Modelling: Model Diagnostics



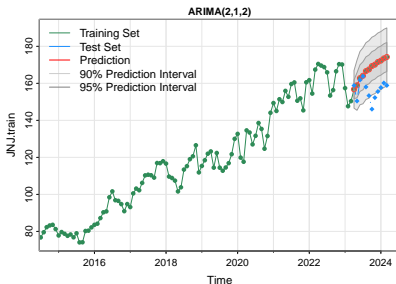
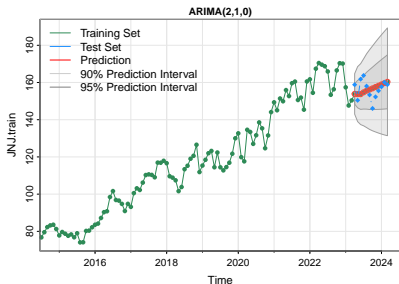
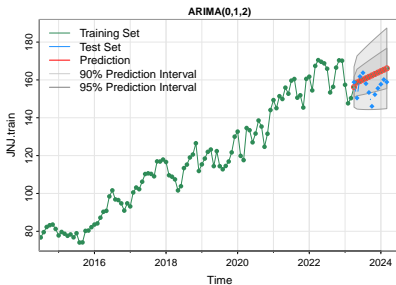
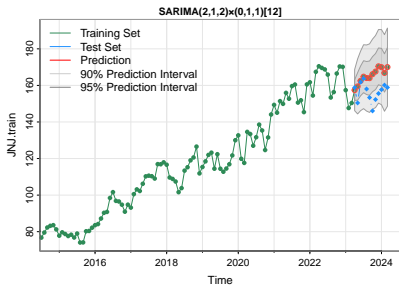
Box-Jenkins Modelling: Model Diagnostics



Box-Jenkins Modelling: Fitness and Prediction

Models	AIC	AICc	BIC	APSE
SARIMA(2,1,2) \times (0,1,1)[12]	6.596083	6.603179	6.757380	117.58989
ARIMA(0,1,2)	6.263767	6.265944	6.363686	62.46785
ARIMA(2,1,0)	6.297085	6.299262	6.397004	29.37942
ARIMA(2,1,2)	6.237146	6.242698	6.387024	174.16904

Box-Jenkins Modelling: Fitness and Prediction



Conclusion

ARIMA(2,1,0) has the smallest APSE among all the models in three methodologies. Prediction in one year: \$159 to \$167

