

Group 8 presentation

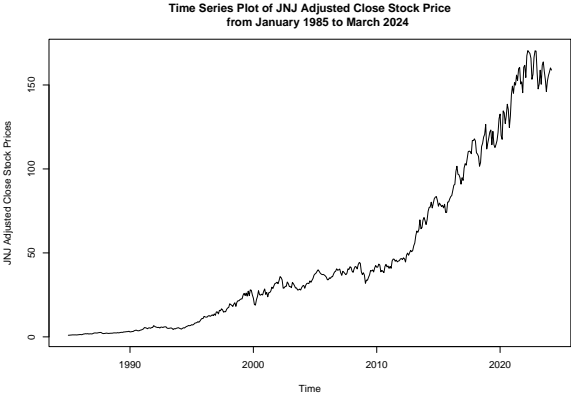
Stat 443 Forecasting
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Xinyi Shen (x77shen)
Dominic Song (z85song)

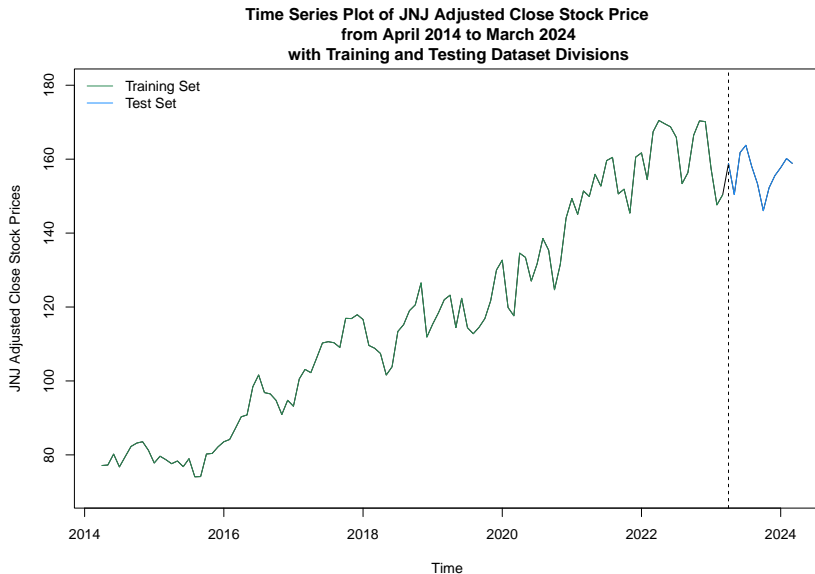
Data Description

Table 1: First Five Rows of JNJ Historical Stock Prices

Date	Open	High	Low	Close	Adj.Close	Volume
1985-01-01	2.242188	2.453125	2.195313	2.437500	0.975024	141102400
1985-02-01	2.390625	2.507813	2.312500	2.460938	0.984401	131019200
1985-03-01	2.437500	2.632813	2.421875	2.625000	1.058037	149992000
1985-04-01	2.609375	2.796875	2.523438	2.742188	1.105271	183592000
1985-05-01	2.726563	2.960938	2.679688	2.937500	1.183994	136675200



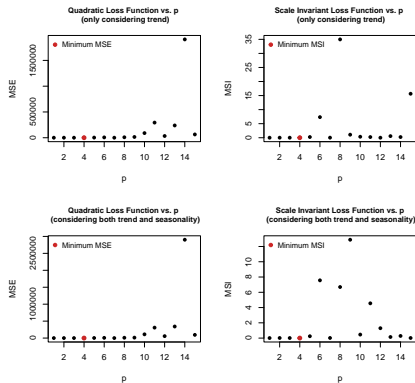
Train and test



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
```

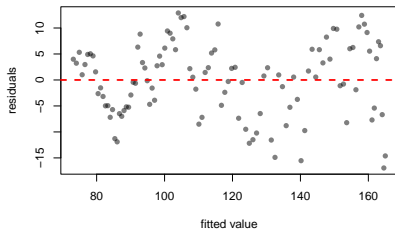
Regression Modelling



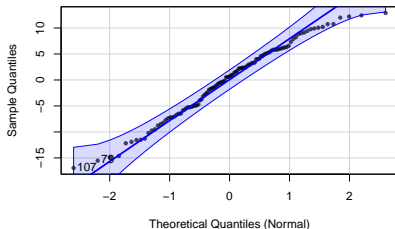
Regression	MSE	MSI
Only consider the trend	120.4273	0.0034556
Consider both the trend and seasonality	140.2979	0.0041335

Regression Modelling

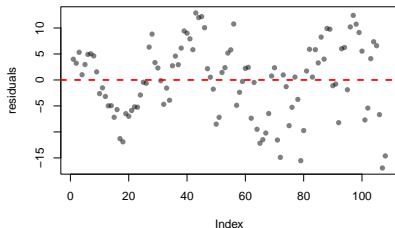
Residuals vs. Fitted Values



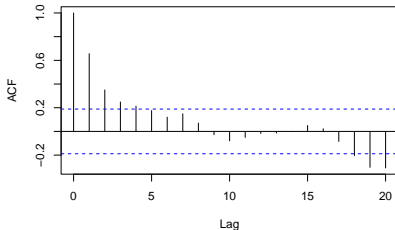
Normal QQ Plot



Residuals vs. Time



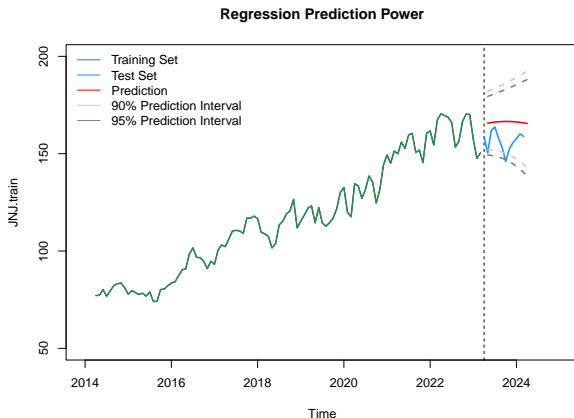
ACF Plot of Residuals



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

```
# simple exponential smoothing
smoother1 = HoltWinters(JNJ.train, gamma = FALSE, beta = FALSE)
# double exponential smoothing
smoother2 = HoltWinters(JNJ.train, gamma = FALSE)
# additive HW
smoother3 = HoltWinters(JNJ.train, seasonal = "additive")
# multiplicative HW
smoother4 = HoltWinters(JNJ.train, seasonal = "multiplicative")
```

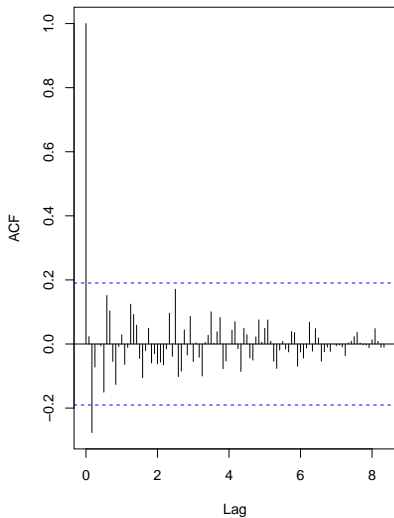
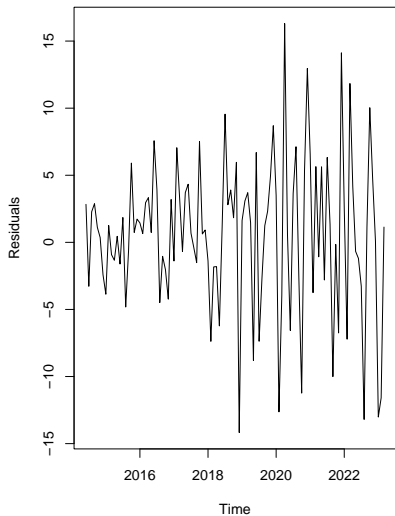
SmoothingModel	APSE
simple exponential	61.92671
double exponential	45.57445
additive HW	62.05079
multiplicative HW	64.51194

Smoothing Methods

```
## 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
```

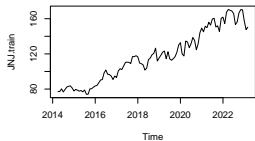
Smoothing Methods

Double exponential model

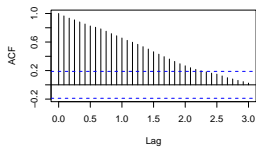


Box-Jenkins Modelling

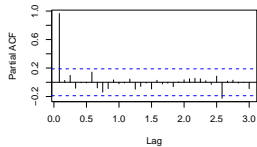
Time Series Plot of JNJ Training Data



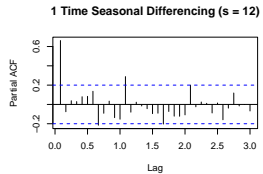
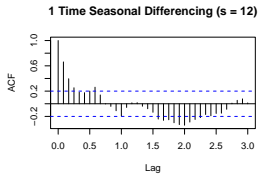
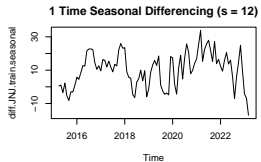
ACF Plot of JNJ Training Data



PACF Plot of JNJ Training Data

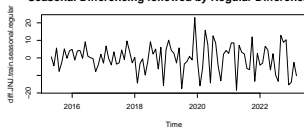


Box-Jenkins Modelling

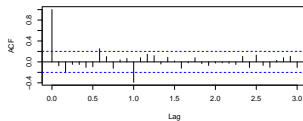


Box-Jenkins Modelling

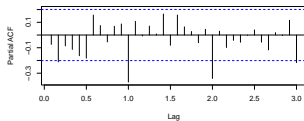
Seasonal Differencing followed by Regular Differencing



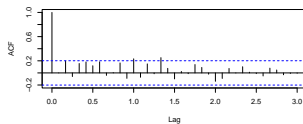
Seasonal Differencing followed by Regular Differencing



Seasonal Differencing followed by Regular Differencing



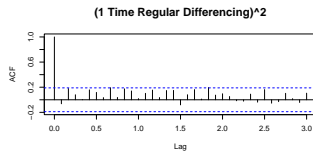
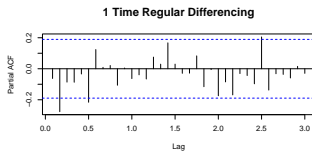
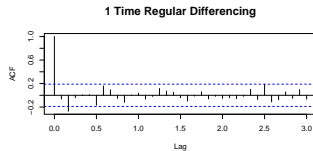
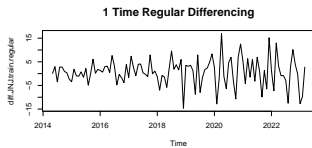
(Seasonal Differencing followed by Regular Differencing)⁴:



Box-Jenkins Modelling

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

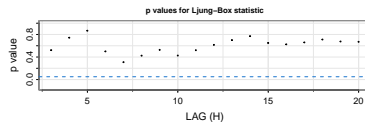
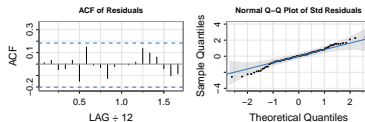
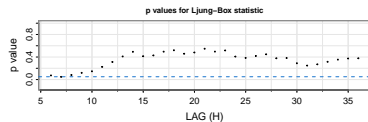
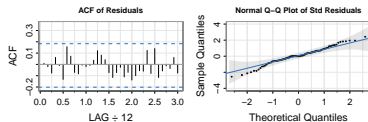
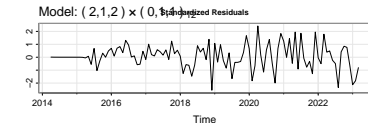
Box-Jenkins Modelling



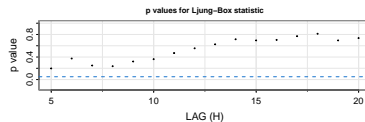
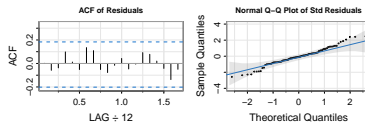
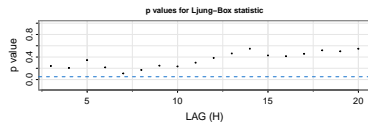
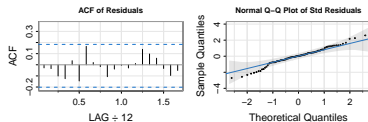
Box-Jenkins Modelling

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



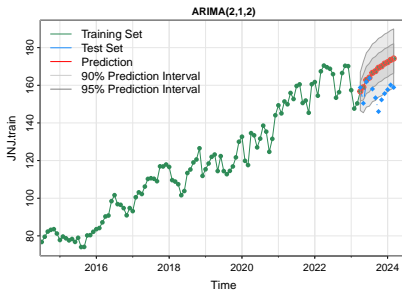
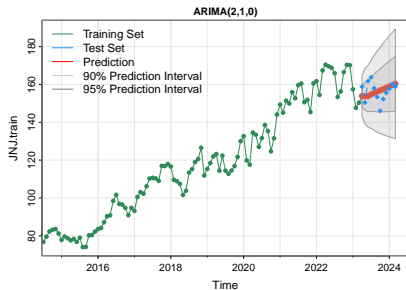
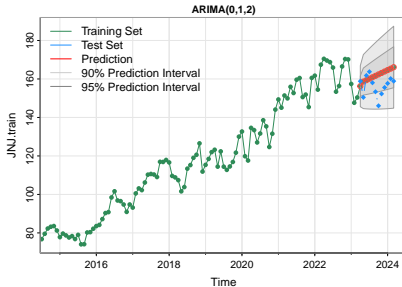
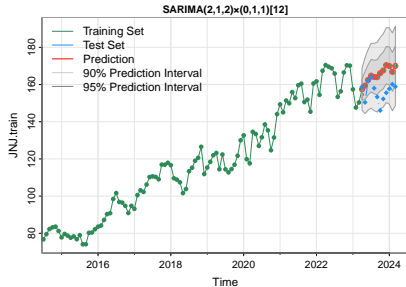
Box-Jenkins Modelling



Box-Jenkins Modelling

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	174.16916

Box-Jenkins Modelling



Conclusion

