Group Assingment

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Contents

Question 1

```
case_data<-read.csv('Case Shipments.csv')
seas_data<-read.csv('Seasonality Index.csv')
seas_data<- rbind(seas_data,seas_data,seas_data,seas_data,seas_data)
```

```
y<-ts(case_data["Case.Shipments"],frequency = 12)
y_tr <- window(y, start=c(2,1),end=c(4,12))
y_te <- window(y, start=c(5,1), end=c(5,12))

y_reg <-case_data[13:60,"Case.Shipments"]

case_data['lag.cp1']<-slide(case_data, Var = "Consumer.Packs", slideBy = -1,NewVar = 'lag.cp1')['lag.cp
case_data['lag.cp2']<-slide(case_data, Var = "Consumer.Packs", slideBy = -2,NewVar = 'lag.cp2')['lag.cp
case_data['lag.da1']<-slide(case_data, Var = "Dealer.Allowance", slideBy = -1,NewVar = 'lag.da1')['lag.
case_data['lag.da2']<-slide(case_data, Var = "Dealer.Allowance", slideBy = -2,NewVar = 'lag.da2')['lag.

X_tr <- as.matrix(case_data[13:48,3:8])
X_te <- as.matrix(case_data[49:60,3:8])
X<- as.matrix(case_data[13:60,3:8])
```

```
mod1_cv<-cv.glmnet(x = X,y = y_reg,nfolds = 10)
best_lam<-mod1_cv$lambda.min
```

```
mod1_cv.coef=predict(mod1_cv,type='coefficients',s=best_lam)
predict(mod1_cv,type='coefficients',s=best_lam)
```

```
## 7 x 1 sparse Matrix of class "dgCMatrix"
##                             1
## (Intercept)       2.990585e+05
## Consumer.Packs    5.779716e-01
## Dealer.Allowance  8.689992e-02
## lag.cp1          -1.904293e-01
## lag.cp2           .
## lag.da1           1.247578e-02
## lag.da2          -1.089666e-02
```

```r
x_red<-X[,c('Consumer.Packs','Dealer.Allowance','lag.cp1','lag.da1','lag.da2')]
mod2_lm<-lm(y_reg~x_red)
summary(mod2_lm)
```

```
##
## Call:
## lm(formula = y_reg ~ x_red)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -148759  -28423     906   31731  185129
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            2.976e+05  1.831e+04  16.256  < 2e-16 ***
## x_redConsumer.Packs    5.926e-01  6.979e-02   8.491 1.17e-10 ***
## x_redDealer.Allowance  8.835e-02  1.029e-02   8.585 8.66e-11 ***
## x_redlag.cp1          -1.966e-01  6.818e-02  -2.884  0.00617 **
## x_redlag.da1           1.387e-02  1.037e-02   1.337  0.18857
## x_redlag.da2          -1.261e-02  1.038e-02  -1.215  0.23126
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 61560 on 42 degrees of freedom
## Multiple R-squared:  0.7693, Adjusted R-squared:  0.7419
## F-statistic: 28.01 on 5 and 42 DF,  p-value: 2.284e-12
```

```r
x_red_tr<-X_tr[,c('Consumer.Packs','Dealer.Allowance','lag.cp1')]
x_red_te<-X_te[,c('Consumer.Packs','Dealer.Allowance','lag.cp1')]
```

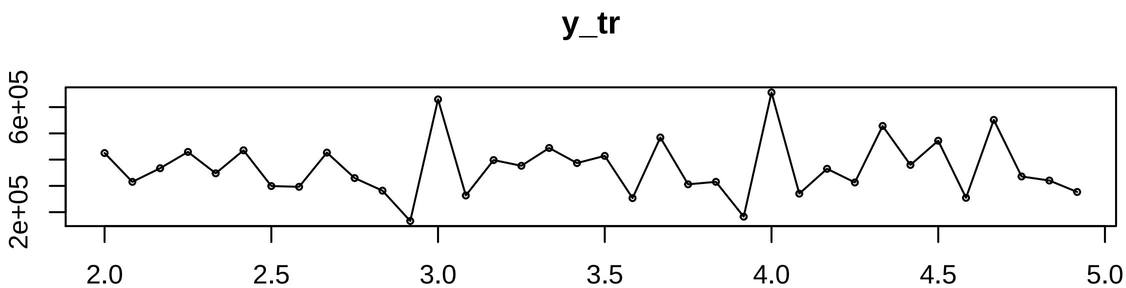
Analysis

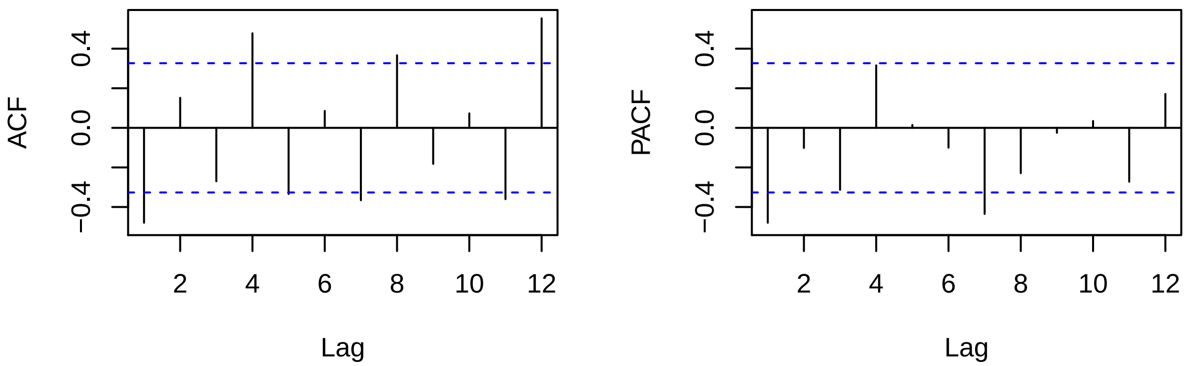
- From the lasso model, only one variable converged to 0. To check statistical significance the non-zero variables were then put into a linear regression. This resulted in only the consumer packs, dealer allowances, and the lagged consumer packs variables being statistically significant.

Question 2

Figure 2.0

```r
tsdisplay(y_tr)
```






```r
mod3<-Arima(y_tr,order = c(1,2,2),seasonal = c(0,0,2),xreg = x_red_tr)
summary(mod3)
```

```
## Series: y_tr
## Regression with ARIMA(1,2,2)(0,0,2)[12] errors
##
## Coefficients:
##           ar1      ma1     ma2    sma1    sma2  Consumer.Packs
##       -0.6054  -1.2112  0.2112  1.5964  0.9998          0.4967
## s.e.   0.2182   0.3439  0.3400  1.4182  1.4501          0.0850
##       Dealer.Allowance  lag.cp1
##                 0.1428  -0.0322
## s.e.            0.0297   0.0599
##
## sigma^2 estimated as 1.249e+09:  log likelihood=-418.39
## AIC=854.78   AICc=862.28   BIC=868.52
##
## Training set error measures:
##                    ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 2070.435 30038.34 21582.25 -0.8361139 6.096753 0.4143205
##                     ACF1
## Training set -0.03810906
```

Figure 2.1

```r
tsdiag(mod3)
```

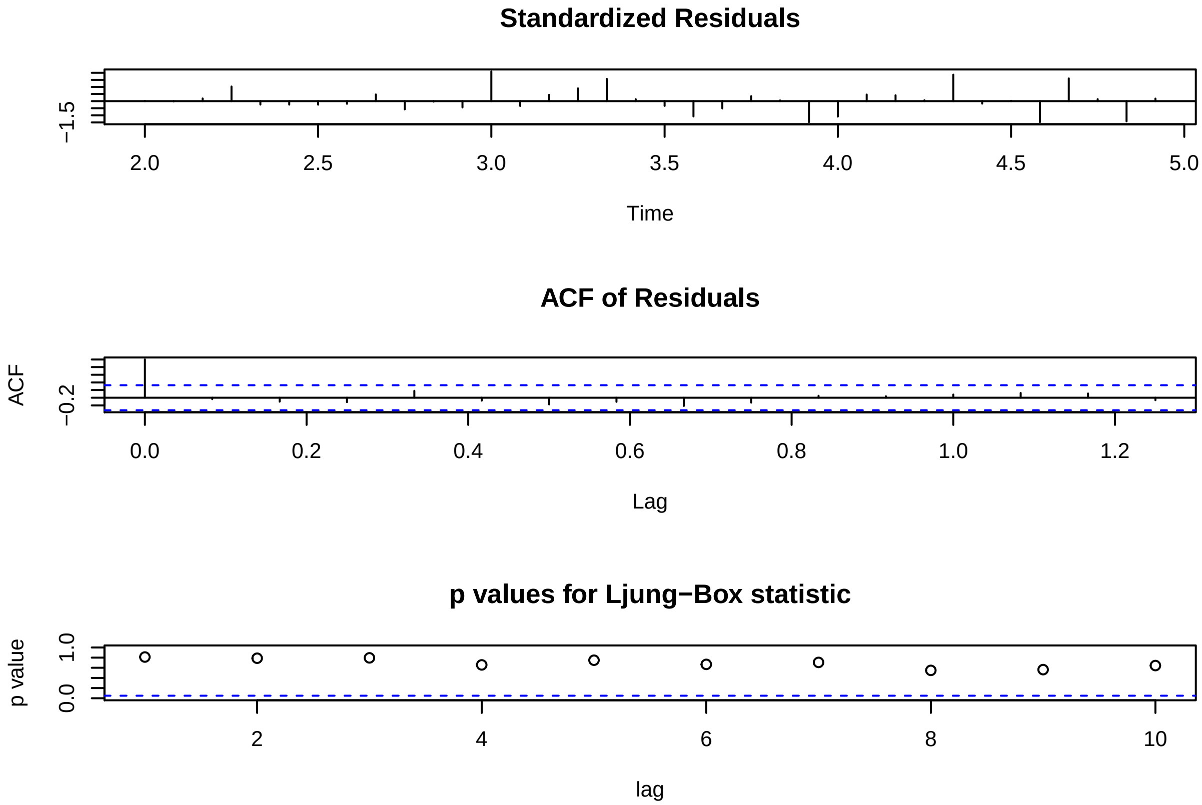


Figure 2.2

```r
tsdisplay(mod3$residuals)
```

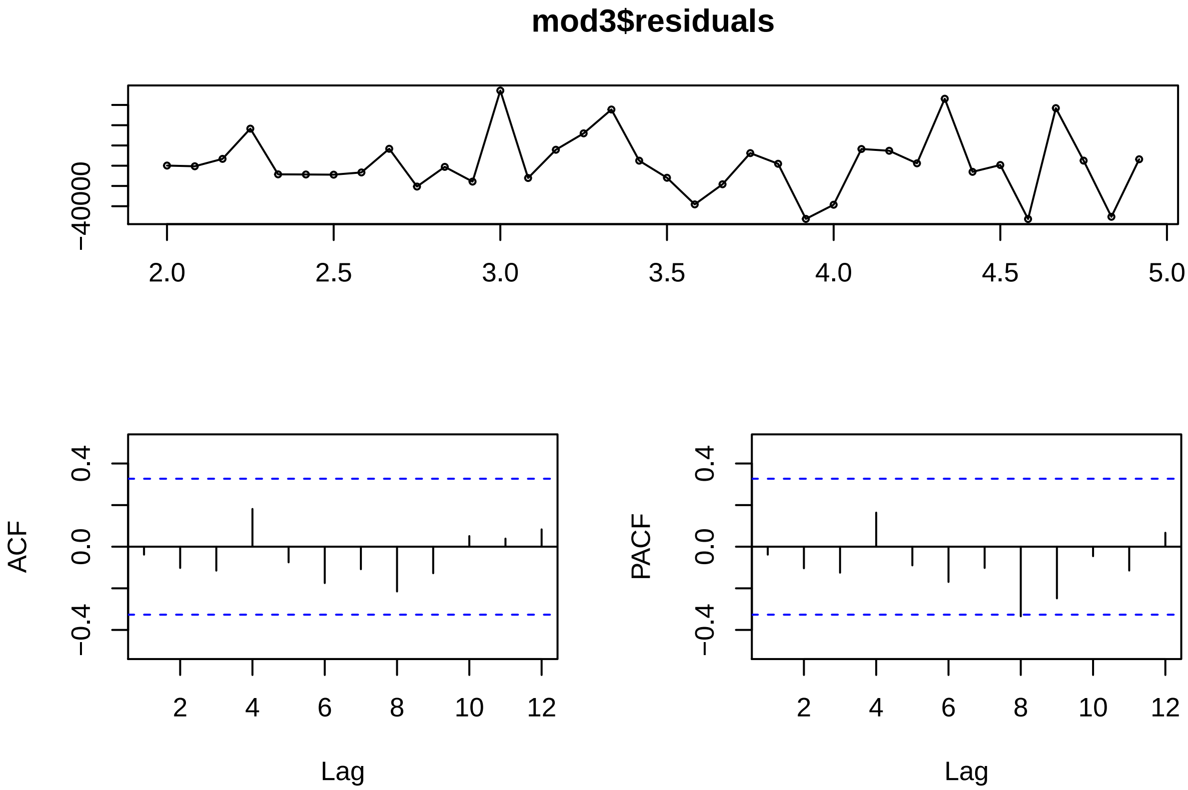
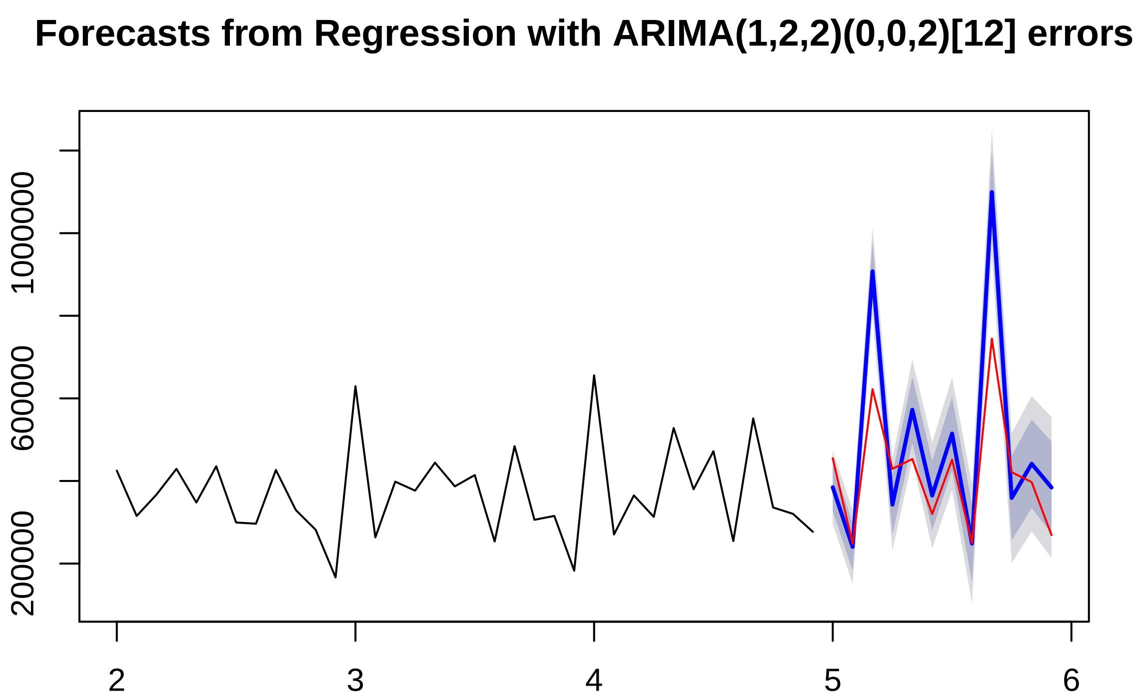


Figure 2.3

```
for_non_seas<-forecast(mod3,xreg =x_red_te,h=12 )
plot(for_non_seas)
lines(y_te,col='red')
```



```
accuracy(for_non_seas,y_te)
```

```
##                       ME      RMSE       MAE         MPE      MAPE
## Training set   2070.435  30038.34  21582.25  -0.8361139  6.096753
## Test set     -66612.054 147006.12 104524.79 -12.3297482 21.285244
##                   MASE        ACF1 Theil's U
## Training set 0.4143205 -0.03810906        NA
## Test set     2.0065919 -0.50167750 0.7030644
```

Analysis

- First an initial guess of an Arima model was made by looking at the acf and pacf of the original data. After the initial guess which can be shown in the Arima output, a diagnostics of the residuals were done to see if the residuals were still auto-correlated. All the p-values in the ljung box test were statistically significant so the residuals are not auto correlated.

Question 3

```
seas_index<-seas_data['Seasonality.Index']/100
y_adj<-ts(case_data['Case.Shipments']/seas_index,frequency = 12)
y_adj1<-case_data['Case.Shipments']/seas_index

y_tr_adj <- window(y_adj, start=c(2,1),end=c(4,12))
y_te_adj <- window(y_adj, start=c(5,1), end=c(5,12))

y_reg_adj <-y_adj1[13:60,"Case.Shipments"]
```

```
mod2_cv<-cv.glmnet(x = X,y = y_reg_adj,nfolds = 10)
best_lam2<-mod2_cv$lambda.min
```

```
mod2_cv.coef=predict(mod2_cv,type='coefficients',s=best_lam2)
predict(mod2_cv,type='coefficients',s=best_lam2)
```

```
## 7 x 1 sparse Matrix of class "dgCMatrix"
##                             1
## (Intercept)       3.152382e+05
## Consumer.Packs    4.146839e-01
## Dealer.Allowance  6.983026e-02
## lag.cp1          -1.575064e-01
## lag.cp2           1.423401e-02
## lag.da1           1.095228e-02
## lag.da2          -1.034004e-02
```

```
x_red<-X[,c('Consumer.Packs','Dealer.Allowance','lag.cp1','lag.cp2','lag.da1','lag.da2')]
mod3_lm<-lm(y_reg_adj~x_red)
summary(mod3_lm)
```

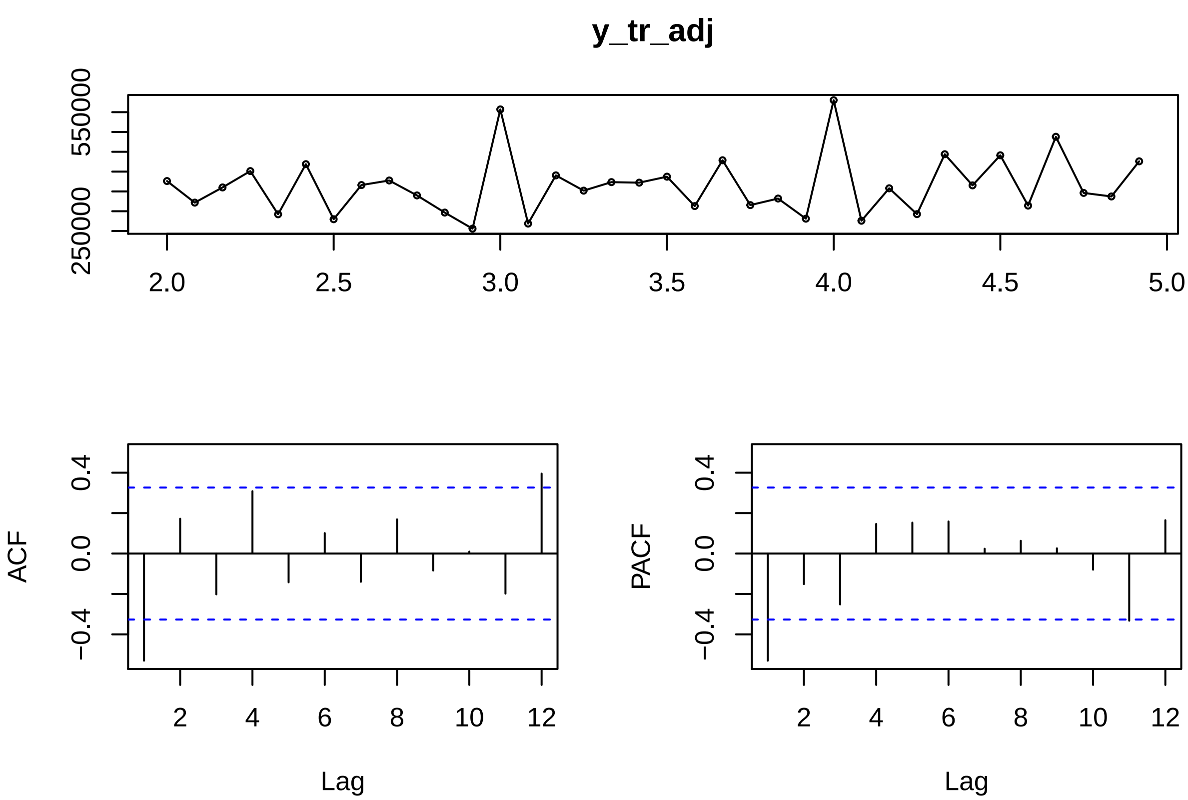
```
##
## Call:
## lm(formula = y_reg_adj ~ x_red)
##
## Residuals:
##    Min     1Q Median     3Q    Max
```

```
## -73660 -23447   -183  20783  94090
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)           3.141e+05  1.200e+04  26.178  < 2e-16 ***
## x_redConsumer.Packs   4.228e-01  4.199e-02  10.068 1.20e-12 ***
## x_redDealer.Allowance 7.044e-02  6.385e-03  11.032 7.61e-14 ***
## x_redlag.cp1         -1.605e-01  4.083e-02  -3.932 0.000317 ***
## x_redlag.cp2          1.799e-02  4.219e-02   0.426 0.671976
## x_redlag.da1          1.177e-02  6.270e-03   1.877 0.067696 .
## x_redlag.da2         -1.114e-02  6.308e-03  -1.766 0.084903 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 36790 on 41 degrees of freedom
## Multiple R-squared:  0.8496, Adjusted R-squared:  0.8276
## F-statistic: 38.61 on 6 and 41 DF,  p-value: 2.401e-15
```

```
x_red_tr<-X_tr[,c('Consumer.Packs','Dealer.Allowance','lag.cp1')]
x_red_te<-X_te[,c('Consumer.Packs','Dealer.Allowance','lag.cp1')]
```

Figure 3.0

```
tsdisplay(y_tr_adj)
```




```
mod3<-Arima(y_tr_adj,order = c(2,2,2),seasonal = c(2,0,1),xreg = x_red_tr)
summary(mod3)
```

```
## Series: y_tr_adj
## Regression with ARIMA(2,2,2)(2,0,1)[12] errors
##
## Coefficients:
##           ar1     ar2      ma1     ma2     sar1     sar2    sma1
##       -0.3108  0.2118  -1.0829  0.0831  -0.4325  -0.9214  0.9552
## s.e.   0.7458  0.4013   0.7304  0.7204   0.1771   0.0620  4.0600
##       Consumer.Packs  Dealer.Allowance  lag.cp1
##               0.4391            0.1008  -0.1561
## s.e.          0.0231            0.0127   0.0200
##
## sigma^2 estimated as 188202179:  log likelihood=-399.44
## AIC=820.87   AICc=832.87   BIC=837.66
##
## Training set error measures:
##                    ME     RMSE      MAE        MPE     MAPE      MASE
## Training set -924.6516 11201.26 8970.035 -0.3582875 2.560787 0.1746097
##                     ACF1
## Training set -0.06095108
```

Figure 3.1

```r
tsdiag(mod3)
```

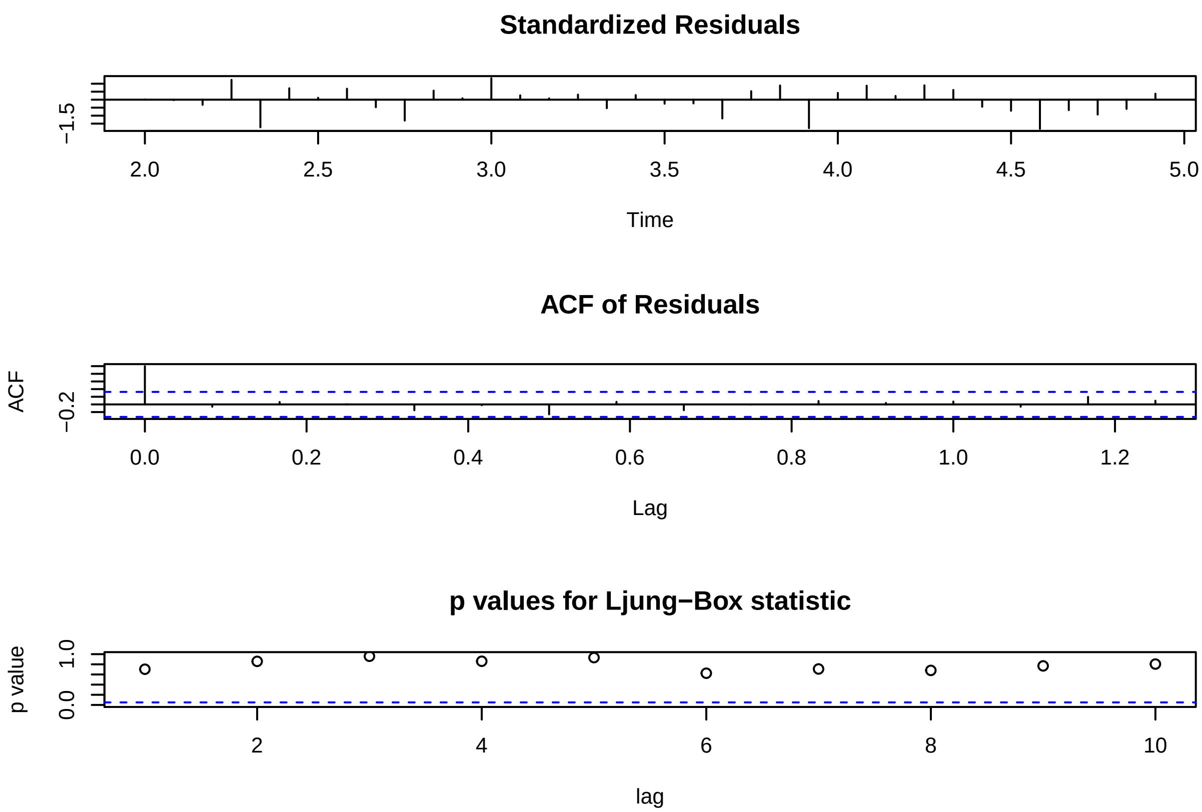
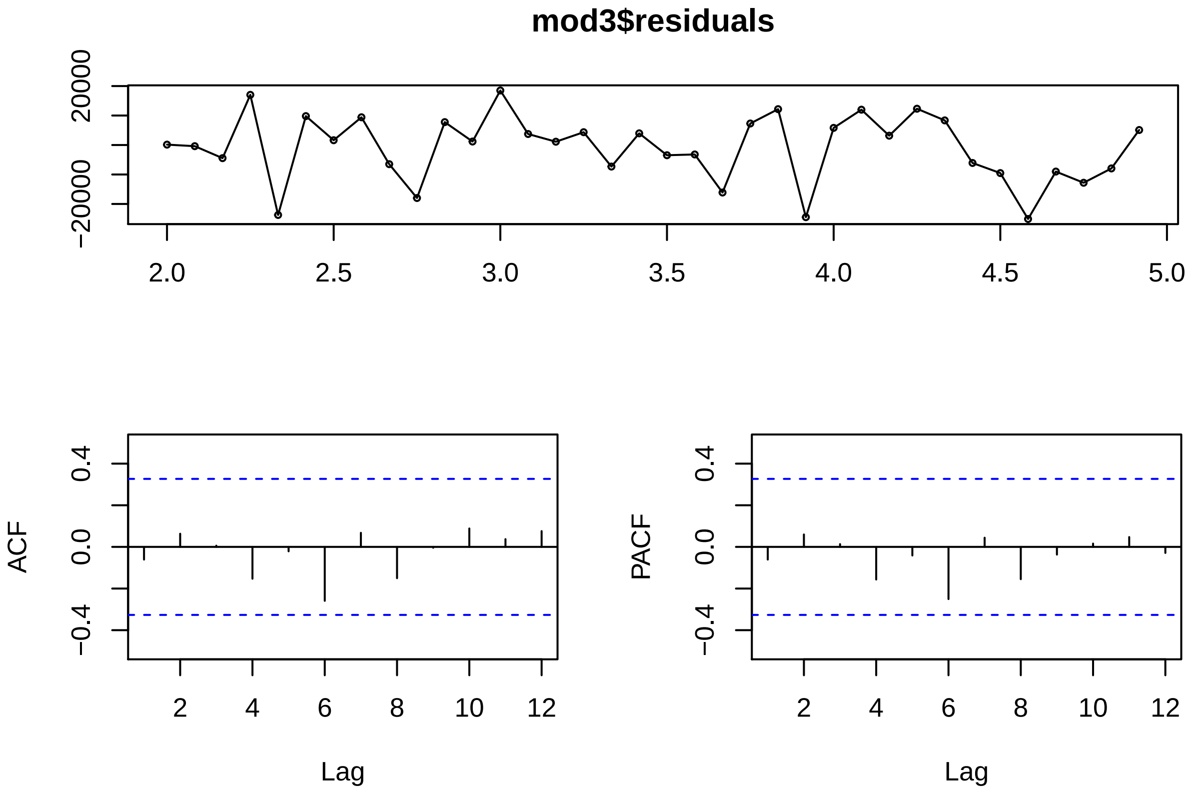


Figure 3.2

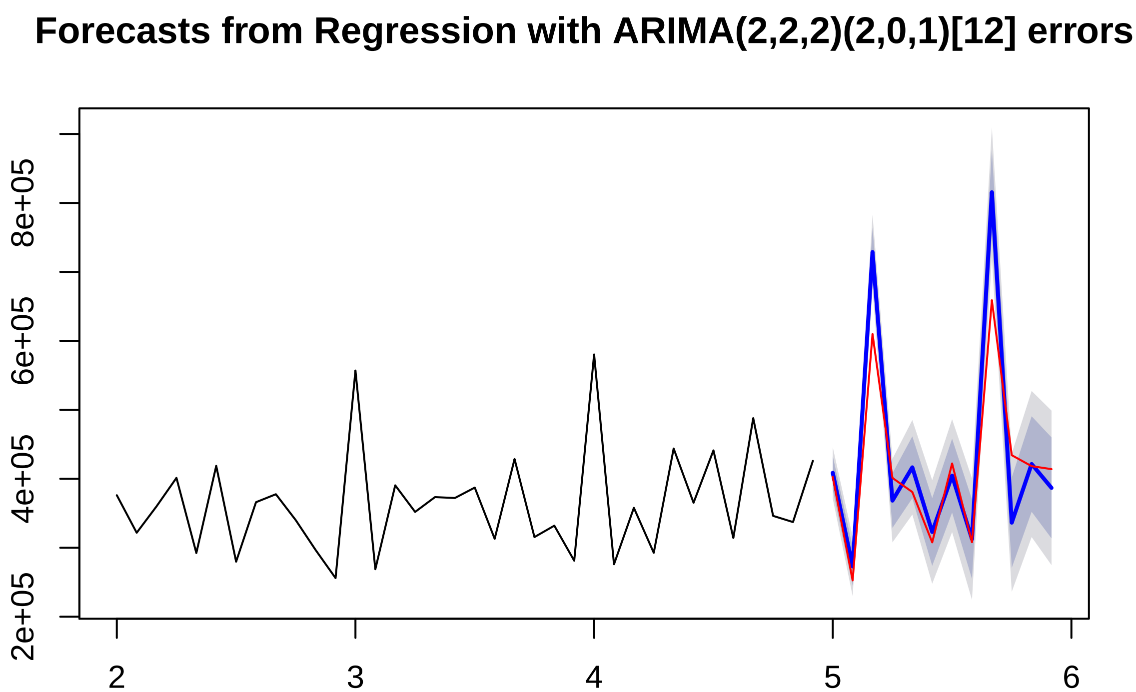
```
tsdisplay(mod3$residuals)
```




```
seas_index_12<-seas_data['Seasonality.Index'][49:60,]
```

Figure 3.2

```
for2<-forecast(mod3,xreg =x_red_te,h=12)
plot(for2)
lines(y_te_adj,col='red')
```




```r
accuracy(for2,y_te_adj)
```

```
##                       ME     RMSE       MAE        MPE     MAPE      MASE
## Training set   -924.6516 11201.26  8970.035 -0.3582875 2.560787 0.1746097
## Test set     -15381.2167 66046.02 44647.420 -2.3142198 9.228300 0.8691019
##                     ACF1 Theil's U
## Training set -0.06095108        NA
## Test set     -0.41983041 0.3656215
```

Analysis

- A similar analysis was conducted on the now adjusted sales data, first a lasso regression was ran to reduce the demonstrability of the data then a linear regression to see statistical significance.
- The third question model has slightly better p values for the Ljung-Box statistic than the second question model, implying that the third model has a bit more statistical validity. We see that the bias for the third model is more than half that of the second model in terms of MPE, and the MASE was .17 to the .41 MASE of the second model. Just looking at the RMSE difference where the third model has an RMSE about one third of the RMSE of the second model should indicate the third model is doing much better. All of the Information Criterion are also lower on the third model than the second model. The second model appears worse in every way.

Question 4

Analysis

- We can see from the result of the dynamic regression in question 3 that the coefficient for consumer packs is 0.4391 which means a unit of consumer packs in time t will result in about 0.44 unit of increase of case shipment increase during time t the same period. However, the effect of lag1 consumer packs of -0.1561 means that this will also result a decrease of about 0.16 unit of case shipment next period t+1. This is the forward buying effect that we got from the regression above.

Question 5

Analysis

- Starting with a lasso regression, none of the variables coefficients converged to zero. So to address their statistical significance they were then put into a linear regression. This showed that only the consumer packs, dealer allowances, and lagged consumer packs were statistically significant. These variables were then put into an arima model which tried to account for its auto correlated errors. The model produced very good forecasts compared to the previous model which wasnt scaled by the seasonal index. The coefficients on consumer packs was .439 and the lagged consumer packs was -.156, indicating a stock up in the subsequent month. The dealer allowance had a smaller yet positive coef. .1008, which didnt have a lagged effect.
- While consumer packs have a larger effect than dealer allowances, consumer packs also have significant stock ups. Given this information, dealer allowances would allow Harmon foods to more stably increase sales, without the harm of stock ups. If Harmon foods wanted to use consumer packs as an advertising strategy they would need to be conscious of the stock ups and prepare their supply chain for lower demand in the subsequent month. I would recommend Dealer Allowances as a main strategy for Harmon Foods because of its predictable sales increase without the stock up risk.