# Eighth meeting notes

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## To prepare for this analysis:

- Step 1: Order of differencing
  - TS plot of residuals from ARIMA(0,0,0) w/ constant in not exactly stationary -> d = 1
- Step 2: AR() or MA()

1. Obtain residual from current model: ARIMA(0,1,0) w/ constant
2. Plot PACF of the residual

- Step 3: Seasonality()

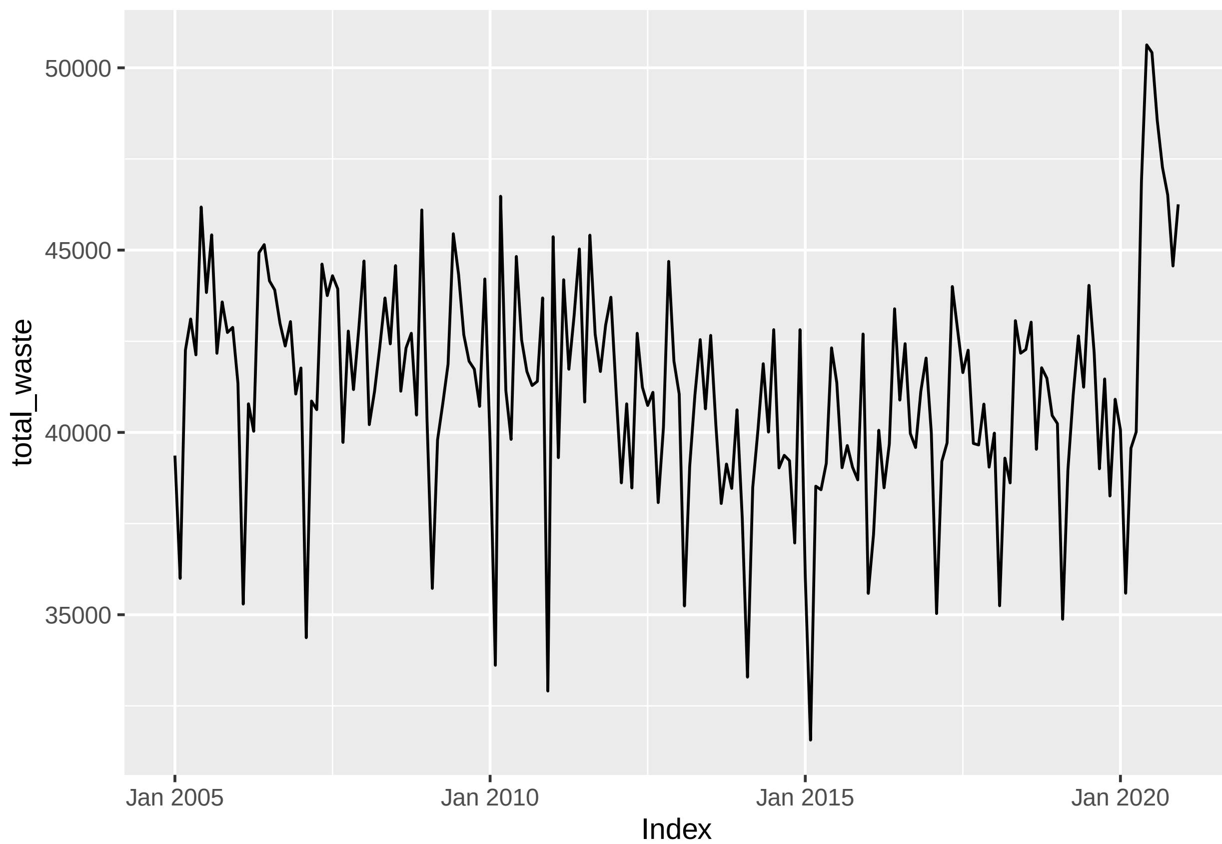
1. Look at the PACF to determine AR() or MA() terms

- To return the RMSE, I had to use the accuracy function from the fabletools package. Which meant that I had to reuse or create the ARIMA models in the same manner shown in the fpp3 book.

## Creating models with zoo() and the arima package from stats()

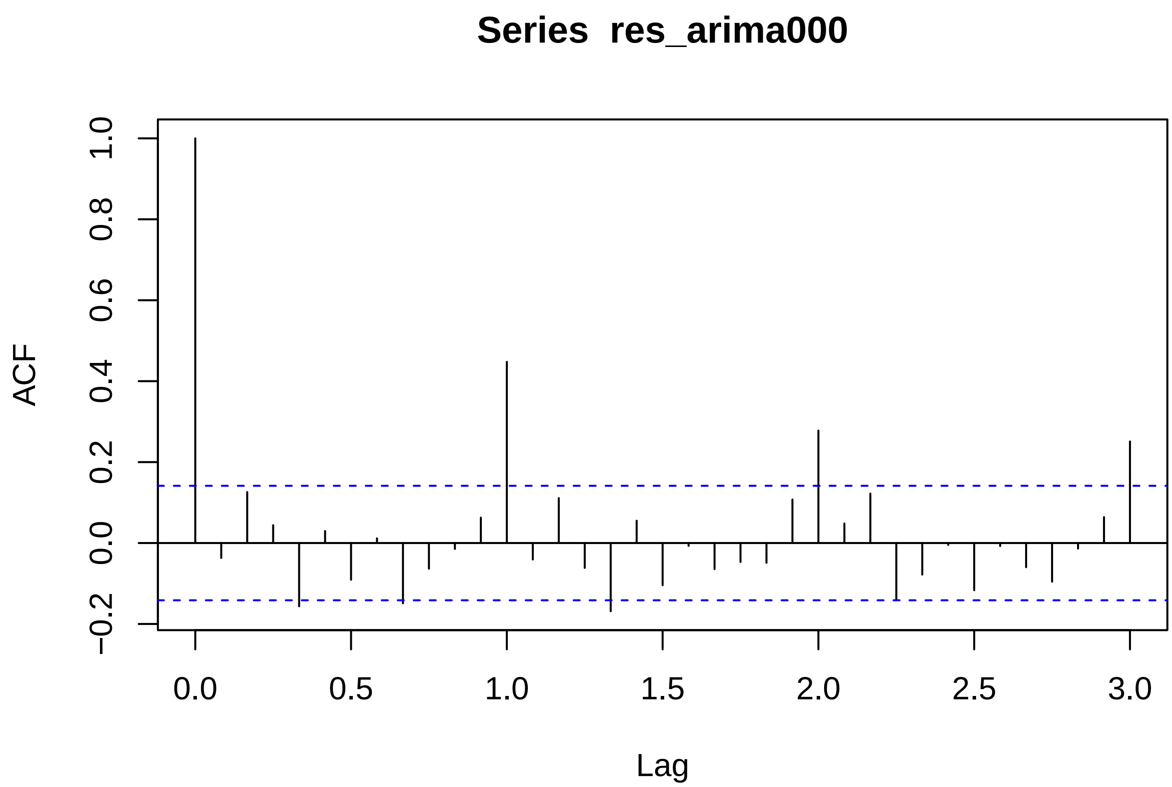
Here we create the ts and create the autoplot of the ts using the zoo package

```
DSNY_BX_zoo_ts <- ts(DSNY_third_bronx[,-1],
                     start = as.yearmon(DSNY_third_bronx$month)[1],
                     frequency = 12)

autoplot(as.zoo(DSNY_BX_zoo_ts))
```

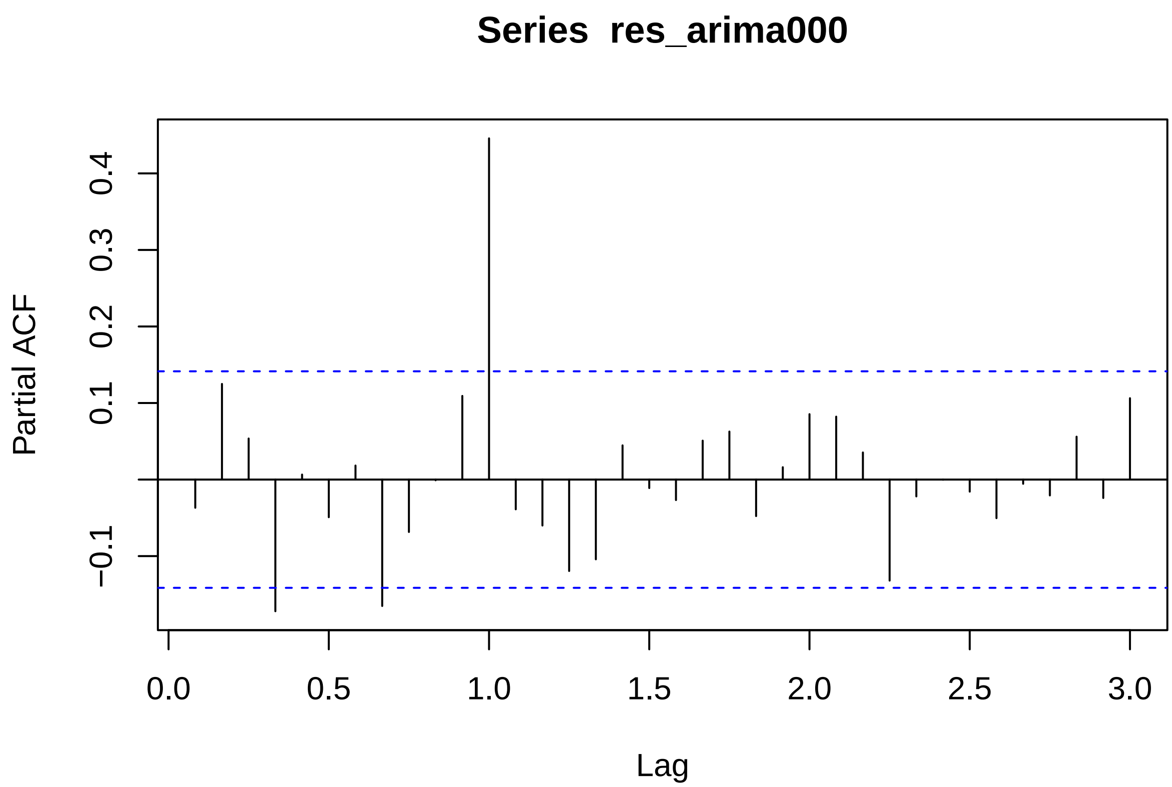



**ARIMA(0,0,0) with constant**

```
zoo_arima000_fit <- arima(DSNY_BX_zoo_ts, order = 1 + c(0,0,0))
#names(zoo_arima000_fit)
res_arima000 <- zoo_arima000_fit$residuals
acf(res_arima000, lag.max = 36)
```




```
pacf(res_arima000, lag.max = 36)
```




```
accuracy(bx_arima000_fit)[4]
```

```
## # A tibble: 1 x 1
##     RMSE
##    <dbl>
## 1 2998.
```

The lags are in decimal format. With the frequency defined as 12, I believe Lag 1.0 = 12, Lag 2.0 = 24, Lag 3.0 = 36.

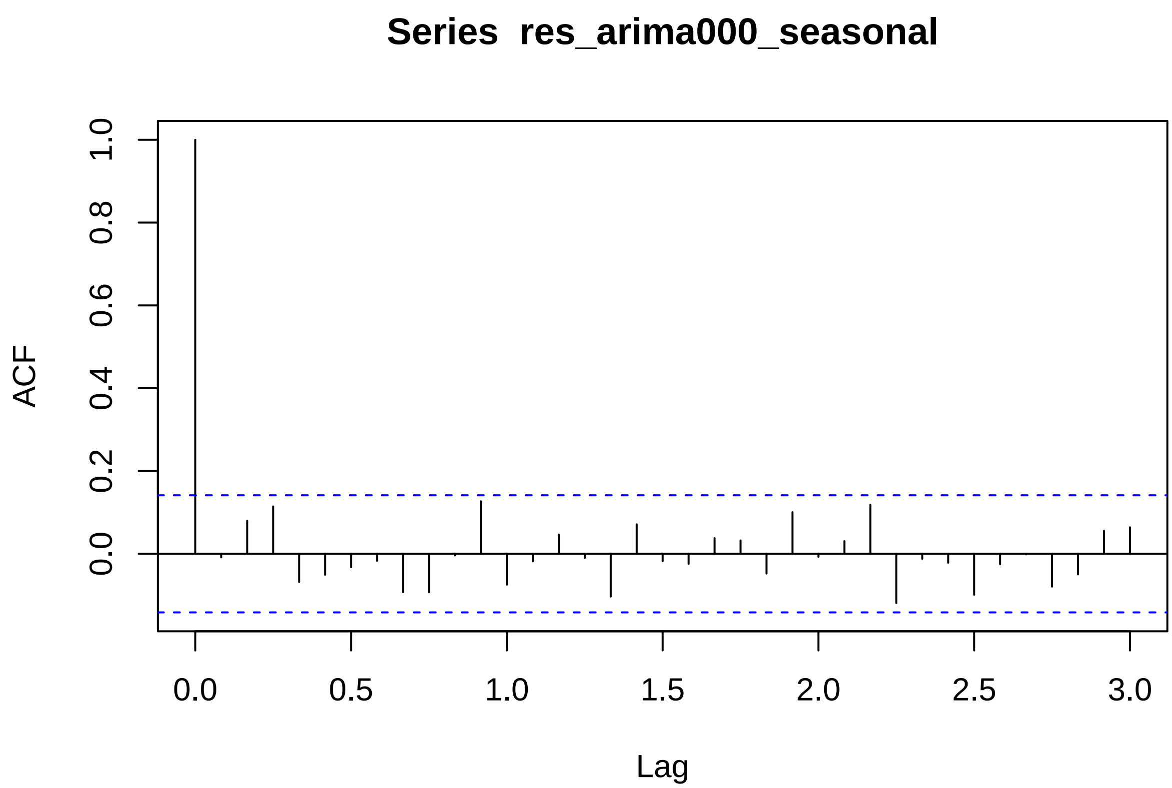
For ARIMA models with differencing, the differenced series follows a zero-mean ARMA model. Documentation by DataCamp.

#### ARIMA(0,0,0) with constant and seasonal

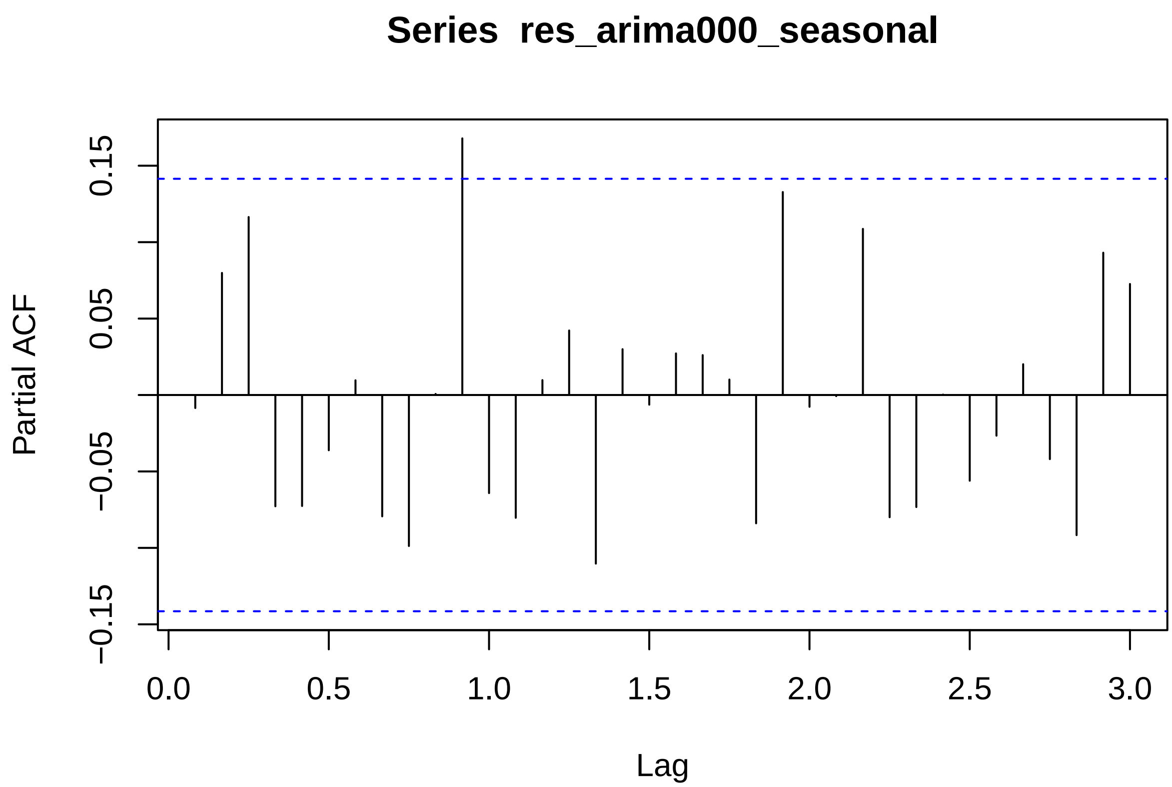
ARIMA(0,0,0)(1,0,0)$_{12}$

```
bx_arima000_fit_cons_seasonal <- bx_ts %>%
  model(arima000_constant_seasonal = ARIMA(total_waste ~ 1 +
                                   pdq(0,0,0) +
                                   PDQ(1,0,0, period = 12)))

zoo_arima000_seasonal_fit <- arima(DSNY_BX_zoo_ts,
                          order = 1 + c(0,0,0),
                          seasonal = list(order = c(1,0L,0L), period = 12))
```

```r
#names(zoo_arima000_fit)
res_arima000_seasonal <- zoo_arima000_seasonal_fit$residuals
acf(res_arima000_seasonal, lag.max = 36)
```




```r
pacf(res_arima000_seasonal, lag.max = 36)
```

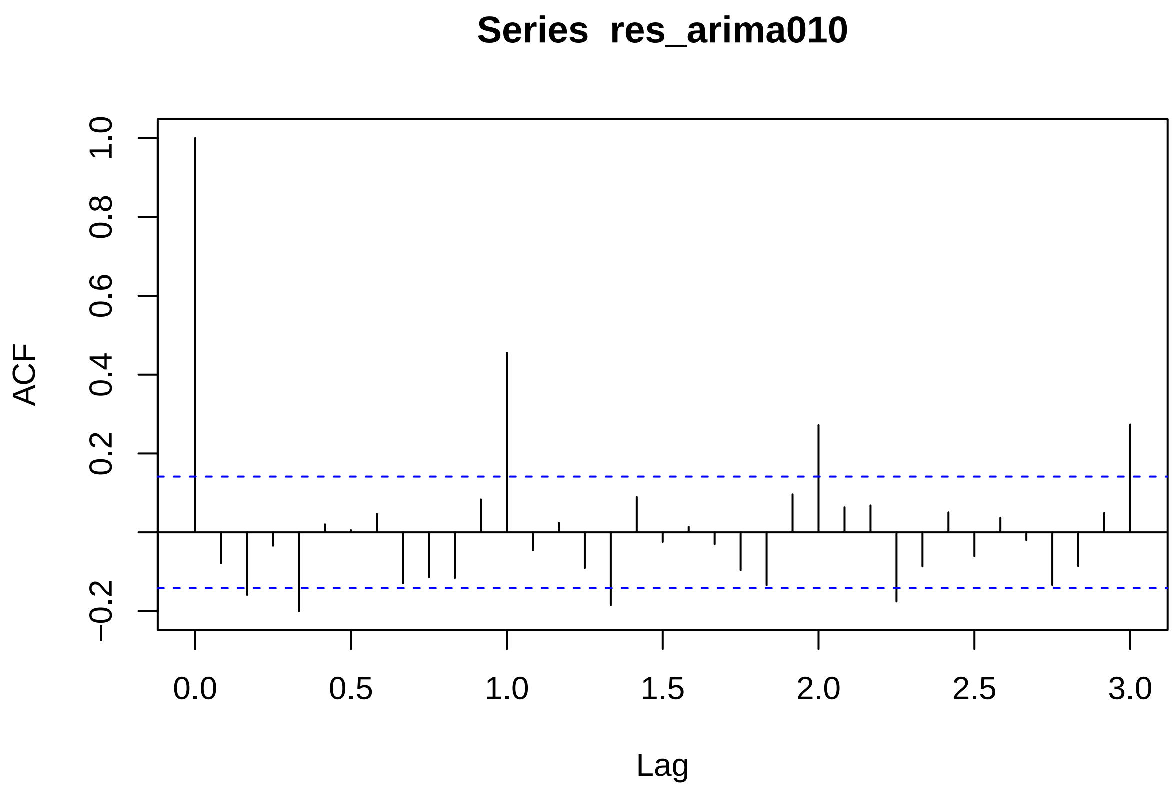



```
accuracy(bx_arima000_fit_cons_seasonal)
```

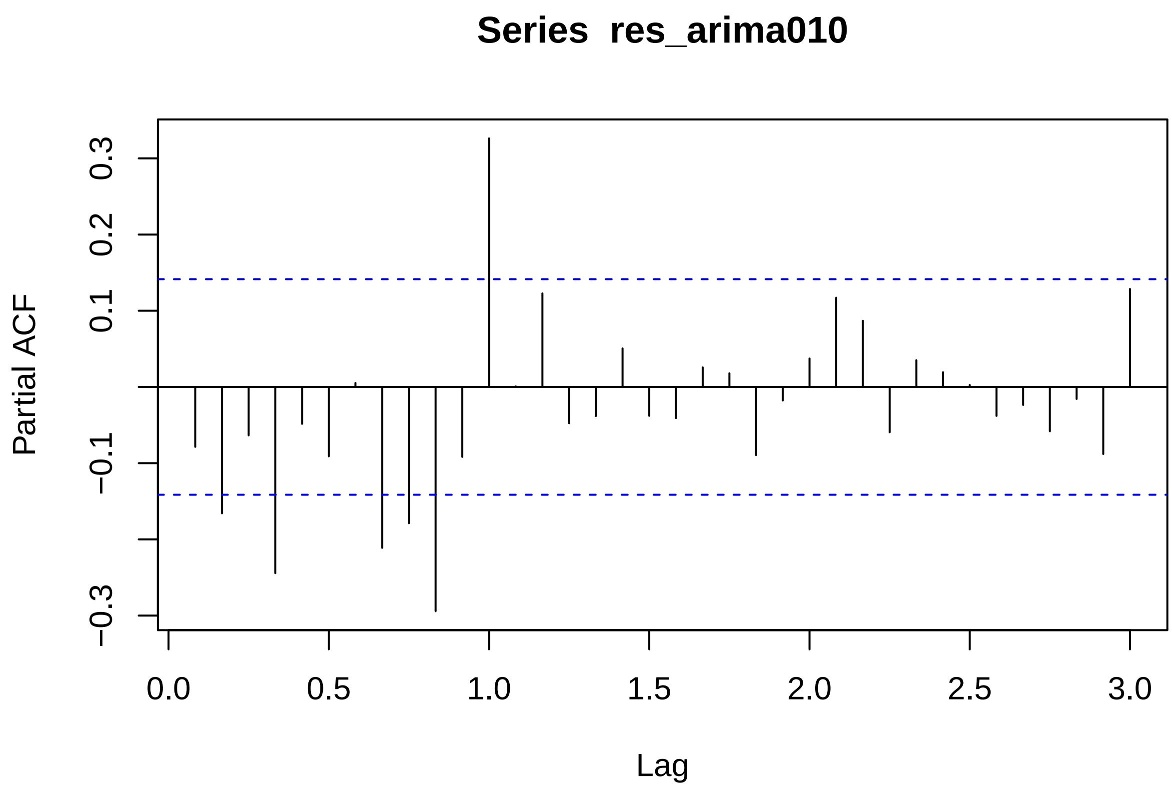
```
## # A tibble: 1 x 10
##   .model                   .type    ME  RMSE   MAE    MPE  MAPE  MASE RMSSE  ACF1
##   <chr>                    <chr> <dbl> <dbl> <dbl>  <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 arima000_constant_seas~ Trai~ -45.0 2482. 1755. -0.486  4.31 0.692 0.746 0.268
```

**ARIMA(0,1,0) with constant/mean**

```
zoo_arima010_fit <- arima(DSNY_BX_zoo_ts,
                          order = 1 + c(0,1,0)) #the PACF plot return the same values
                          #with or without the include.mean = parameter
res_arima010 <- zoo_arima010_fit$residuals
acf(res_arima010, lag.max = 36)
```



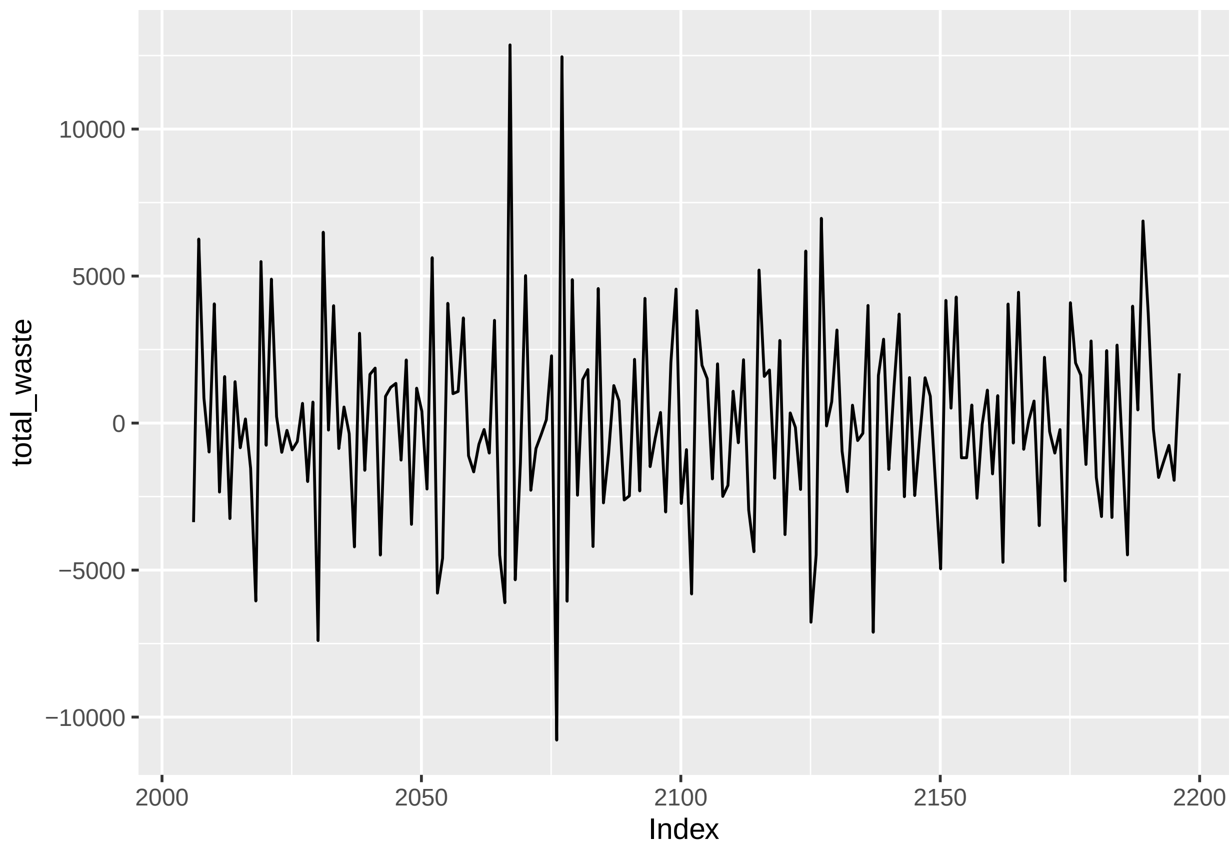

```
pacf(res_arima010, lag.max = 36)
```




```
accuracy(bx_arima010_fit)[4]
```

```
## # A tibble: 1 x 1
##    RMSE
##   <dbl>
## 1 3317.
```

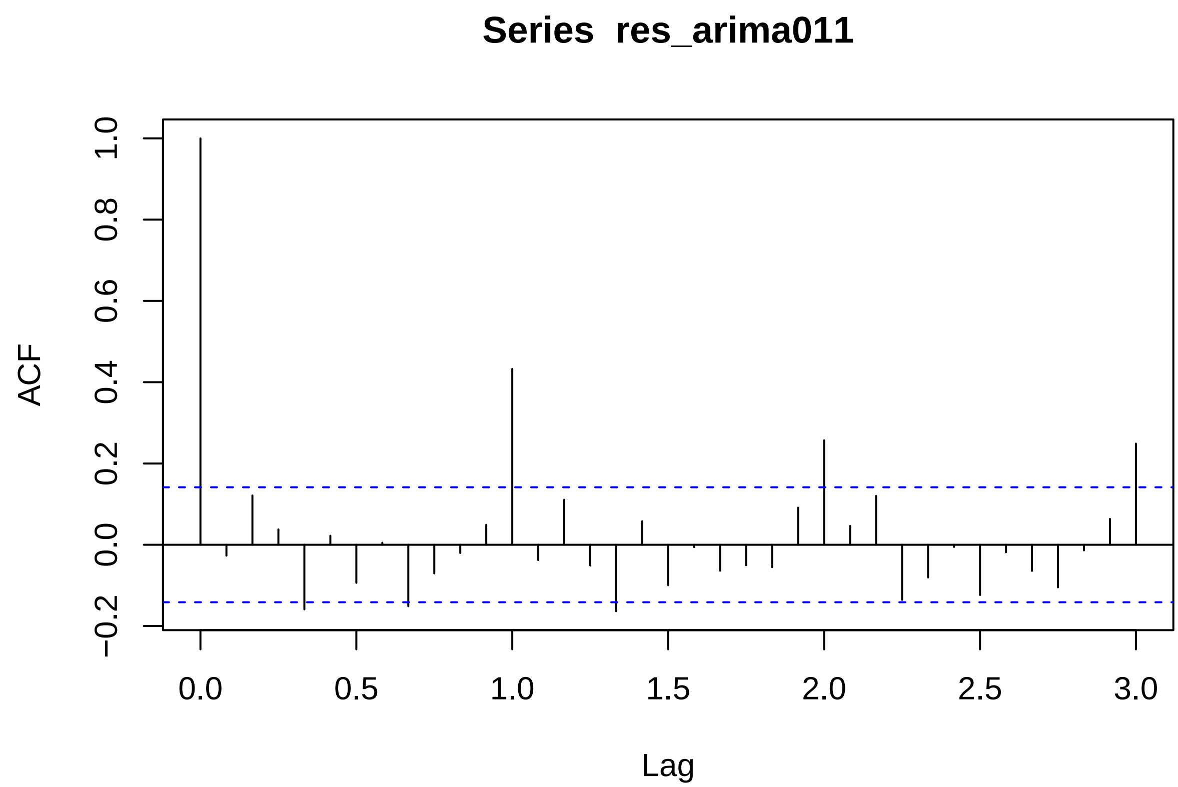
```
autoplot(as.zoo(difference(DSNY_BX_zoo_ts),1))
```



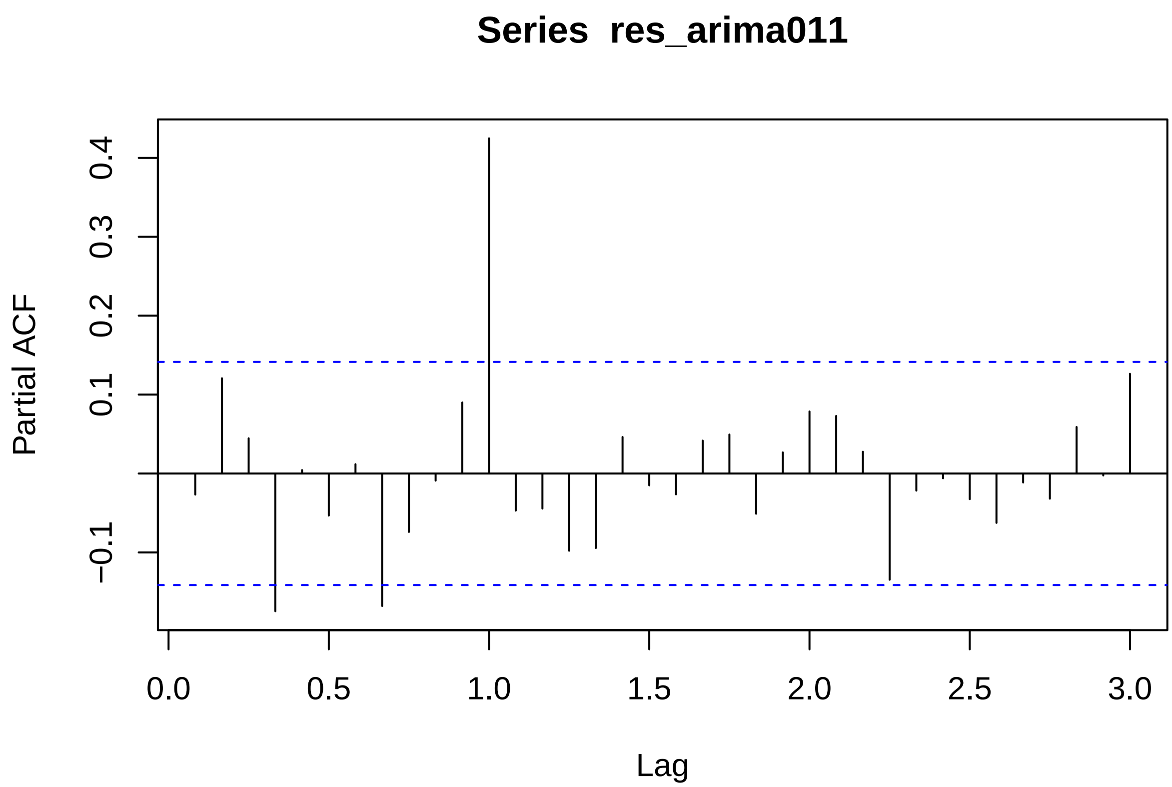

A constant term has been added with '1 + c(0,1,0)'. As discussed before, a negative ACF value is indicative of the need to add an MA() parameter. Here we see that lag 3 is no longer significant, perhaps we try to add MA(1) and MA(2) arguments to our **differenced** time series.

#### ARIMA(0,1,1) with a constant

```
bx_arima011_fit_cons <- bx_ts %>%
  model(arima011_constant = ARIMA(total_waste ~ 1 + pdq(0,1,1)))
zoo_arima011_fit <- arima(DSNY_BX_zoo_ts,
                          order = 1 + c(0,1,1))
res_arima011 <- zoo_arima011_fit$residuals
acf(res_arima011, lag.max = 36)
```




```
pacf(res_arima011, lag.max = 36)
```



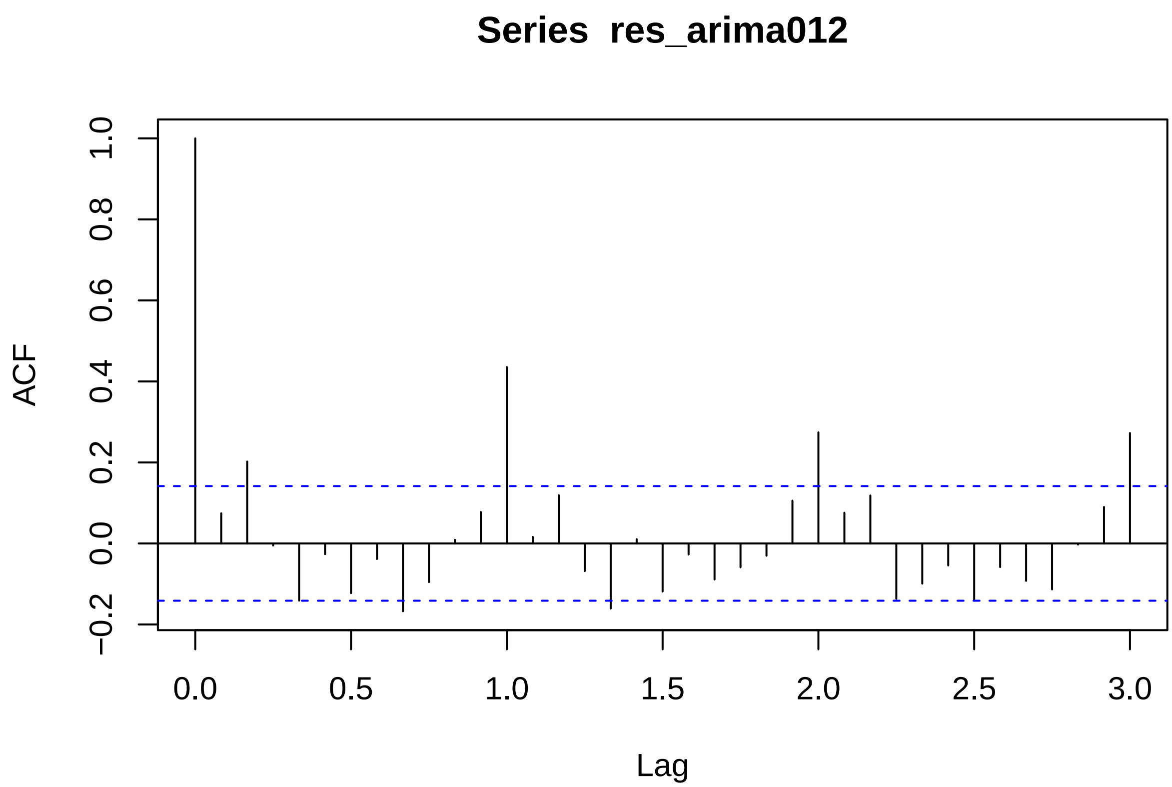

```
accuracy(bx_arima011_fit_cons)[4]
```

```
## # A tibble: 1 x 1
##    RMSE
##   <dbl>
## 1 2818.
```

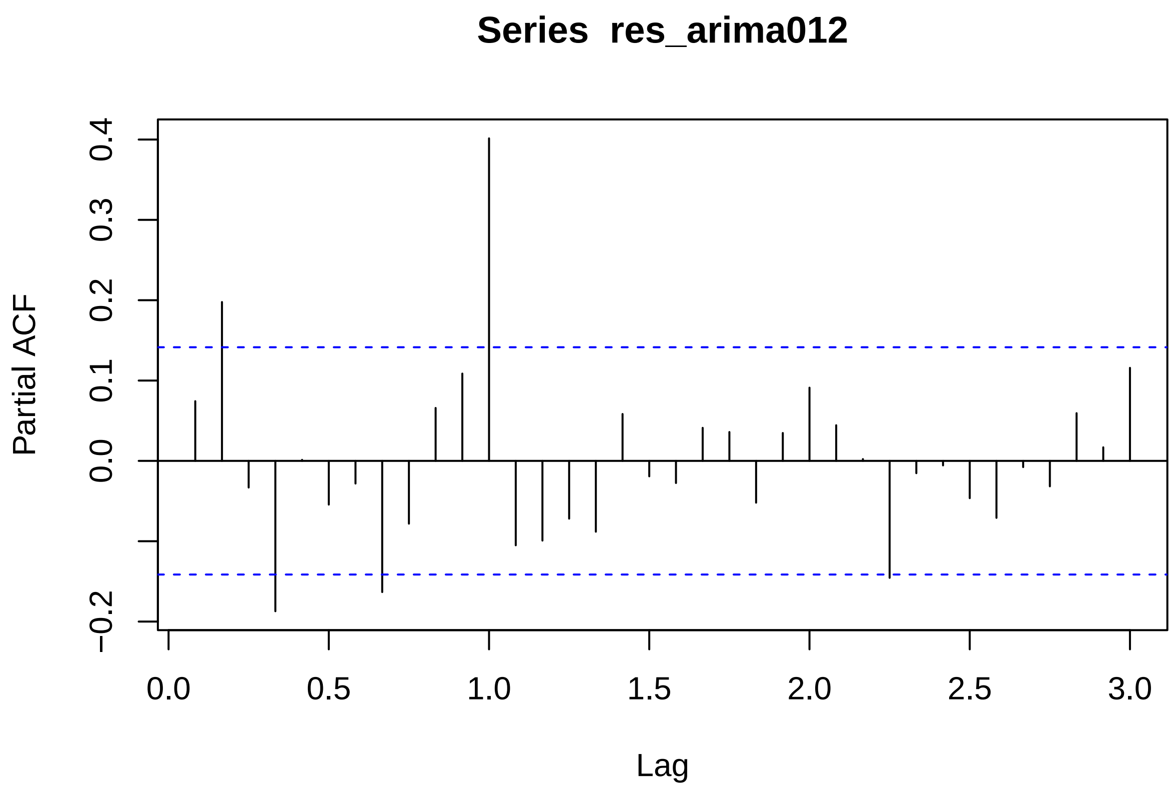
We can see that the RMSE of this model decreased, when compared to the ARIMA model with d = 1, and no other argument. There definitely should be a seasonal argument, as we see a seasonal pattern of significant lags at each integer lag.

#### ARIMA(0,1,2) with a constant

```
bx_arima012_cons_fit <- bx_ts %>%
  model(arima012_cons = ARIMA(total_waste ~ 1 + pdq(0,1,2)))

zoo_arima012_fit <- arima(DSNY_BX_zoo_ts,
                          order = 1+ c(0,1,2))

res_arima012 <- zoo_arima012_fit$residuals
acf(res_arima012, lag.max = 36)
```




```
pacf(res_arima012, lag.max = 36)
```




```r
accuracy(bx_arima012_cons_fit)[4]
```

```
## # A tibble: 1 x 1
##    RMSE
##   <dbl>
## 1 2765.
```

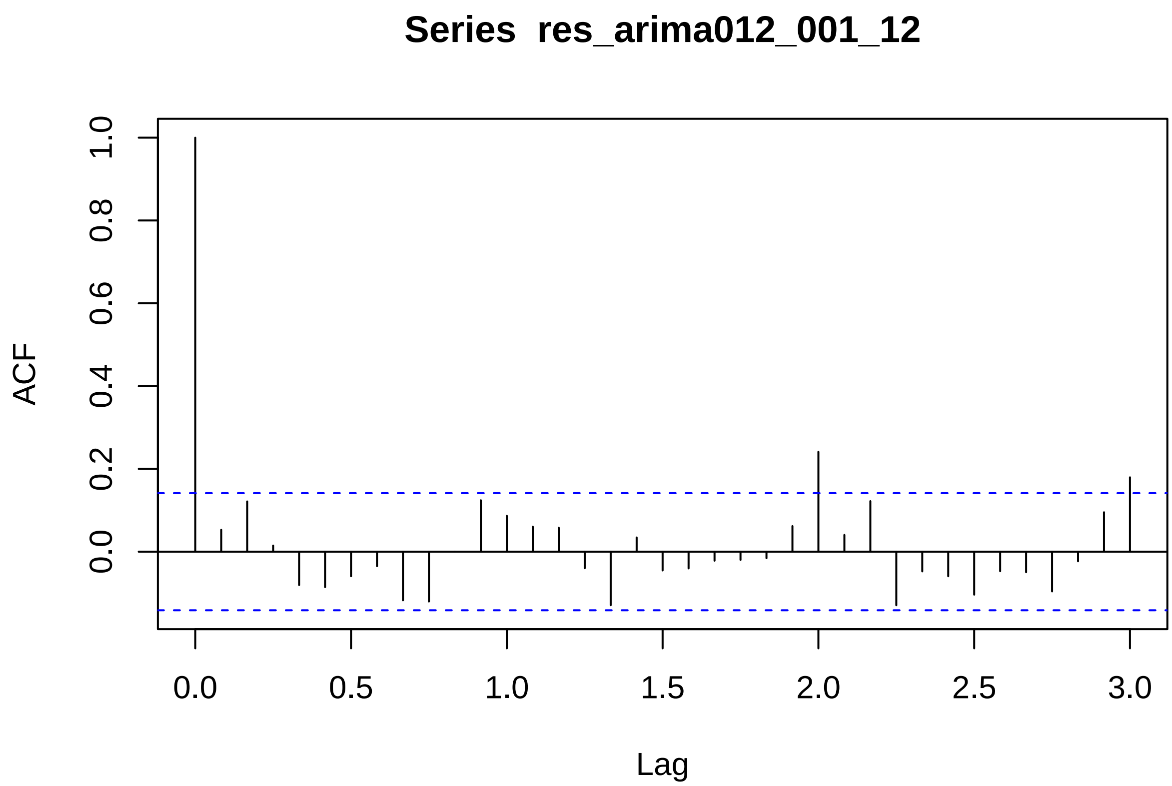
The RMSE continues to decrease. Lags (2,4,8) are significant in the PACF(). I am not sure if the lag 2 value of the PACF() is encouraging us to add an AR(2) argument. I would believe that this would remove any progress we have made. For now, I will attempt an MA(1) model. I also think it is best to address the seasonal lags.

#### ARIMA(0,1,2)(0,0,1) with a constant and seasonal period = 12

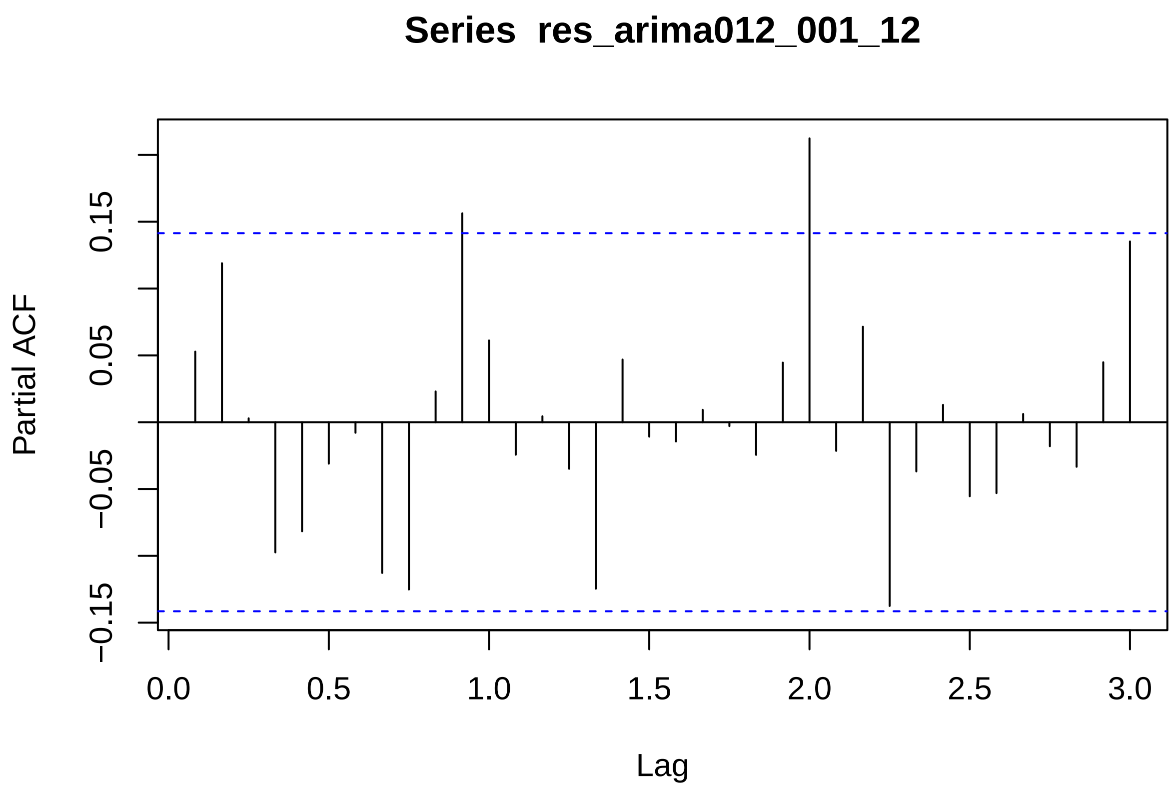
ARIMA(0,1,2)(0,0,1)$_{12}$

```r
bx_arima012_cons_001_12 <- bx_ts %>%
  model(bx_arima012_001_12 = ARIMA(total_waste ~ 1 +
                                    pdq(0,1,2) +
                                    PDQ(0,0,1, period = 12)))

zoo_arima012_001_12fit <- arima(DSNY_BX_zoo_ts,
                                order = 1 + c(0,1,2),
                                seasonal = list(order = c(0L,0L,1),
```

```
                                                        period = 12))

res_arima012_001_12 <- zoo_arima012_001_12fit$residuals
acf(res_arima012_001_12, lag.max = 36)
```




```
pacf(res_arima012_001_12, lag.max = 36)
```




```
accuracy(bx_arima012_cons_001_12)[4]
```

```
## # A tibble: 1 x 1
##    RMSE
##   <dbl>
## 1 2471.
```

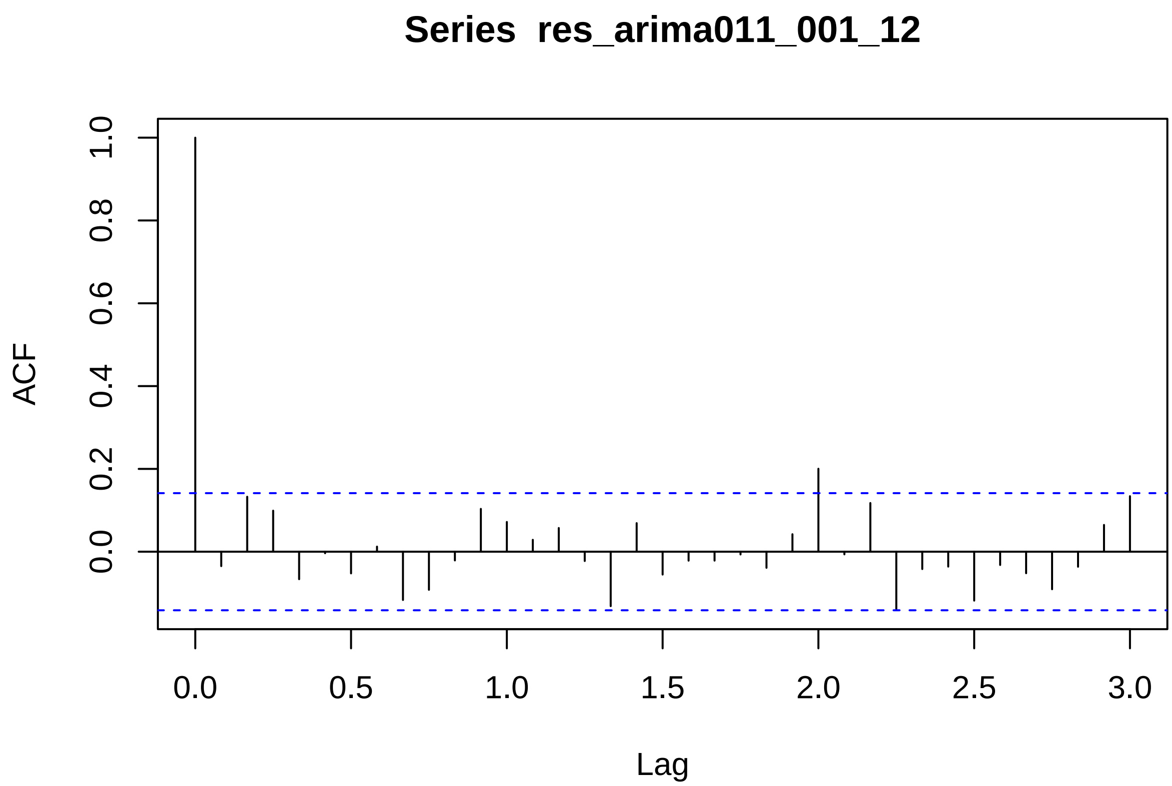
It appears that the seasonal lags in the PACF() plot appear to still be significant. It also appears that we have bounded the PACF values between (-0.15, 0.2). The RMSE is now the lowest of them all. From meeting 6, I believe that this was the best ARIMA() fitting of them all. But I will try to reduce the MA() parameter by one.

### ARIMA(0,1,1)(0,0,1) with a constant and seasonal period = 12

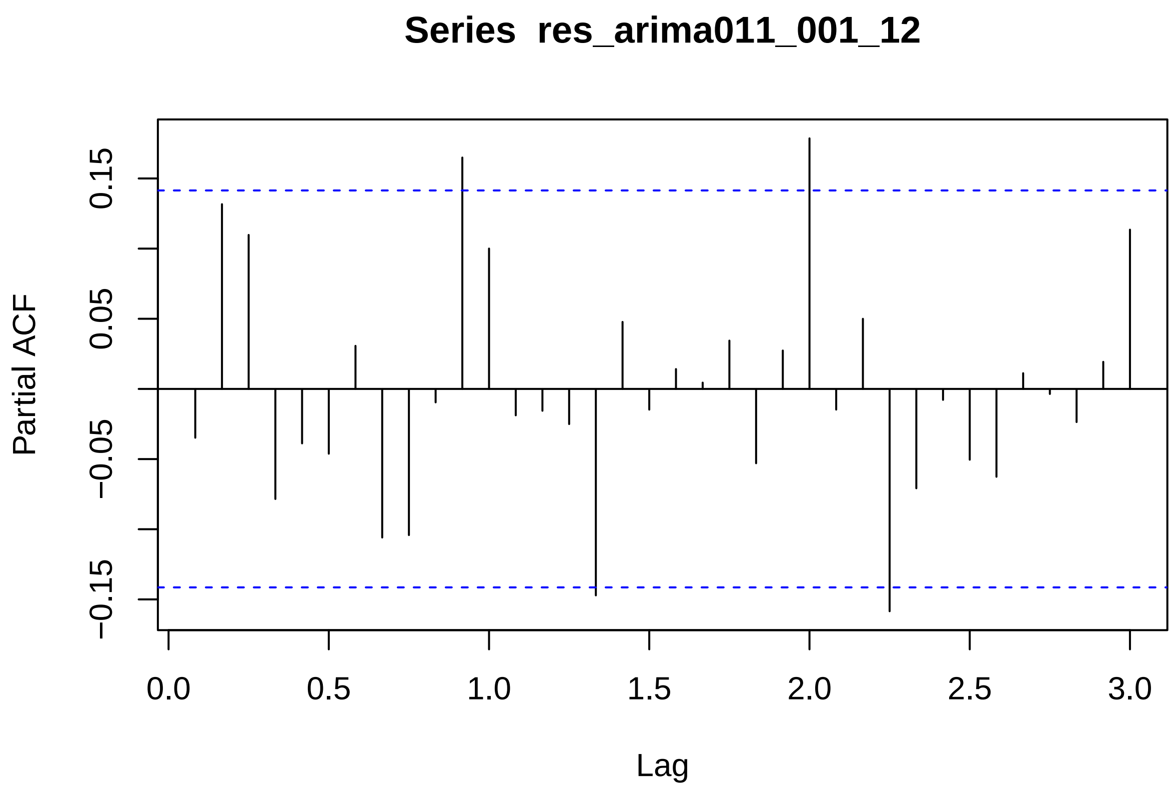
ARIMA(0,1,1)(0,0,1)$_{12}$

```
bx_arima011_cons_001_12 <- bx_ts %>%
  model(bx_arima011_cons_001_12 = ARIMA(total_waste ~ 1 +
                                          pdq(0,1,1) +
                                          PDQ(0,0,1, period = 12)))

zoo_arima011_001_12fit <- arima(DSNY_BX_zoo_ts,
                                order = 1 + c(0,1,1),
                                seasonal = list(order = c(0L,0L,1),
```

```
                                                                      period = 12))

res_arima011_001_12 <- zoo_arima011_001_12fit$residuals
acf(res_arima011_001_12, lag.max = 36)
```




```
pacf(res_arima011_001_12, lag.max = 36)
```




```
accuracy(bx_arima011_cons_001_12)[4]
```

```
## # A tibble: 1 x 1
##    RMSE
##   <dbl>
## 1 2486.
```

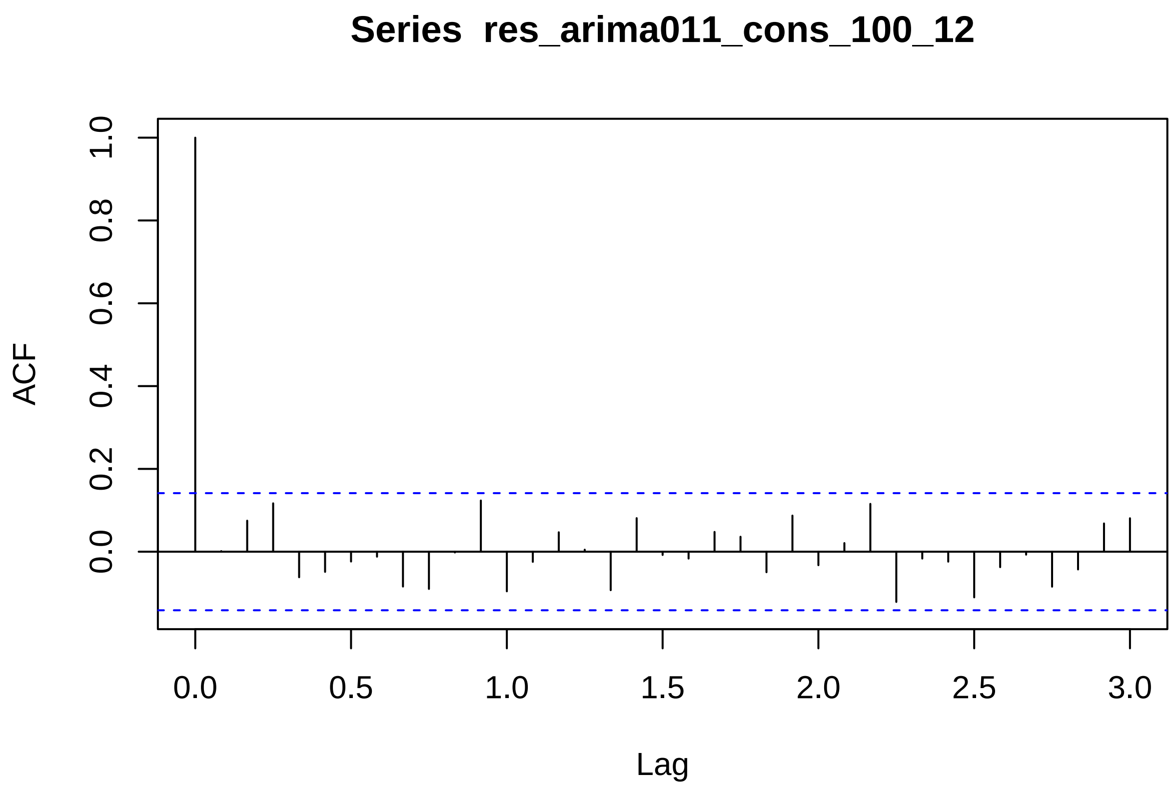
In the ACF Plot(), the seasonal lags continue to be significant, as in they pass the 95% threshold. A similar story with the PACF(), but the non-seasonal lags appear to be close to the 95% confidence levels. The PACF values are small as well, so it would not be a major deal breaker. With our period = 12, and seasonal lags are positive. This indicates that it is best to add an AR() seasonal argument.

### ARIMA(0,1,1)(1,0,0) with a constant, seasonal AR() and seasonal period = 12

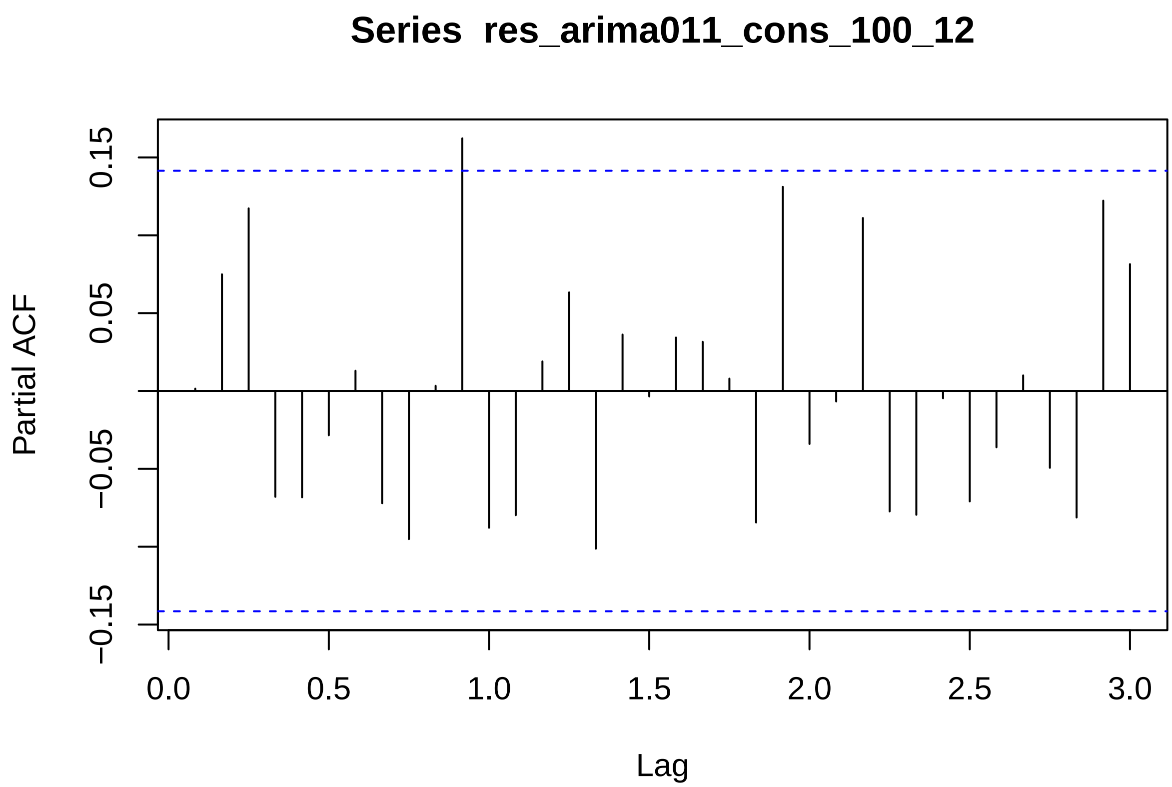
ARIMA(0,1,1)$(1,0,0)_{12}$

```
bx_arima011_cons_100_12 <- bx_ts %>%
  model(bx_arima011_cons_100_12 = ARIMA(total_waste ~ 1 +
                                        pdq(0,1,1) +
                                        PDQ(1,0,0, period = 12)))

zoo_arima011_cons_100_12fit <- arima(DSNY_BX_zoo_ts,
                                order = 1 + c(0,1,1),
                                seasonal = list(order = c(1,0L,0L),
```

```r
                                                period = 12))

res_arima011_cons_100_12 <- zoo_arima011_cons_100_12fit$residuals
acf(res_arima011_cons_100_12, lag.max = 36)
```




```r
pacf(res_arima011_cons_100_12, lag.max = 36)
```




```r
accuracy(bx_arima011_cons_100_12)
```

```
## # A tibble: 1 x 10
##   .model                  .type    ME  RMSE   MAE    MPE  MAPE  MASE RMSSE   ACF1
##   <chr>                   <chr> <dbl> <dbl> <dbl>  <dbl> <dbl> <dbl> <dbl>  <dbl>
## 1 bx_arima011_cons_100_~ Trai~  46.2 2341. 1646. -0.202  4.05 0.649 0.704 0.0236
```

This model returns the lowest RMSE. The seasonal lags in th PACF are no longer significant. All non-seasonal lags, except for lag = 11, are insignificant.

### In conclusion

The models with the most promising ACF and PACF plots, and RMSE are ARIMA$(0,1,1)(1,0,0)_{12}$, ARIMA$(0,0,0)(1,0,0)_{12}$.