Análisis de la serie de tiempo de Johnson-Johnson por modelos SARIMA

Contents

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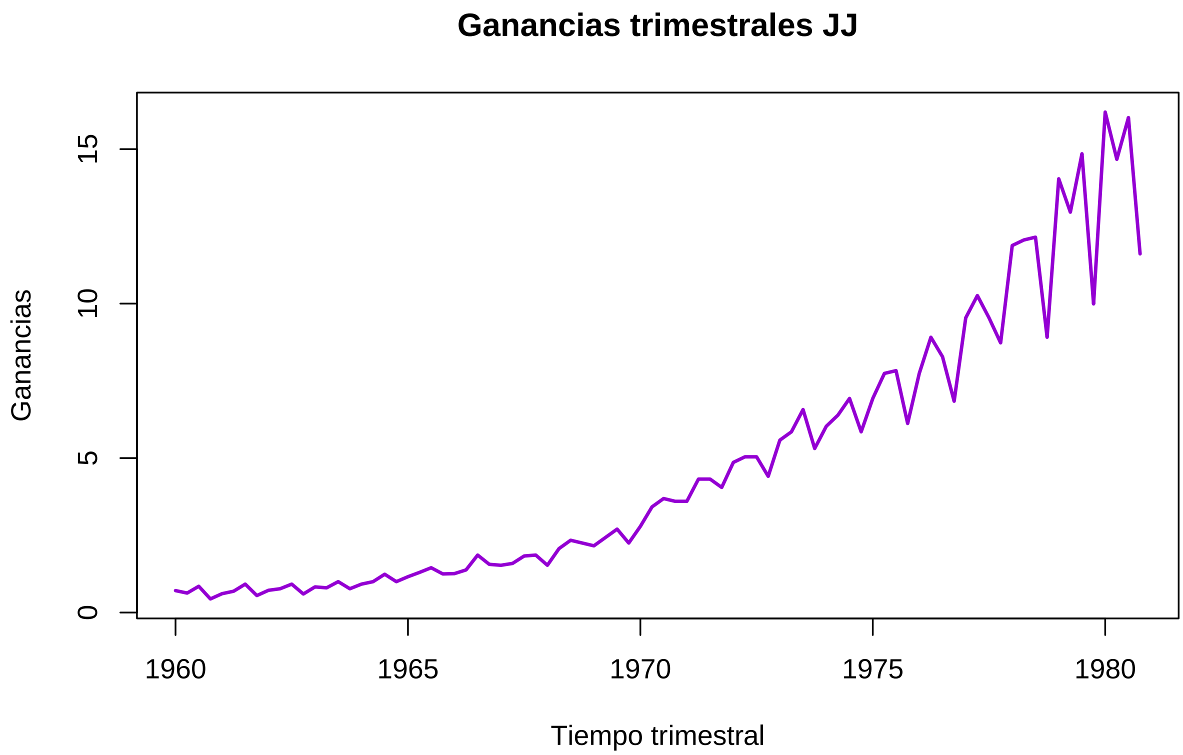
```
## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: MASS

## Warning: package 'forecast' was built under R version 4.1.1

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

##
## Attaching package: 'forecast'

## The following object is masked from 'package:astsa':
##
##     gas
```

Ajustando JJ data (Continuación)

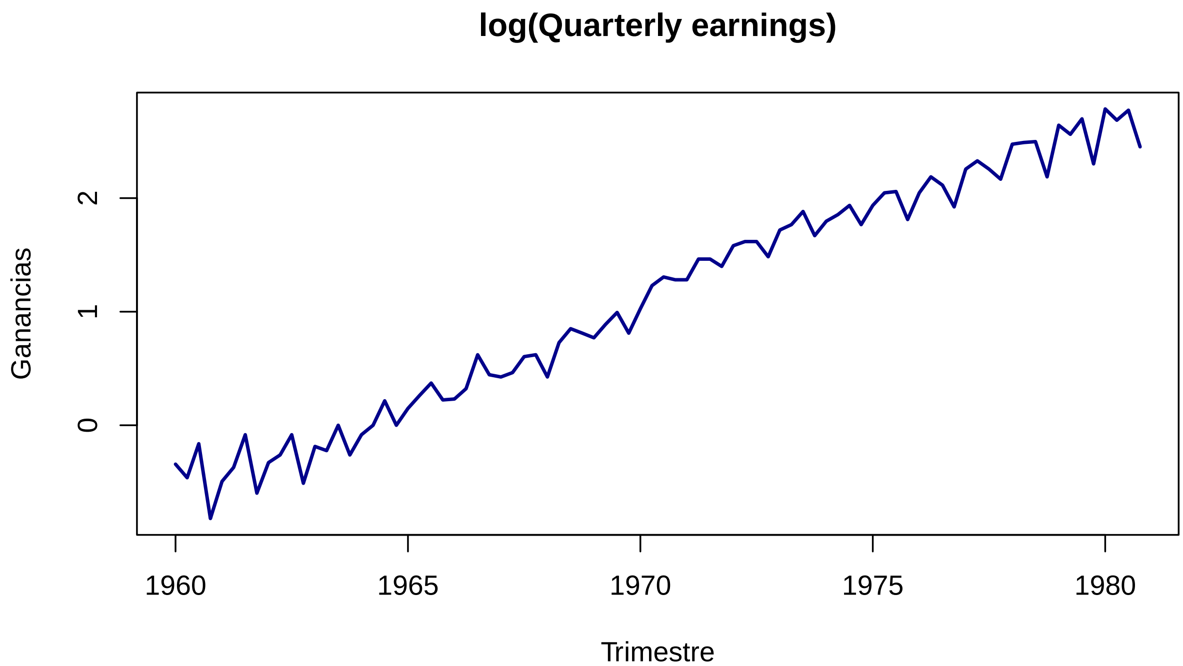
> "Ganancias trimestrales por acción de Johnson y Johnson, 84 trimestres (21 años) medidos desde el primer trimestre de 1960 hasta el último trimestre de 1980."

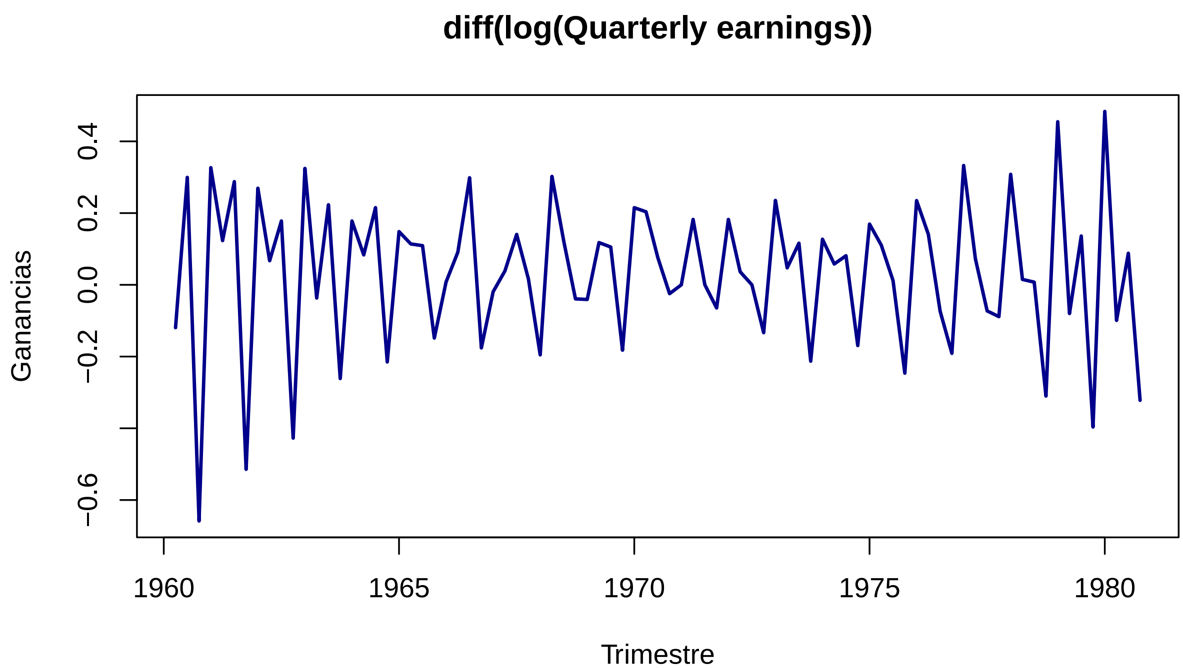
Haciendo un recuento de la serie analizada, haciendo su respectivo gráfico



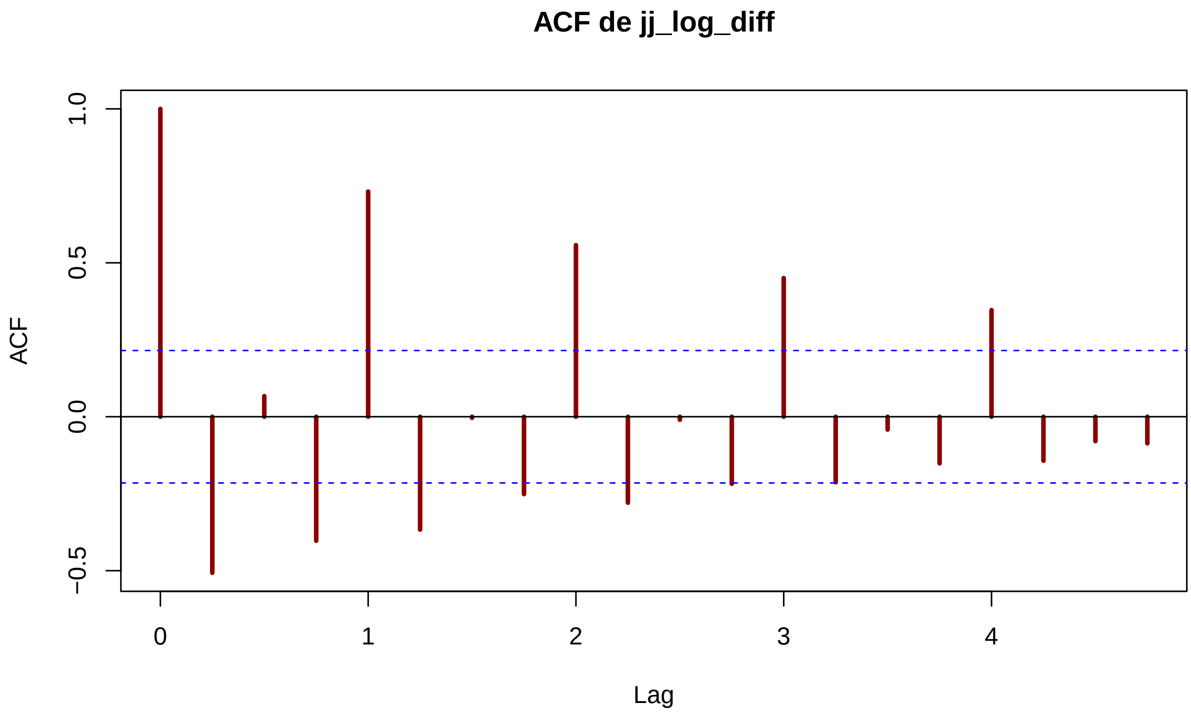
Distintas transformaciones

Logaritmo a la serie

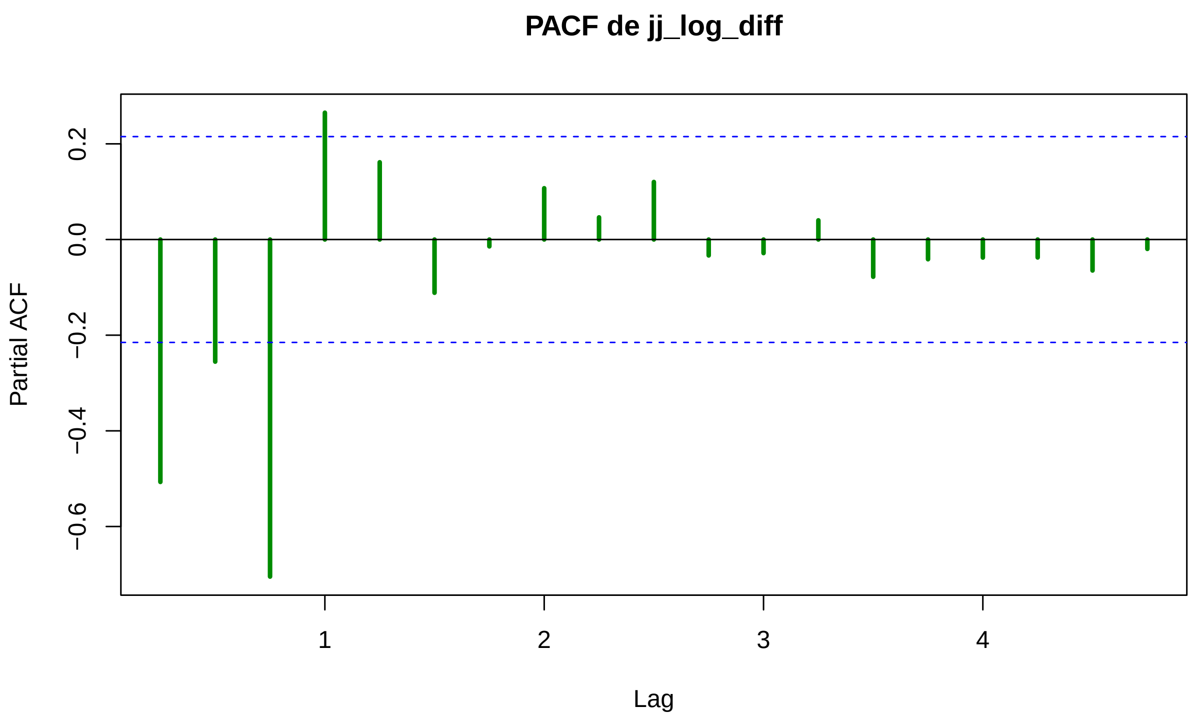




ACF y PACF

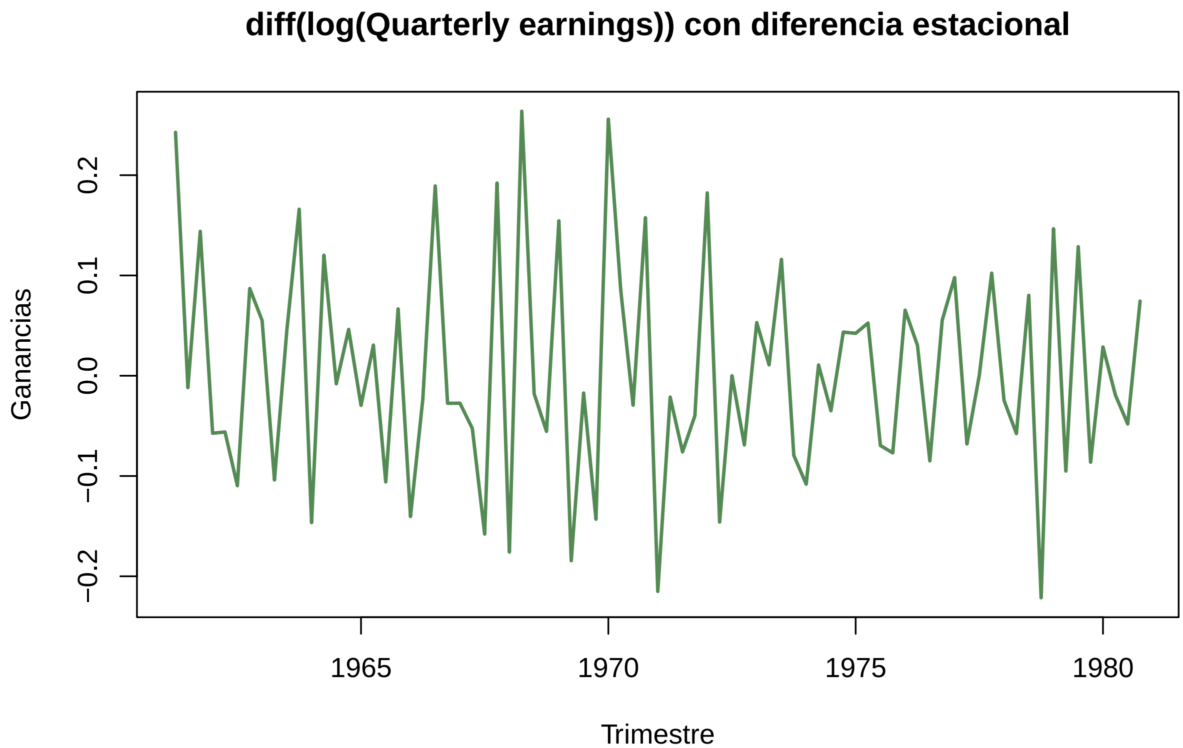


ACF de jj_log_diff
ACF
1.0
0.5
0.0
−0.5
0
1
2
3
4
Lag



PACF de jj_log_diff
Partial ACF
0.2
0.0
−0.2
−0.4
−0.6
1
2
3
4
Lag

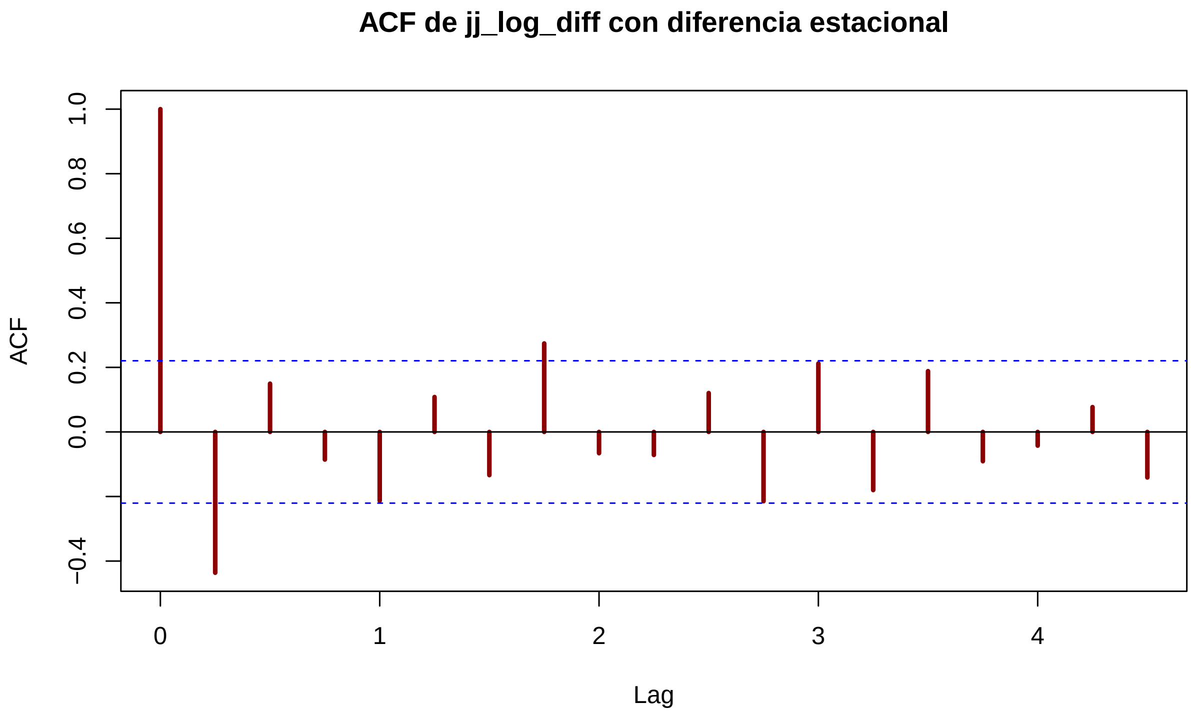
Diferencia estacional con la diferencia del logaritmo



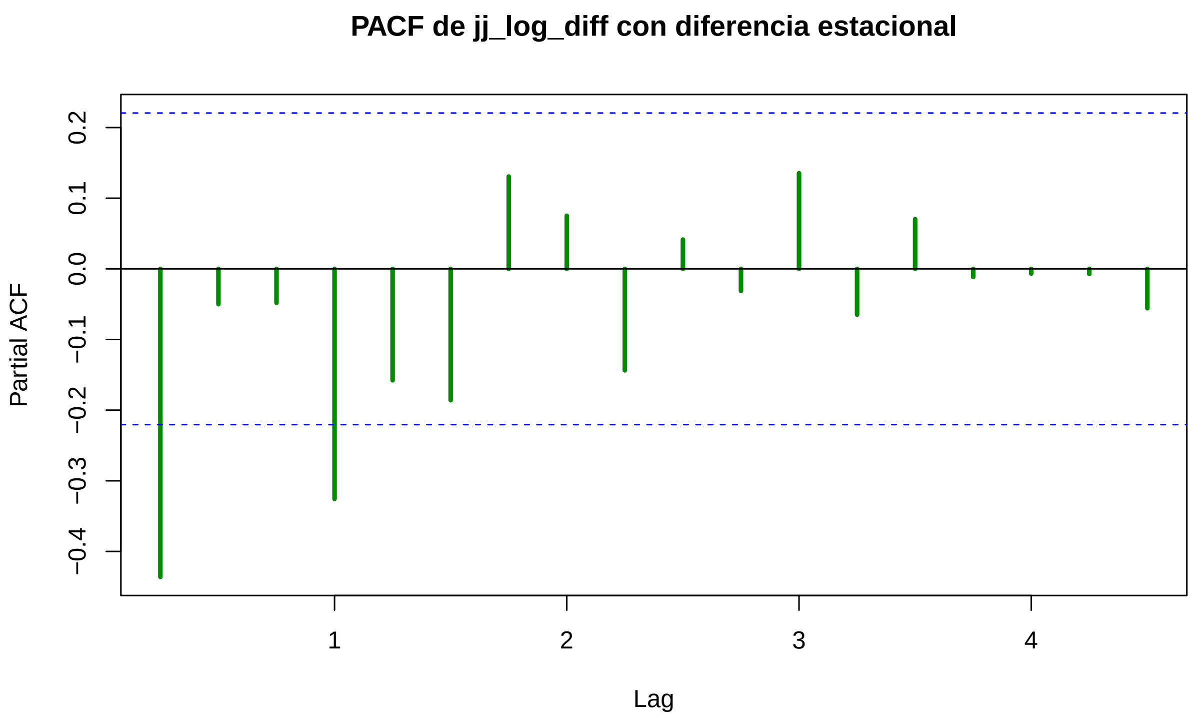
Prueba Ljung - Box

```
##
##  Box-Pierce test
##
## data:  jj_log_diff_diff_4
## X-squared = 20.95, df = 4.3694, p-value = 0.0004658
```

ACF y PACF



ACF de jj_log_diff con diferencia estacional
ACF
1.0
0.8
0.6
0.4
0.2
0.0
−0.4
0
1
2
3
4
Lag



PACF de jj_log_diff con diferencia estacional
Partial ACF
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
1
2
3
4
Lag

Ajuste de diferentes modelos

```
## Modelo ( 0 1 0 0 1 0 4 ) AIC= -124.0685  SSE= 0.9377871  p-VALUE= 0.0002610795
## Modelo ( 0 1 0 0 1 1 4 ) AIC= -126.3493  SSE= 0.8856994  p-VALUE= 0.0001606542
## Modelo ( 0 1 0 1 1 0 4 ) AIC= -125.9198  SSE= 0.8908544  p-VALUE= 0.0001978052
## Modelo ( 0 1 0 1 1 1 4 ) AIC= -124.3648  SSE= 0.8854554  p-VALUE= 0.000157403
## Modelo ( 0 1 1 0 1 0 4 ) AIC= -145.5139  SSE= 0.6891988  p-VALUE= 0.03543717
## Modelo ( 0 1 1 0 1 1 4 ) AIC= -150.7528  SSE= 0.6265214  p-VALUE= 0.6089542
## Modelo ( 0 1 1 1 1 0 4 ) AIC= -150.9134  SSE= 0.6251634  p-VALUE= 0.7079173
## Modelo ( 0 1 1 1 1 1 4 ) AIC= -149.1317  SSE= 0.6232876  p-VALUE= 0.6780876
## Modelo ( 1 1 0 0 1 0 4 ) AIC= -139.8248  SSE= 0.7467494  p-VALUE= 0.03503386
## Modelo ( 1 1 0 0 1 1 4 ) AIC= -146.0191  SSE= 0.6692691  p-VALUE= 0.5400205
## Modelo ( 1 1 0 1 1 0 4 ) AIC= -146.0319  SSE= 0.6689661  p-VALUE= 0.5612964
## Modelo ( 1 1 0 1 1 1 4 ) AIC= -144.3766  SSE= 0.6658382  p-VALUE= 0.5459445
## Modelo ( 1 1 1 0 1 0 4 ) AIC= -145.8284  SSE= 0.667109  p-VALUE= 0.2200484
## Modelo ( 1 1 1 0 1 1 4 ) AIC= -148.7706  SSE= 0.6263677  p-VALUE= 0.594822
## Modelo ( 1 1 1 1 1 0 4 ) AIC= -148.9175  SSE= 0.6251104  p-VALUE= 0.7195469
## Modelo ( 1 1 1 1 1 1 4 ) AIC= -144.4483  SSE= 0.6097742  p-VALUE= 0.3002702
```

Ajustando al mejor modelo

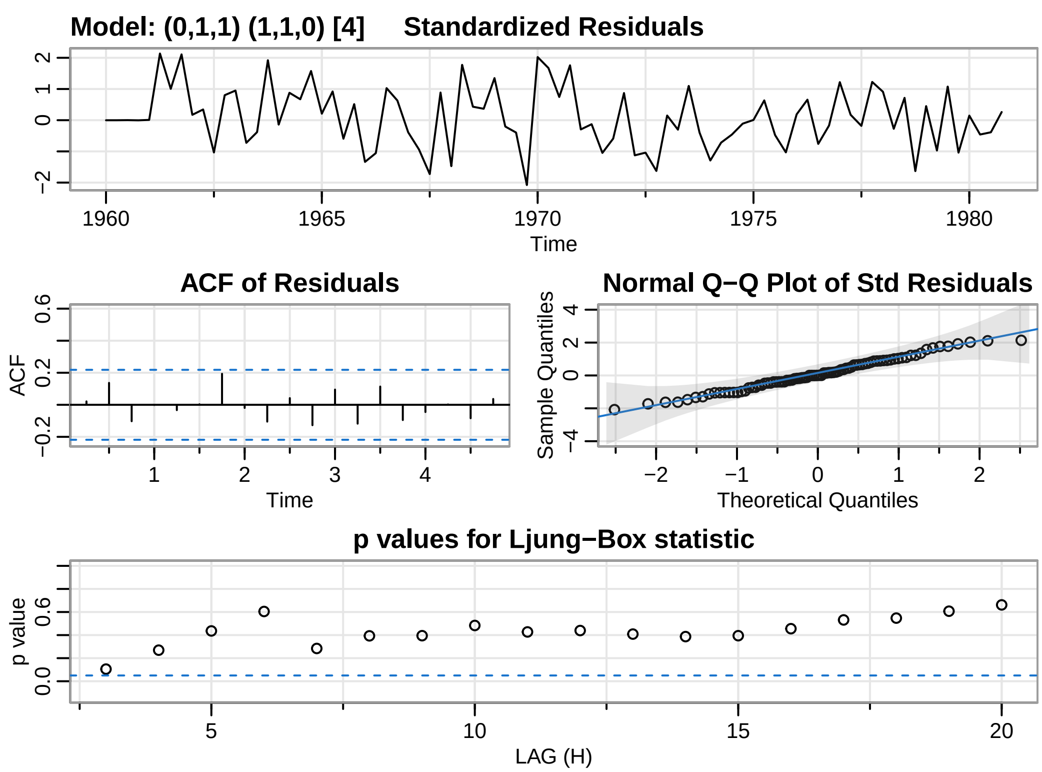
```
##
## Call:
## arima(x = log(jj), order = c(0, 1, 1), seasonal = list(order = c(1, 1, 0), period = 4))
##
## Coefficients:
##           ma1     sar1
##       -0.6796  -0.3220
## s.e.   0.0969   0.1124
##
## sigma^2 estimated as 0.007913:  log likelihood = 78.46,  aic = -150.91
```

Finalmente tenemos como modelo:

$$
\begin{aligned}
&Y_t = Y_{t-1} + 0.678Y_{t-4} - 0.678Y_{t-5} + 0.322Y_{t-8} - 0.322Y_{t-9} + Z_t - 0.6796Z_{t-1} \\
&Z_t \sim N(0, 0.007913) \\
&Y_t = \log(Ganancias_t)
\end{aligned}
$$

Otra manera de ajustar

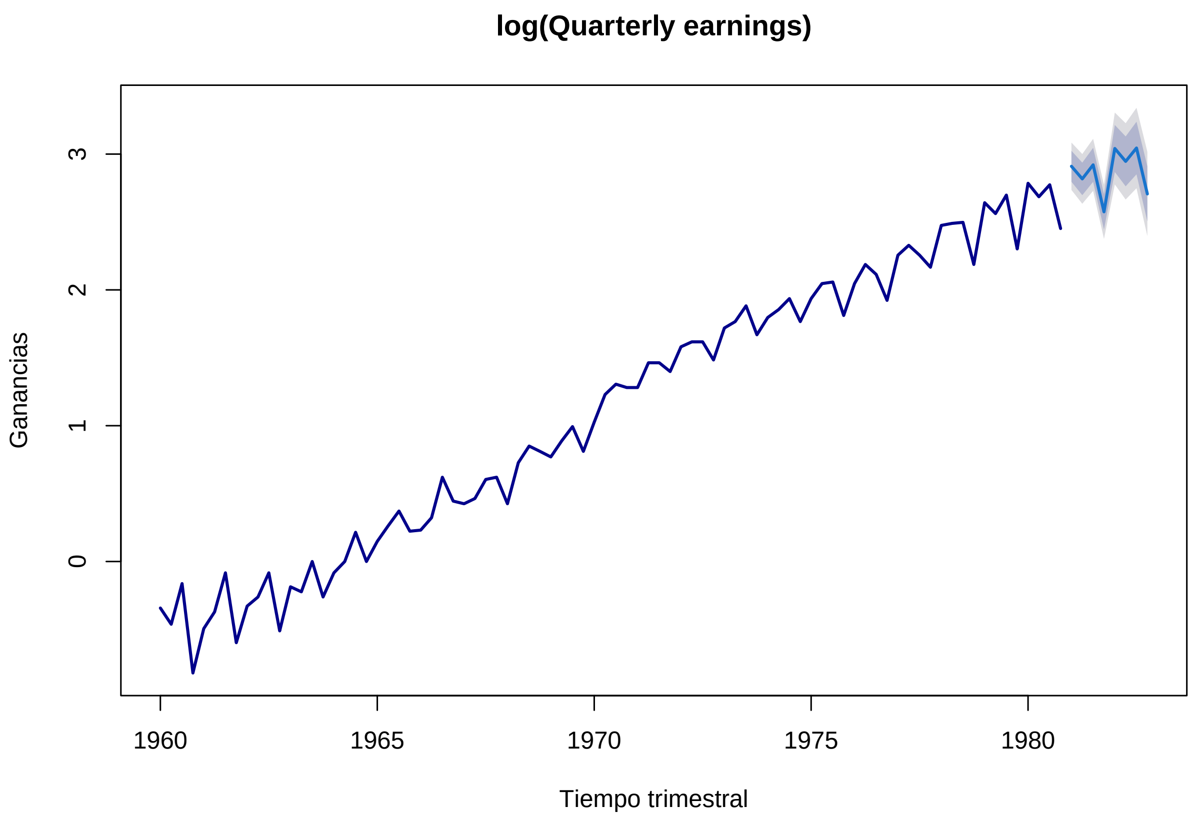
```
## initial  value -2.237259
## iter   2 value -2.429075
## iter   3 value -2.446738
## iter   4 value -2.455821
## iter   5 value -2.459761
## iter   6 value -2.462511
## iter   7 value -2.462602
## iter   8 value -2.462749
## iter   9 value -2.462749
## iter   9 value -2.462749
## iter   9 value -2.462749
## final  value -2.462749
## converged
## initial  value -2.411490
## iter   2 value -2.412022
## iter   3 value -2.412060
## iter   4 value -2.412062
## iter   4 value -2.412062
## iter   4 value -2.412062
## final  value -2.412062
## converged
```




```
## $fit
##
## Call:
## arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D, Q), period = S),
```

```
##     include.mean = !no.constant, transform.pars = trans, fixed = fixed, optim.control = list(trace =
##         REPORT = 1, reltol = tol))
##
## Coefficients:
##           ma1     sar1
##       -0.6796  -0.3220
## s.e.   0.0969   0.1124
##
## sigma^2 estimated as 0.007913:  log likelihood = 78.46,  aic = -150.91
##
## $degrees_of_freedom
## [1] 77
##
## $ttable
##      Estimate     SE t.value p.value
## ma1   -0.6796 0.0969 -7.0104  0.0000
## sar1  -0.3220 0.1124 -2.8641  0.0054
##
## $AIC
## [1] -1.840408
##
## $AICc
## [1] -1.838555
##
## $BIC
## [1] -1.753721
```

Pronóstico



	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
1981 Q1	2.897541	2.782989	3.012093	2.722348	3.072734
1981 Q2	2.819607	2.698858	2.940357	2.634937	3.004278
1981 Q3	2.916669	2.793396	3.039941	2.728139	3.105198
1981 Q4	2.598883	2.473572	2.724194	2.407236	2.790529
1982 Q1	3.015049	2.841963	3.188136	2.750336	3.279762
1982 Q2	2.954676	2.773250	3.136101	2.677209	3.232143
1982 Q3	3.059134	2.872681	3.245587	2.773979	3.344289
1982 Q4	2.744766	2.553837	2.935696	2.452765	3.036768