Annex

Tourist arrivals in Spain

Nicolás Jiménez Muñoz and Aina Vila Arbusà

```
Call:
arima(x = d1d12)nseries, order = c(2, 0, 0), seasonal = list(order = <math>c(2, 0, 0))
    0), period = 12))
Coefficients:
               ar2 sar1 sar2
-0.3341 -0.4586 -0.2184
                                             intercept
          ar1
      -0.6830
                                                -1e-04
                         0.0717
       0.0655
               0.0647
                                    0.0770
                                                 1e-03
sigma^2 estimated as 0.002158: log likelihood = 351.39, aic = -690.77
arima(x = d1d12)nseries, order = c(0, 0, 4), seasonal = list(order = c(1, 0, 4))
    0), period = 12))
Coefficients:
      ma1 ma2 ma3
-0.7366 0.0949 0.0733
0.0699 0.0900 0.0915
                                     ma4
                                              sar1 intercept
                                 -0.1299
                                           -0.3589
                                                        -1e-04
                                0.0697
sigma^2 estimated as 0.002206: log likelihood = 349.62, aic = -685.23
Call:
arima(x = d1d12)nseries, order = c(2, 0, 0), seasonal = list(order = c(1, 0, 0))
    0), period = 12))
Coefficients:
          ar1
                        sar1
-0.3684
0.0649
                    ar2
                                   intercept
-0.7127 -0.3564
s.e. 0.0638 0.0635
                                      -0.0001
                                       0.0012
sigma^2 estimated as 0.002251: log likelihood = 347.48, aic = -684.96
Call:
arima(x = d1d12)nseries, order = c(0, 0, 4), seasonal = list(order = c(0, 0, 4))
    1), period = 12))
Coefficients:
                   ma2
          ma1
                            ma3
                                     ma4
                                              smal intercept
      -0.7086
               0.0818 0.0706
                                -0.1444
                                          -0.4749
                                                         0e+00
                                 0.0689
                                           0.0778
       0.0708 0.0878 0.0894
                                                         5e-04
sigma^2 estimated as 0.002119: log likelihood = 353.23, aic = -692.45
```

```
Call:
    arima(x = d1d12lnseries, order = c(2, 0, 0), seasonal = list(order = c(0, 0, 1), period = 12))

Coefficients:
    ar1    ar2    smal intercept
    -0.6863   -0.3341   -0.4642    -1e-04
    s.e.    0.0655    0.0645    0.0760    9e-04

sigma^2 estimated as 0.002179: log likelihood = 350.4, aic = -690.8

Figure 2: model estimation with d1d12lnseries.
```

Figure 3: intercept significance of each model.

```
Call:
arima(x = lnseries, order = c(2, 1, 0), seasonal = list(order = c(2, 1, 0),
   period = 12)
Coefficients:
                          sar1
         ar1
                  ar2
                                   sar2
                       -0.4586
      -0.6830 -0.3341
                                -0.2184
                       0.0717
     0.0655
              0.0647
                                 0.0770
sigma^2 estimated as 0.002158: log likelihood = 351.38, aic = -692.76
Call:
arima(x = lnseries, order = c(0, 1, 4), seasonal = list(order = c(1, 1, 0),
   period = 12))
Coefficients:
         ma1
                 ma2
                         ma3
                                  ma4
      -0.7365
              0.0949 0.0733
                              -0.1299
                                       -0.3589
      0.0699 0.0900 0.0915
                              0.0697
                                        0.0653
sigma^2 estimated as 0.002206: log likelihood = 349.61, aic = -687.21
Call:
arima(x = lnseries, order = c(2, 1, 0), seasonal = list(order = c(1, 1, 0),
   period = 12))
Coefficients:
         ar1
                  ar2
                          sar1
      -0.7127
               -0.3563
                       -0.3684
              0.0635
s.e. 0.0638
                        0.0649
sigma^2 estimated as 0.002251: log likelihood = 347.47, aic = -686.95
Call:
arima(x = lnseries, order = c(0, 1, 4), seasonal = list(order = c(0, 1, 1),
   period = 12))
Coefficients:
                 ma2
                         ma3
                                  ma4
                                          sma1
         ma1
      -0.7086
              0.0817
                      0.0706
                              -0.1445
                                       -0.4750
                              0.0689
      0.0708 0.0878 0.0894
                                       0.0777
sigma^2 estimated as 0.002119: log likelihood = 353.23, aic = -694.45
```

	T_Value <dbl></dbl>
ar1	-10.429090
ar2	-5.166715
sar1	-6.399923
sar2	-2.838294_
Figure 5 : mod1 significance test.	

	T_Value <dbl></dbl>
ma1	-10.5324704
ma2	1.0543841
ma3	0.8008811
ma4	-1.8631577
sar1	-5.4956136
Figure 6: mod2 significance test.	

ar1	
	-11.175206
ar2	-5.612554
sar1	-5.678867

	T_Value <dbl></dbl>
ma1	-10.0126429
ma2	0.9309191
ma3	0.7898606
ma4	-2.0967179
sma1	-6.1129571
Figure 8: mod4 significance test.	

	T_Value <dbl></dbl>
ar1	-10.471170
ar2	-5.176650
sma1	-6.105575
Figure 9 : mod5 significance test.	

```
Call:
 arima(x = lnseries, order = c(0, 1, 4), seasonal = list(order = c(1, 1, 0), period = 12), fixed = c(NA, NA, 0, NA, NA))
 Coefficients:
        ma1 ma2
-0.7508 0.1442
                      ma2 ma3
                                        ma4
                            0 -0.0960
0 0.0557
                                             -0.3547
         0.0703 0.0700
                                               0.0650
sigma^2 estimated as 0.002213: log likelihood = 349.3, aic = -688.6
arima(x = Inseries, order = c(0, 1, 4), seasonal = list(order = c(0, 1, 1), period = 12), fixed = c(NA, 0, NA, NA, NA))
 Coefficients:
           ma1
                  ma2
                           ma3
                                       ma4
                                                 sma1
                   0 0.1177
                     0 0.1177 -0.1505 -0.4833
0 0.0717 0.0680 0.0776
        -0.6735
       0.0582
sigma^2 estimated as 0.002127: log likelihood = 352.77, aic = -695.54
Figure 10: mod2 and mod4 re-estimation.
```

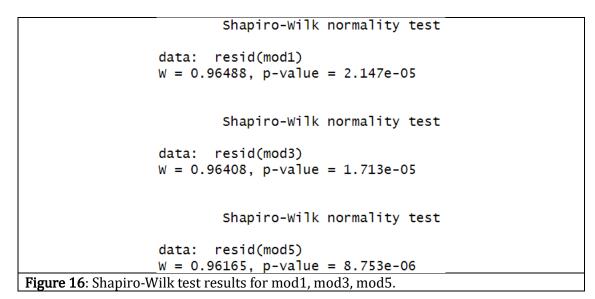
	T_Value <dbl></dbl>
ma1	-10.685880
ma2	2.059399
ma3	0.000000
ma4	-1.475624
sar1	-5.047720_
Figure 11: mod2_2 significance test.	

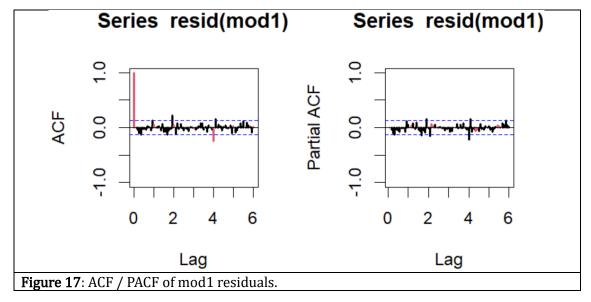
	T_Value <dbl></dbl>
ma1	-11.568549
ma2	0.000000
ma3	1.729705
ma4	-1.941014
sma1	-8.300908
Figure 12: mod4_2 significance test.	

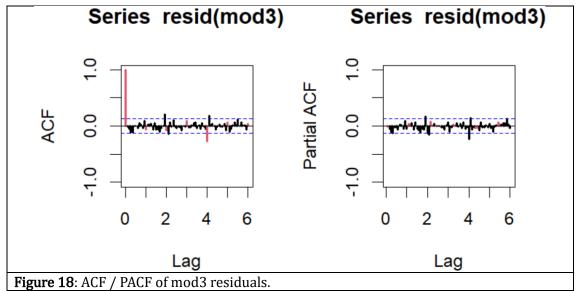
```
Call:
 arima(x = lnseries, order = c(0, 1, 2), seasonal = list(order = c(1, 1, 0),
     period = 12))
Coefficients:
                     ma2
            ma1
                              sar1
        -0.7594
                 0.1008 -0.3523
 s.e. 0.0665 0.0674
                          0.0650
sigma^2 estimated as 0.002245: log likelihood = 347.8, aic = -687.6
 Call:
arima(x = lnseries, order = c(0, 1, 4), seasonal = list(order = c(0, 1, 1), period = 12), fixed = c(NA, 0, 0, NA, NA))
 Coefficients:
            ma1 ma2 ma3 ma4 sma1
6441 0 0 -0.0815 -0.4861
0546 0 0 0.0566 0.0776
        -0.6441
        0.0546
s.e.
sigma^2 estimated as 0.002154: log likelihood = 351.42, aic = -694.84
Figure 13: mod2 and mod4 second re-estimation.
```

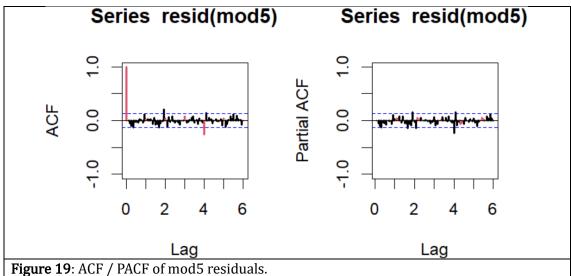
	T_Value <dbl></dbl>
ma1	-11.417333
ma2	1.496675
sar1	-5.418128
Figure 14 : mod2_3 significance test.	-

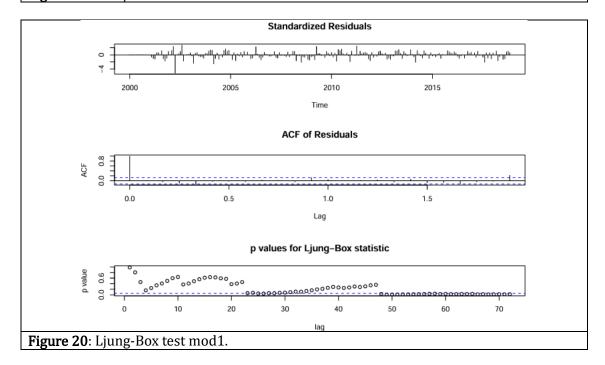
	T_Value <dbl></dbl>
ma1	-11.804107
ma2	0.000000
ma3	0.000000
ma4	-1.493259
sma1	-8.590764
Figure 15: mod4_3 significance test.	

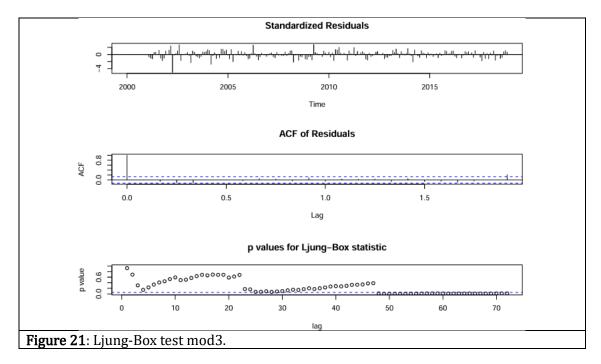


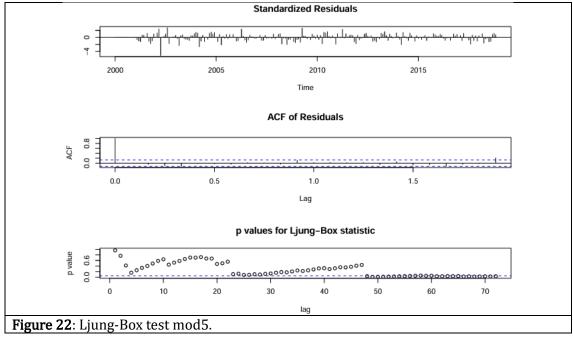












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[1] 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443 1.065443
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[1] 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.086772 1.08672 1.08672 1.08672 1.08672 1.08672 1.08672 1.08672 1.08672 1.08672
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Figure 24: modulus of the polynomial roots (mod3).

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[1] 1.730061 1.730061

[1] 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.066025 1.0
```

Date	Forecast	Lower_Bound	Upper_Bound
<date></date>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>
2019-12-01	4.203541	3.837683	4.604279
2020-01-01	4.264251	3.875761	4.691682
2020-02-01	4.427394	3.990401	4.912242
2020-03-01	5.531977	4.921818	6.217777
2020-04-01	7.262775	6.417025	8.219992
2020-05-01	8.517321	7.465363	9.717513
2020-06-01	9.001774	7.827482	10.352235
2020-07-01	10.864516	9.383040	12.579900
2020-08-01	11.088786	9.511310	12.927892
2020-09-01	9.434078	8.039148	11.071053
2020-10-01	8.075854	6.839254	9.536042
2020-11-01	4.789325	4.031543	5.689541

```
arima(x = lnseries, order = c(2, 1, 0), seasonal = list(order = c(2, 1, 0), period = 12), xreg = data.frame(vEa, vTD))
Coefficients:
       ar1
-0.5457
                ar2 sar1 sar2 VEa VTD
-0.2016 -0.2964 -0.0486 0.0737 -0.0025
0.0679 0.0728 0.0761 0.0082 0.0007
      0.0676
sigma^2 estimated as 0.001568: log likelihood = 386.69, aic = -759.38
Call:
arima(x = lnseries, order = c(2, 1, 0), seasonal = list(order = c(2, 1, 0),
    period = 12), xreg = data.frame(vEa))
Coefficients:
       ar1 ar2 sai = -0.5996 -0.2635 -0.2514 -0.0424 0.0765 0.0660 0.0665 0.0718 0.0757 0.0083
      0.0660
sigma^2 estimated as 0.001654: log likelihood = 381.08, aic = -750.17
arima(x = lnseries, order = c(2, 1, 0), seasonal = list(order = c(2, 1, 0),
    period = 12), xreg = data.frame(vTD))
Coefficients:
       ar1
-0.6160
                      ar2
                               sar1
                                          sar2
                 -0.2407
                            -0.5099 -0.2455
                                                 -0.0033
       0.0686
                 0.0685
                           0.0722 0.0768
                                                 0.0008
sigma^2 estimated as 0.002013: log likelihood = 358.58, aic = -705.16
Figure 27: Calendar effects model proposals.
```

	T_Value <dbl></dbl>
ar1	-8.0745270
ar2	-2.9691097
sar1	-4.0722995
sar2	-0.6394446
vEa	9.0325030
vTD	-3.5539561
Figure 28 : t-test on the model with calendar effects.	

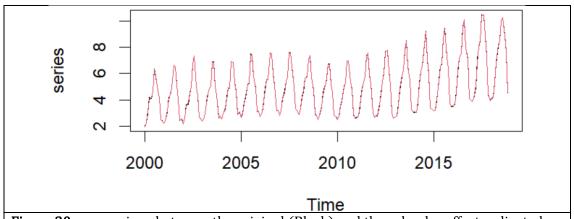


Figure 30: comparison between the original (Black) and the calendar effects adjusted series (red).

Obs type_detected :int> <chr></chr>	W_coeff <dbl></dbl>	ABS_L_Ratio date <dbl> <chr></chr></dbl>	PercVar <dbl></dbl>	
27 AO	0.07317274	3.149224 Mar 2002	107.59164	
32 AO	0.10469745	4.164723 Aug 2002	111.03746	
50 AO	0.06951395	3.188600 Feb 2004	107.19870	
88 TC	-0.07210436	3.096986 Apr 2007	93.04338	
124 AO	-0.09086129	3.723054 Apr 2010	91.31444	
148 AO	-0.06974023	3.129660 Apr 2012	93.26361	
160 LS	0.08609274	3.598692 Apr 2013	108.99074_	
Figure 31: outlier detection on the calendar effects adjusted series.				

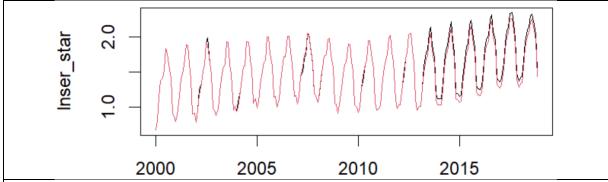
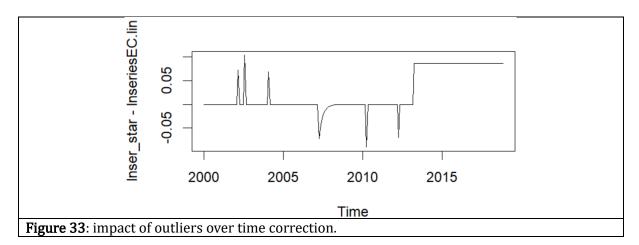
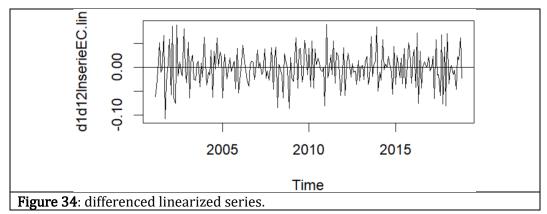
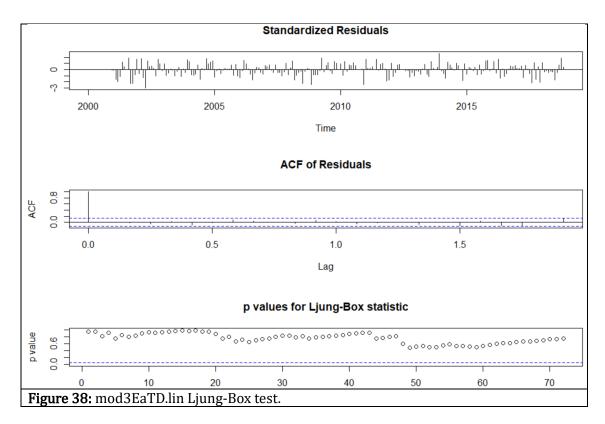


Figure 32: series adjusted with calendar effects (black) and series we would expect if outliers had not occurred in the adjusted series for calendar effects (red).





	<dbl></dbl>
ar1	-7.453109
ar2	-2.662033
sar1	-2.499212



[1] 1.153457