Econometrics Test Exercise 6

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Questions

This test exercise uses data that are available in the data file TestExer6. The question of interest is to model monthly inflation in the Euro area and to investigate whether inflation in the United States of America has predictive power for inflation in the Euro area. Monthly data on the consumer price index (CPI) for the Euro area and the USA are available from January 2000 until December 2011. The data for January 2000 until December 2010 are used for specification and estimation of models, and the data for 2011 are left out for forecast evaluation purposes.

(a) Make time series plots of the CPI of the Euro area and the USA, and also of their logarithm $log(CPI)$ and of the two monthly inflation series $DP = \Delta log(CPI)$. What conclusions do you draw from these plots?

(b) Perform the Augmented Dickey-Fuller (ADF) test for the two $log(CPI)$ series. In the ADF test equation, include a constant (α), a deterministic trend term $(\beta\, t)$, three lags of $DP = \Delta log(CPI)$ and, of course, the variable of interest $log(CPI_{t-1})$ and its standard error and t-value, and draw your conclusion.

(c) As the two series of $log(CPI)$ are not cointegrated (you need not check this), we continue by modeling the monthly inflation series $DPEUR = \Delta log(CPIEUR)$ for the Euro area. Determine the sample autocorrelations and the sample partial autocorrelations of this series to motivate the use of the following AR model: $DPEUR_t = \alpha + \beta_1\, DPEUR_{t-6} + \beta_2\, DPEUR_{t-12} + \epsilon_t$ Estimate the parameters of this model (sample Jan 2000 - Dec 2010).

(d) Extend the AR model of part (c) by adding lagged values of monthly inflation in the USA at lags 1, 6, and 12. Check that the coefficient at lag 6 is not significant, and estimate the ADL model $DPEUR_t = \alpha + \beta_1\, DPEUR_{t-6} + \beta_2\, DPEUR_{t-12} + \gamma_1\, DPUSA_{t-1} + \gamma_2\, DPUSA_{t-12} + \epsilon_t$ (sample Jan 2000 - Dec 2010).

(e) Use the models of parts (c) and (d) to make two series of 12 monthly inflation forecasts for 2011. At each month, you should use the data that are then available, for example, to forecast inflation for September 2011 you can use the data up to and including August 2011. However, do not re-estimate the model and use the coefficients as obtained in parts (c) and (d). For each of the two forecast series, compute the values of the root mean squared error $(RMSE)$, mean absolute error (MAE), and the sum of the forecast errors (SUM). Finally, give your interpretation of the outcomes.

Exercise initialization

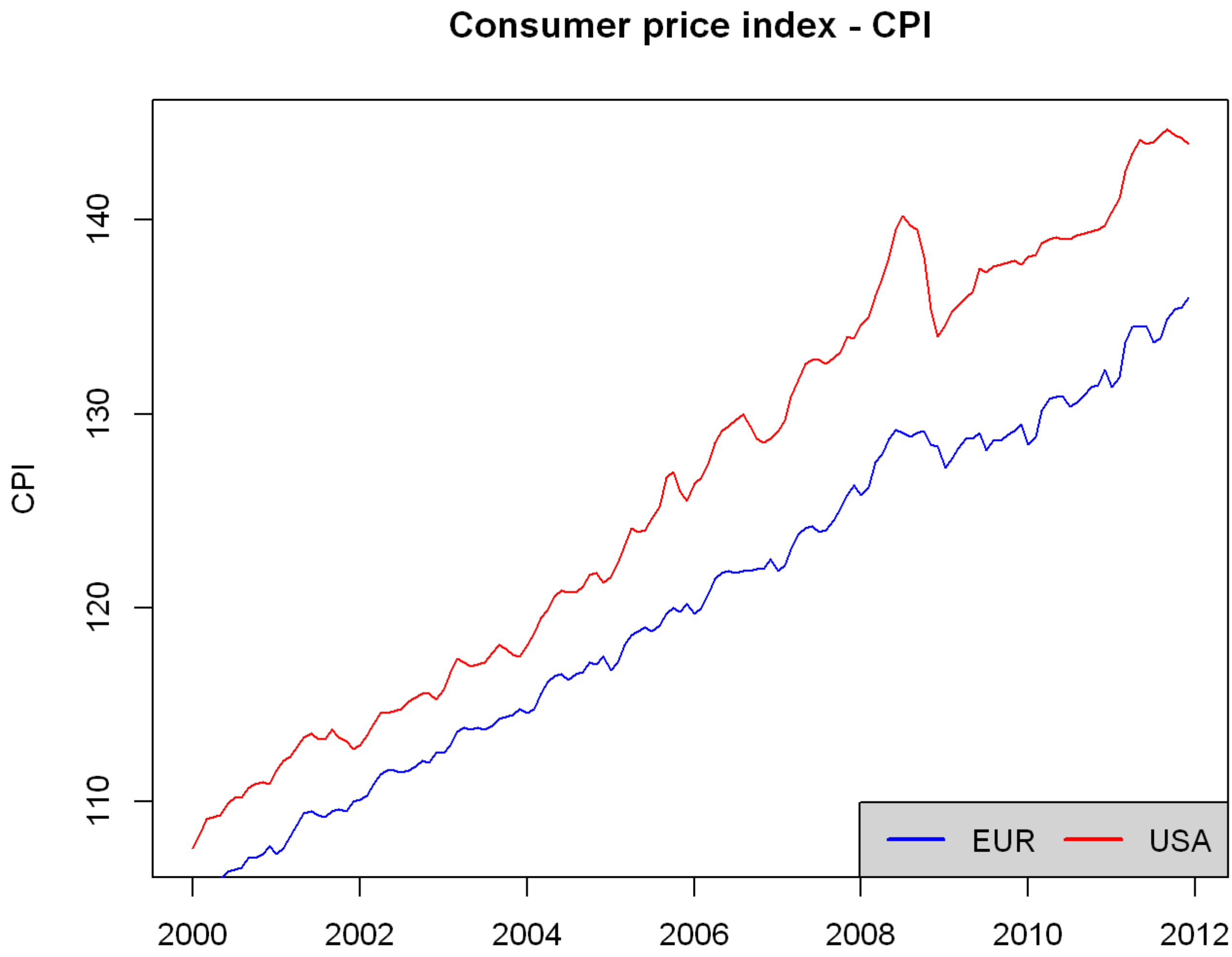
Loading & preparing data…

```
## 'data.frame':    144 obs. of  12 variables:
##  $ YYYYMM : Factor w/ 144 levels "2000M01","2000M02",..: 1 2 3 4 5 6 7 8 9 10 ...
##  $ TREND  : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ CPI_EUR: num  105 105 106 106 106 ...
##  $ CPI_USA: num  108 108 109 109 109 ...
##  $ LOGPEUR: num  4.65 4.66 4.66 4.66 4.66 ...
##  $ LOGPUSA: num  4.68 4.68 4.69 4.69 4.69 ...
##  $ DPEUR  : num  NA 0.00285 0.003788 0.000945 0.000944 ...
##  $ DPUSA  : num  NA 0.006485 0.00736 0.000916 0.000915 ...
##  $ NA     : logi  NA NA NA NA NA NA ...
##  $ Year   : int  2000 2000 2000 2000 2000 2000 2000 2000 2000 2000 ...
##  $ Month  : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ Date   : POSIXct, format: "2000-01-01" "2000-02-01" ...
```

```
##      YYYYMM        TREND           CPI_EUR         CPI_USA     
##  2000M01:  1   Min.   :  1.00   Min.   :105.1   Min.   :107.6  
##  2000M02:  1   1st Qu.: 36.75   1st Qu.:112.5   1st Qu.:115.8  
##  2000M03:  1   Median : 72.50   Median :120.0   Median :126.7  
##  2000M04:  1   Mean   : 72.50   Mean   :120.2   Mean   :126.4  
##  2000M05:  1   3rd Qu.:108.25   3rd Qu.:128.6   3rd Qu.:137.3  
##  2000M06:  1   Max.   :144.00   Max.   :136.0   Max.   :144.7  
##  (Other):138                                                   
##     LOGPEUR         LOGPUSA          DPEUR               DPUSA          
##  Min.   :4.655   Min.   :4.678   Min.   :-0.008611   Min.   :-0.019745  
##  1st Qu.:4.723   1st Qu.:4.751   1st Qu.: 0.000000   1st Qu.: 0.000000  
##  Median :4.787   Median :4.842   Median : 0.001794   Median : 0.002203  
##  Mean   :4.787   Mean   :4.836   Mean   : 0.001802   Mean   : 0.002033  
##  3rd Qu.:4.857   3rd Qu.:4.923   3rd Qu.: 0.003885   3rd Qu.: 0.004906  
##  Max.   :4.913   Max.   :4.975   Max.   : 0.013554   Max.   : 0.011910  
##                                  NA's   :1           NA's   :1          
##     NA               Year          Month      
##  Mode:logical   Min.   :2000   Min.   : 1.00  
##  NA's:144       1st Qu.:2003   1st Qu.: 3.75  
##                 Median :2006   Median : 6.50  
##                 Mean   :2006   Mean   : 6.50  
##                 3rd Qu.:2008   3rd Qu.: 9.25  
##                 Max.   :2011   Max.   :12.00  
##                                               
##       Date                    
##  Min.   :2000-01-01 00:00:00  
##  1st Qu.:2002-12-24 06:00:00  
##  Median :2005-12-16 12:00:00  
##  Mean   :2005-12-15 23:00:00  
##  3rd Qu.:2008-12-08 18:00:00  
##  Max.   :2011-12-01 00:00:00  
## 
```

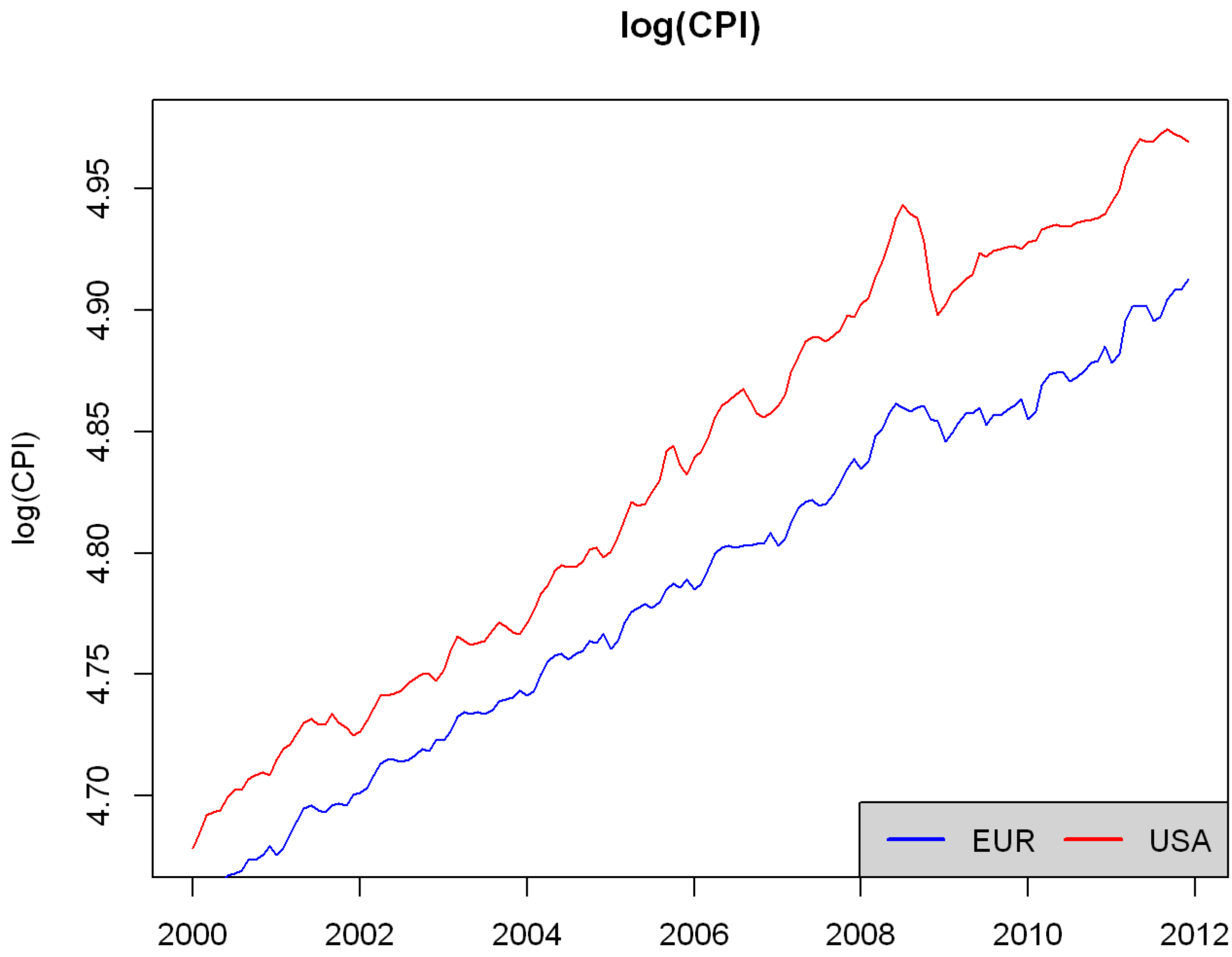
(a) Time series plots

(a) Make time series plots of the CPI of the Euro area and the USA, and also of their logarithm $log(CPI)$ and of the two monthly inflation series $DP = \Delta log(CPI)$. What conclusions do you draw from these plots?



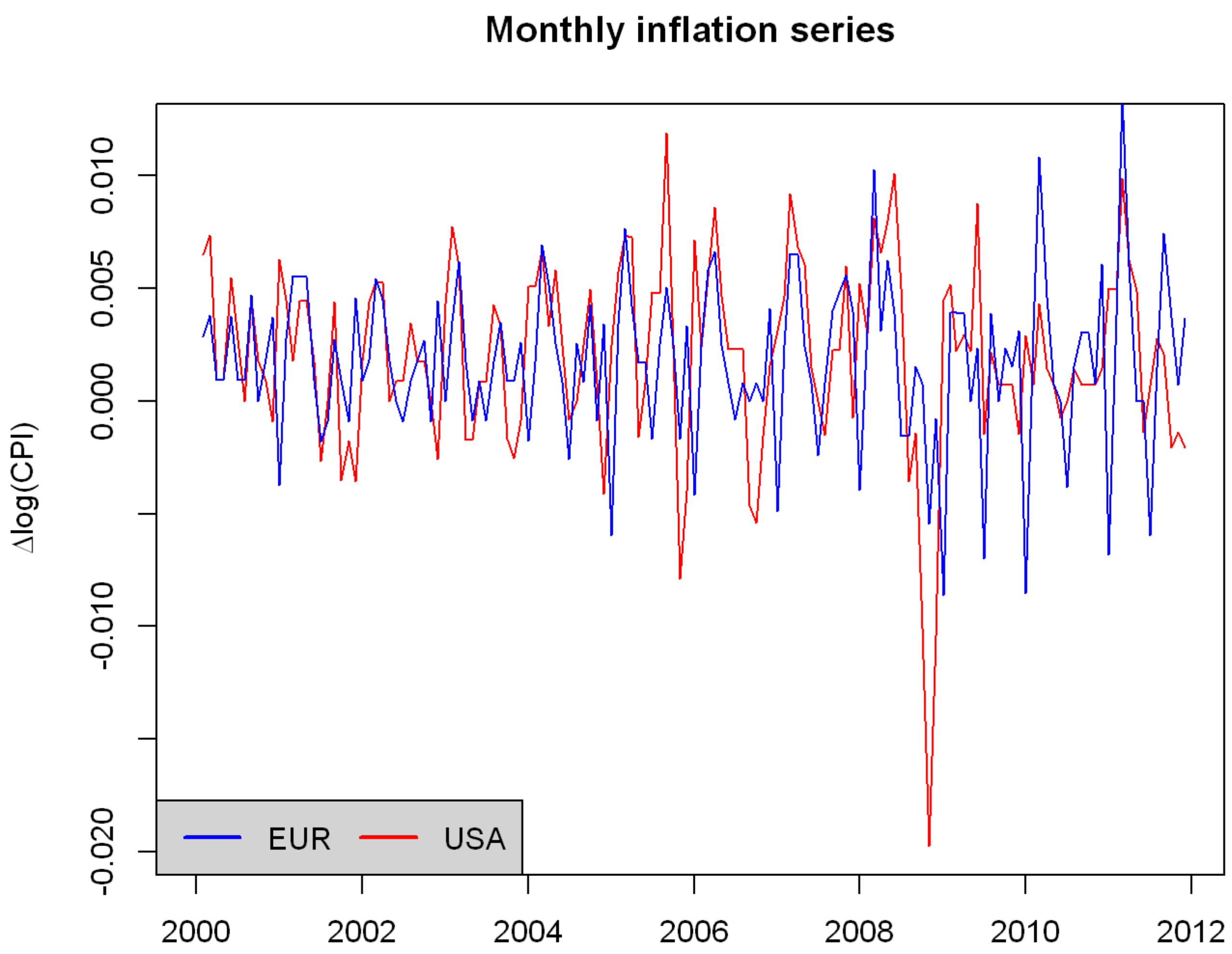
The two consumer price index (CPI) plots indicate that:

- USA and EURO prices seem to be correlated.
- USA prices are typically higher than EURO prices, and the difference seems to slightly increase over time.
- Both indexes are steadily increasing over time, with very few exceptions (i.e. year 2008).
- The indexes increasing trend seems to be rather logarithmic than linear.



The CPI logarithm $log(CPI)$ plots indicate exactly the same things, and the corresponding diagram looks very much similar to the previous one.

The apparently linear logarithmic increase confirms that the indexes increase over time is probably logarithmic rather than linear.



The monthly inflation series $DP = \Delta log(CPI)$ plots indicate that:

- USA and EURO inflation series seem to be correlated.
- Both inflation series seems to be stationary.
- USA inflation usually seems to fluctuate more than EURO inflation, with the exception of the most recent years (i.e. 2009 and later).
- There was a negative inflation peak (indicating a significant deflation), especially in the USA, at the year 2008. This observation is consistent with the unusual CPI decrease shown by the previous diagrams.

(b) Augmented Dickey-Fuller (ADF) testing

(b) Perform the Augmented Dickey-Fuller (ADF) test for the two $log(CPI)$ series. In the ADF test equation, include a constant (α), a deterministic trend term (βt), three lags of $DP = \Delta log(CPI)$ and, of course, the variable of interest $log(CPI_{t-1})$ and its standard error and t-value, and draw your conclusion.

As the data have a clear (increasing) trend direction, the ADF test with deterministic trend is chosen to be performed.

The corresponding model to be tested is the following, for $L = 3$ for three lags of $DP = \Delta log(CPI)$ and a 5% critical value of -3.5 (meaning: reject H_0 of non-stationarity if $t_{\hat{\rho}} < -3.5$):

$$\Delta y_t = \alpha + \beta t + \rho y_{t-1} + \gamma_1 \Delta y_{t-1} + \ldots + \gamma_L \Delta y_{t-L} + \epsilon_t$$

The results:

```
print(adf1 <- adf.test(dat$LOGPEUR, 'stationary', k = lag_order))
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  dat$LOGPEUR
## Dickey-Fuller = -2.8263, Lag order = 3, p-value = 0.2324
## alternative hypothesis: stationary
```

```
print(adf2 <- adf.test(dat$LOGPUSA, 'stationary', k = lag_order))
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  dat$LOGPUSA
## Dickey-Fuller = -2.7345, Lag order = 3, p-value = 0.2706
## alternative hypothesis: stationary
```

ADF testing results

Variable	ADF statistic	p-value
LOGPEUR	**-2.83**	0.232
LOGPUSA	**-2.73**	0.271

Conclusion:

> For both variables, the ADF statistic is greater than the critical value of -3.5. Therefore, the non-stationarity hypothesis is **not rejected**.

(c) Autocorrelations determination and AR model motivation

(c) As the two series of $log(CPI)$ are not cointegrated (you need not check this), we continue by modeling the monthly inflation series $DPEUR = \Delta log(CPIEUR)$ for the Euro area. Determine the sample autocorrelations and the sample partial autocorrelations of this series to motivate the use of the following AR model: $DPEUR_t = \alpha + \beta_1 \, DPEUR_{t-6} + \beta_2 \, DPEUR_{t-12} + \epsilon_t$ Estimate the parameters of this model (sample Jan 2000 - Dec 2010).

In order to estimate the lags with the largest auto-correlation and partial auto-correlation values, in the Jan 2000 - Dec 2010 sample, the sample was filtered appropriately and the corresponding (P)ACF functions ran for all possible lags. The detailed results of this test are shown in Appendix A.

The lags with the largest values found during that process, were 6 and 12:

lags	AC	PAC
6	0.403	0.374
12	0.554	0.398

Thus, the findings motivate using lags 6 and 12 with the AR model. And as this is not an MA model (residuals are not included), AR model could be estimated using the **OLS method** (instead of the MLE method).

Estimating the AR model for lags 6 and 12 and using OLS, produces the following Autoregressive Fit Model:

```
ar_digits = 3
ar_method = 'ols'

ar12 <- ar(datWork$DPEUR[2:(12*11-1)], order.max = 12,
           method = ar_method)
ar           <- round(ar12$ar,          digits = ar_digits)
ar.intercept <- round(ar12$x.intercept, digits = ar_digits)
ar12
```

```
##
## Call:
## ar(x = datWork$DPEUR[2:(12 * 11 - 1)], order.max = 12, method = ar_method)
##
## Coefficients:
##       1        2        3        4        5        6        7        8
##  0.0590   0.0014  -0.0972   0.0082  -0.1393   0.1943  -0.0567  -0.1271
##       9       10       11       12
## -0.0431  -0.1074   0.0602   0.5168
##
## Intercept: -2.316e-05 (0.000223)
##
## Order selected 12  sigma^2 estimated as  5.857e-06
```

Conclusion:

The AR model estimated for lags up to 12, is:

$$
\begin{aligned}
D\hat{PEUR}_t = 0 \\
&+ 0.059 \cdot DPEUR_{t-1} \\
&+ 0.001 \cdot DPEUR_{t-2} \\
&- 0.097 \cdot DPEUR_{t-3} \\
&+ 0.008 \cdot DPEUR_{t-4} \\
&- 0.139 \cdot DPEUR_{t-5} \\
&+ 0.194 \cdot DPEUR_{t-6} \qquad \longleftarrow \\
&- 0.057 \cdot DPEUR_{t-7} \\
&- 0.127 \cdot DPEUR_{t-8} \\
&- 0.043 \cdot DPEUR_{t-9} \\
&- 0.107 \cdot DPEUR_{t-10} \\
&+ 0.06 \cdot DPEUR_{t-11} \\
&+ 0.517 \cdot DPEUR_{t-12} \qquad \longleftarrow \\
&+ \epsilon_t
\end{aligned}
$$

Or (even simpler), for lags 6 and 12 alone:

$$
\begin{aligned}
D\hat{PEUR}_t = 0 \\
&+ 0.194 \cdot DPEUR_{t-6} \qquad \longleftarrow \\
&+ 0.517 \cdot DPEUR_{t-12} \qquad \longleftarrow \\
&+ \epsilon_t
\end{aligned}
$$

(d) AR model extending and ADL model estimation

(d) Extend the AR model of part (c) by adding lagged values of monthly inflation in the USA at lags 1, 6, and 12. Check that the coefficient at lag 6 is not significant, and estimate the ADL model $DPEUR_t = \alpha + \beta_1\, DPEUR_{t-6} + \beta_2\, DPEUR_{t-12} + \gamma_1\, DPUSA_{t-1} + \gamma_2\, DPUSA_{t-12} + \epsilon_t$ (sample Jan 2000 - Dec 2010).

The suggested AR model extension, with the lagged values of monthly inflation in the USA at lags 1, 6, and 12 as an explanatory factor, initially will be an ADL model like this:

$$
\begin{aligned}
DP\hat{EUR}_t = \alpha \\
&+ \beta_1 \cdot DPEUR_{t-6} \\
&+ \beta_2 \cdot DPEUR_{t-12} \\
&+ \gamma_1 \cdot DPUSA_{t-1} \\
&+ \gamma_6 \cdot DPUSA_{t-6} \\
&+ \gamma_2 \cdot DPUSA_{t-12} \\
&+ \epsilon_t
\end{aligned}
$$

First ADL model estimation

```
# Convert sample Jan 2000 - Dec 2010 to timeseries object(s) for dynlm(.) function
dpEur <- ts(datWork$DPEUR, start =2)
dpUsa <- ts(datWork$DPUSA, start =2)
# Estimating Autoregressive Distributed Lag model: ADL(p; r).
model <- dynlm(dpEur ~ L(dpEur, 6) + L(dpEur, 12) + L(dpUsa, 1) + L(dpUsa, 6) + L(dpUsa, 12))
print(ADL.summary <- summary(model))
```

```
##
## Time series regression with "ts" data:
## Start = 15, End = 133
##
## Call:
## dynlm(formula = dpEur ~ L(dpEur, 6) + L(dpEur, 12) + L(dpUsa,
##     1) + L(dpUsa, 6) + L(dpUsa, 12))
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0065866 -0.0016535 -0.0000118  0.0012630  0.0082682
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.0004407  0.0002853   1.545    0.125
## L(dpEur, 6)   0.2029891  0.0785520   2.584    0.011 *
## L(dpEur, 12)  0.6367464  0.0874766   7.279 4.78e-11 ***
## L(dpUsa, 1)   0.2264287  0.0511286   4.429 2.20e-05 ***
## L(dpUsa, 6)  -0.0560565  0.0547645  -1.024    0.308
## L(dpUsa, 12) -0.2300418  0.0541695  -4.247 4.47e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.002272 on 113 degrees of freedom
## Multiple R-squared:  0.5602, Adjusted R-squared:  0.5408
## F-statistic: 28.79 on 5 and 113 DF,  p-value: < 2.2e-16
```

First ADL model estimation results:

Variable	Coefficient	Std.Error	t.stat	p.value
(Intersept)	0	3e-04	1.5445	0.1253
$DPEUR_{t-6}$	0.203	0.0786	2.5841	0.011
$DPEUR_{t-12}$	0.637	0.0875	7.279	0
$DPUSA_{t-1}$	0.226	0.0511	4.4286	0

Variable	Coefficient	Std.Error	t.stat	p.value
$DPUSA_{t-6}$	-0.056	0.0548	-1.0236	0.3082
$DPUSA_{t-12}$	-0.23	0.0542	-4.2467	0
…	…	…	…	…
R^2:	0.5602	**F-statistic:**	28.79 on 5 and 113 DF	…

Conclusion:

> The coefficient $DPUSA_{t-6}$ is indeed not-significant. ($value = -0.056$, $t - statistic = -1.0236$, $p - value = 0.3082$).
>
> Therefore, the ADL model can be simplified like this:
>
> $$\begin{aligned} D\hat{PEUR}_t = \alpha \\ & + \beta_1 \cdot DPEUR_{t-6} \\ & + \beta_2 \cdot DPEUR_{t-12} \\ & + \gamma_1 \cdot DPUSA_{t-1} \\ & + \gamma_2 \cdot DPUSA_{t-12} \\ & + \epsilon_t \end{aligned}$$
>
> Model characteristics: $R^2 = 0.5602$, F-statistic: 28.79 on 5 and 113 DF

Simplified ADL model estimation

```
# Estimating Autoregressive Distributed Lag model: ADL(p; r).
model <- dynlm(dpEur ~ L(dpEur, 6) + L(dpEur, 12) + L(dpUsa, 1) + L(dpUsa, 12))
print(ADL.summary <- summary(model))
```

```
##
## Time series regression with "ts" data:
## Start = 15, End = 133
##
## Call:
## dynlm(formula = dpEur ~ L(dpEur, 6) + L(dpEur, 12) + L(dpUsa,
##     1) + L(dpUsa, 12))
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0067809 -0.0016356  0.0000532  0.0013660  0.0082448
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.0003391  0.0002676   1.267   0.2076
## L(dpEur, 6)   0.1687310  0.0710801   2.374   0.0193 *
## L(dpEur, 12)  0.6551529  0.0856263   7.651 6.93e-12 ***
## L(dpUsa, 1)   0.2326460  0.0507772   4.582 1.19e-05 ***
## L(dpUsa, 12) -0.2264880  0.0540694  -4.189 5.55e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.002273 on 114 degrees of freedom
## Multiple R-squared:  0.5561, Adjusted R-squared:  0.5406
## F-statistic: 35.71 on 4 and 114 DF,  p-value: < 2.2e-16
```

Variable	Coefficient	Std.Error	t.stat	p.value
(Intersept)	0	3e-04	1.2673	0.2076
$DPEUR_{t-6}$	0.169	0.0711	2.3738	0.0193
$DPEUR_{t-12}$	0.655	0.0856	7.6513	0
$DPUSA_{t-1}$	0.233	0.0508	4.5817	0
$DPUSA_{t-12}$	-0.226	0.0541	-4.1888	1e-04
…	…	…	…	…
R^2:	0.5561	**F-statistic:**	35.71 on 4 and 114 DF	…

Conclusion:

The simplified ADL model is:

$$\begin{aligned} D\hat{PEUR}_t = 0 & \\ & + 0.169 \cdot DPEUR_{t-6} \\ & + 0.655 \cdot DPEUR_{t-12} \\ & + 0.233 \cdot DPUSA_{t-1} \\ & - 0.226 \cdot DPUSA_{t-12} \\ & + \epsilon_t \end{aligned}$$

Model characteristics: R^2 = 0.5561, F-statistic: 35.71 on 4 and 114 DF

(e) 2011 forecasting

(e) Use the models of parts (c) and (d) to make two series of 12 monthly inflation forecasts for 2011. At each month, you should use the data that are then available, for example, to forecast inflation for September 2011 you can use the data up to and including August 2011. However, do not re-estimate the model and use the coefficients as obtained in parts (c) and (d). For each of the two forecast series, compute the values of the root mean squared error $(RMSE)$, mean absolute error (MAE), and the sum of the forecast errors (SUM). Finally, give your interpretation of the outcomes.

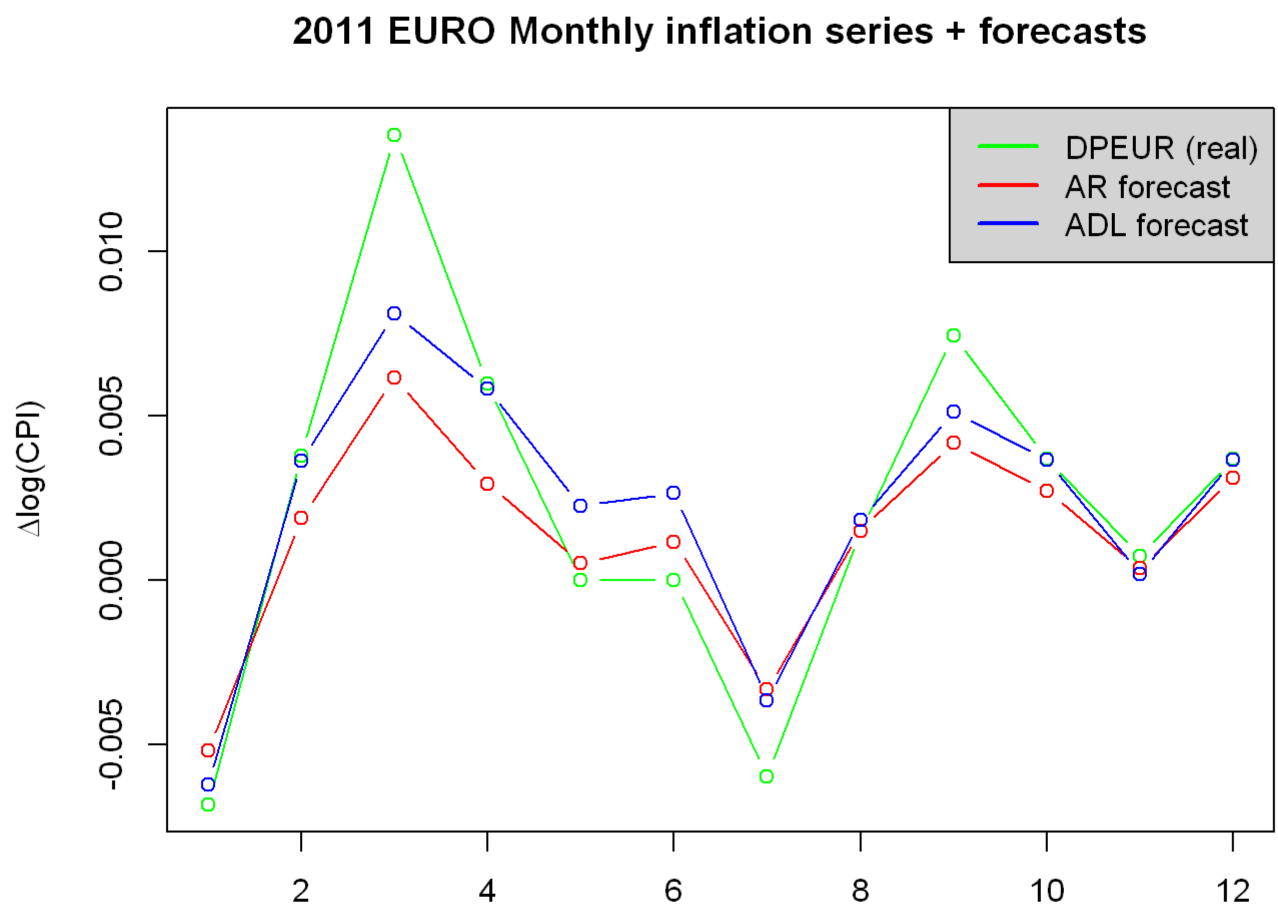
The (simpler) **AR model** estimated in part (c):

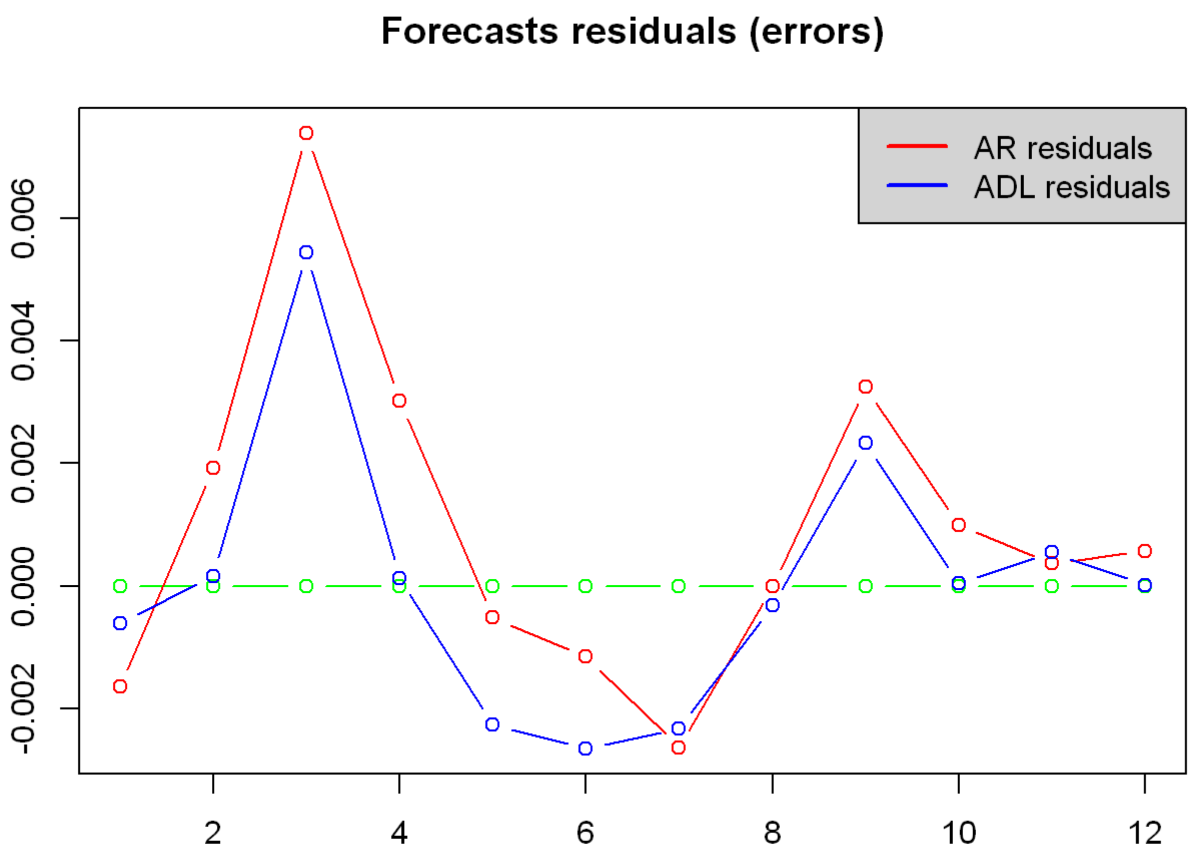
$$D\hat{PEUR}_t = 0 + 0.194 \cdot DPEUR_{t-6} + 0.517 \cdot DPEUR_{t-12} + \epsilon_t$$

and the simplified **ADL model** estimated in part (d):

$$\begin{aligned} D\hat{PEUR}_t = & \ 0 + 0.169 \cdot DPEUR_{t-6} + 0.655 \cdot DPEUR_{t-12} \\ & + 0.233 \cdot DPUSA_{t-1} - 0.226 \cdot DPUSA_{t-12} + \epsilon_t \end{aligned}$$

are used to forecast the EURO 2011 monthly inflation series, and compared against **the real 2011 values**:


2011 EURO Monthly inflation series + forecasts
DPEUR (real)
AR forecast
ADL forecast
Δlog(CPI)
0.010
0.005
0.000
-0.005
2
4
6
8
10
12



Forecasting evaluation

	RMSE	MAE	SUM
AR model forecasting	0.0028	0.0020	0.0115
ADL model forecasting	0.0021	0.0014	0.0005

Conclusion:

Clearly, the ADL model performed better forecasts than the AR model, as it scored less at all errors scores.

This is especially true about the SUM errors score, which was about ~24 times higher for the AR model. These scores indicate that while the AR model suffered by a ~1.15% forecasting overestimation, the ADL model suffered only by a 0.05% forecasting overestimation, a significant difference!

This means that the insight used in part (d), about using the USA monthly inflation series at lags 1 and 12 in order to forecast the EURO monthly inflation, was towards to the right direction.

Appendix A

(c) Autocorrelations determination and AR model motivation

Autocorrelation functions (P)ACF results, for all possible lags:

```
demean <-  TRUE

# Select sample Jan 2000 - Dec 2010
datWork <- dat[1:(12*11),]

nn <- nrow(datWork) - 1
# Prepare results data.frame
ac <- data.frame(lag = 1:nn)
ac$AC <- NA;    ac$PAC <- NA
for (i in 1:nn) {
    acf <- acf(datWork$DPEUR, lag.max = i, type = 'correlation',
               na.action = na.pass, plot = FALSE, demean = demean)
    #print(acf)
    pcf <- acf(datWork$DPEUR, lag.max = i, type = 'partial',
               na.action = na.pass, plot = FALSE, demean = demean)
    #print(pcf)
    ac[i, 1] <- i
    ac[i, 2] <- acf$acf[i + 1, 1, 1]
    ac[i, 3] <- pcf$acf[i + 0, 1, 1]
}

# Print-out ac data.frame as a table
kable(ac, format = "markdown", align = 'c', digits = ac_digits)
```

lag	AC	PAC
1	0.083	0.083
2	-0.109	-0.117
3	-0.199	-0.183
4	-0.159	-0.148
5	-0.088	-0.120
6	0.403	0.374
7	-0.035	-0.195
8	-0.173	-0.166
9	-0.162	-0.068
10	-0.111	-0.076
11	0.015	0.042
12	0.554	0.398
13	0.011	-0.140

lag	AC	PAC
14	-0.162	-0.075
15	-0.183	-0.037
16	-0.231	-0.208
17	-0.053	0.041
18	0.309	-0.075
19	-0.054	-0.150
20	-0.159	-0.014
21	-0.149	-0.142
22	-0.107	-0.008
23	0.017	-0.039
24	0.516	0.187
25	0.004	-0.075
26	-0.104	0.020
27	-0.119	0.041
28	-0.155	-0.023
29	-0.027	0.021
30	0.308	-0.047
31	-0.022	-0.003
32	-0.129	-0.048
33	-0.157	-0.128
34	-0.127	-0.084
35	0.049	0.027
36	0.487	0.114
37	0.029	-0.043
38	-0.076	0.044
39	-0.109	0.004
40	-0.163	0.026
41	-0.036	-0.031
42	0.238	-0.100
43	-0.027	0.033
44	-0.078	0.037
45	-0.146	-0.076

lag	AC	PAC
46	-0.116	-0.013
47	0.022	-0.034
48	0.408	0.027
49	-0.006	-0.066
50	-0.012	0.070
51	-0.081	0.041
52	-0.141	0.025
53	-0.058	-0.053
54	0.233	0.023
55	-0.054	-0.016
56	-0.060	-0.025
57	-0.113	0.005
58	-0.120	-0.080
59	-0.009	-0.020
60	0.354	-0.001
61	0.012	-0.009
62	-0.030	-0.041
63	-0.042	0.040
64	-0.129	0.022
65	-0.022	0.035
66	0.165	-0.061
67	0.008	0.086
68	-0.061	-0.014
69	-0.087	0.011
70	-0.093	0.062
71	0.014	-0.040
72	0.246	-0.075
73	-0.002	-0.035
74	0.006	0.000
75	-0.044	-0.042
76	-0.111	0.004
77	-0.004	0.043

lag	AC	PAC
78	0.143	-0.002
79	-0.033	-0.017
80	-0.035	0.004
81	-0.048	0.103
82	-0.093	-0.031
83	-0.014	-0.015
84	0.192	-0.022
85	0.031	0.091
86	0.024	0.003
87	0.017	-0.007
88	-0.088	0.032
89	-0.013	-0.002
90	0.071	-0.022
91	-0.060	-0.127
92	-0.050	-0.019
93	-0.034	0.052
94	-0.028	0.084
95	0.039	0.069
96	0.143	-0.021
97	-0.027	0.017
98	-0.027	-0.113
99	0.002	0.017
100	-0.073	-0.037
101	-0.016	-0.030
102	0.068	0.054
103	-0.043	-0.011
104	-0.037	0.004
105	-0.010	0.003
106	-0.033	-0.034
107	0.032	0.037
108	0.105	0.000
109	-0.024	0.013

lag	AC	PAC
110	-0.059	-0.072
111	-0.002	-0.044
112	-0.047	0.007
113	-0.009	-0.073
114	0.043	-0.043
115	-0.009	0.041
116	0.005	0.062
117	0.030	-0.027
118	-0.017	0.014
119	-0.031	-0.067
120	0.021	-0.027
121	0.009	0.042
122	-0.004	0.006
123	0.011	-0.026
124	-0.010	-0.033
125	-0.010	-0.035
126	0.008	0.006
127	0.001	0.041
128	-0.003	-0.035
129	0.006	-0.048
130	0.003	-0.011
131	NA	NA

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