Stochastic Process and Forecasting Assignment

Nick Head

15 April 2015

Question 2

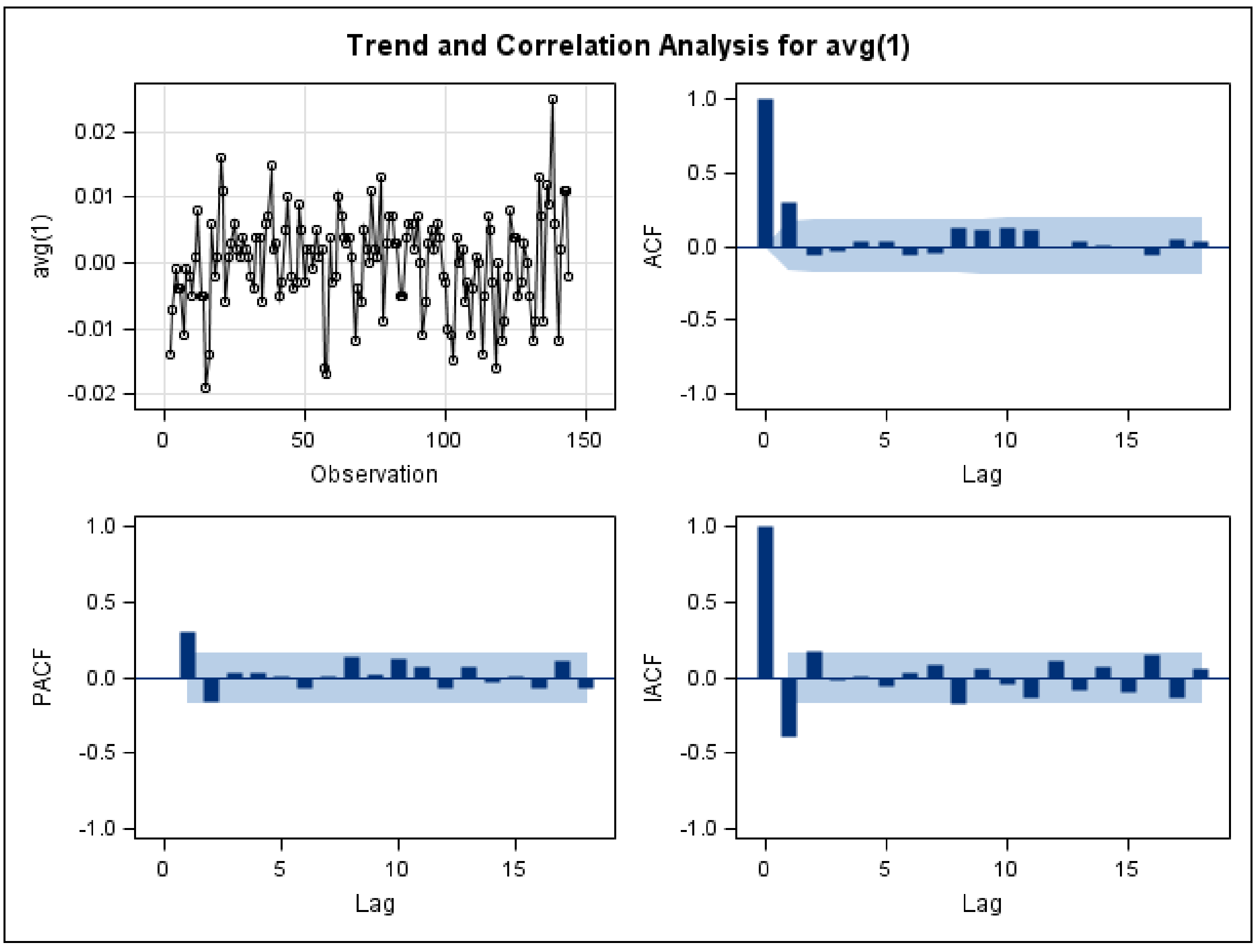
i)

The following SAS code was used to identify and estimate appropriate univariate ARIMA models for each of the avg and end exchange rate time series:

```
proc arima data=LatDol;
identify var=avg(1) nlag=18;
estimate q=1 noint;
identify var=end nlag=18;
estimate p=1;
run;
```

The diagnostics plots indicates that the first difference of Avg has an ACF cut-off at lag 1, thereby leading us to believe the data follows an Arima(0,1,1) model with the following model equation:

$$\Delta Y_t = -0.36347\epsilon_{t-1} + \epsilon_t$$



In addition the Ljung-Box chi-square statistics do not have any significant p-values, giving further weight to the chosen model:

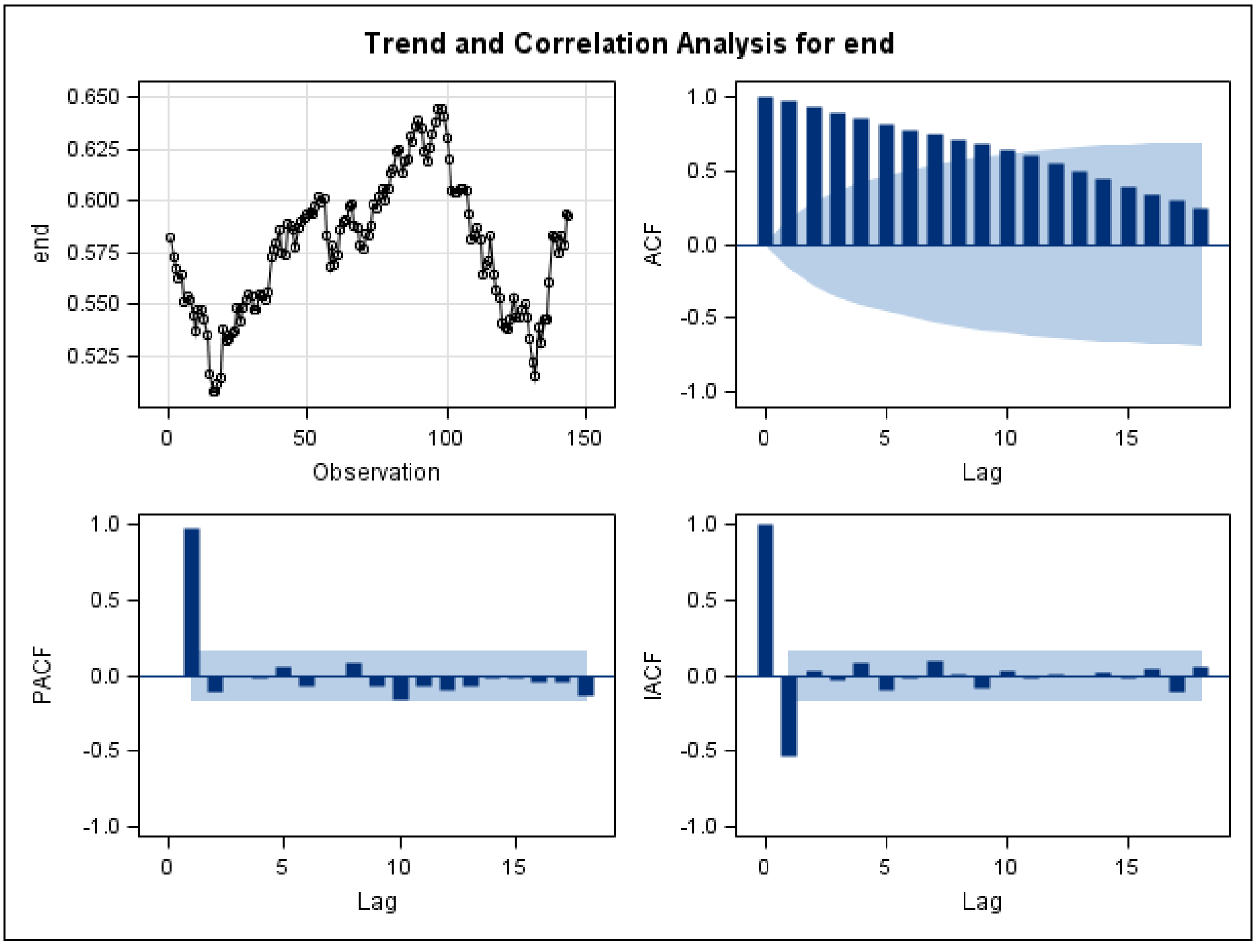
```
Autocorrelation Check of Residuals
```

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.30	5	0.9346	-0.010	-0.041	-0.034	0.032	0.046	-0.051
12	8.50	11	0.6681	-0.071	0.133	0.046	0.079	0.104	-0.066
18	11.49	17	0.8299	0.059	-0.022	0.030	-0.087	0.075	0.015
24	16.13	23	0.8497	-0.014	-0.121	-0.044	-0.074	-0.025	-0.066

End is found to follow an AR(1) model with the following model equation:

$$Y_t = 0.58167 + 0.96945 Y_{t-1} + \epsilon_t$$

This model was identified by the lag 1 cut-off in the PACF as shown in the diagnostics plots below:



In addition the Ljung-Box chi-square statistics do not have any significant p-values, giving further weight to the chosen model:

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations

6	2.84	5	0.7239	0.116	0.043	0.007	-0.048	0.040	0.006
12	11.19	11	0.4279	-0.050	0.081	0.153	0.092	0.081	0.076
18	13.25	17	0.7192	-0.035	-0.019	-0.019	-0.022	0.095	-0.033
24	18.91	23	0.7064	-0.024	-0.076	-0.109	-0.044	-0.028	-0.108

ii)

The following SAS code identifies and fits a VAR(p) model to the bivariate data:

```
proc varmax data=LatDol;
model end avg /
minic = (type=sbc p=(0:10) q=0) noint dif=(end(1) avg(1)) PRINT=DIAGNOSE;
output lead=3;
run;
```

Which gives the following truncated output:

Model Parameter Estimates

Equation	Parameter	Estimate	Standard Error	t Value	Pr > |t|	Variable
end	AR1_1_1	0.03600	0.11185	0.32	0.7480	end(t-1)
	AR1_1_2	0.11050	0.12356	0.89	0.3727	avg(t-1)
avg	AR1_2_1	0.70995	0.07553	9.40	0.0001	end(t-1)
	AR1_2_2	-0.22236	0.08344	-2.66	0.0086	avg(t-1)

Covariances of Innovations

Variable	end	avg
end	0.00007	0.00004
avg	0.00004	0.00003

Based off which the fitted model is as follows:

$$\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} .03600 & 0.11050 \\ .70995 & 0.22236 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix} + \epsilon_t$$

The following Portmanteau Statistics shows significant p-values at all lags indicating that this VAR(1) model does not fit adequatly:

Portmanteau Test for Cross Correlations of Residuals

Up To Lag	DF	Chi-Square	Pr > ChiSq
2	4	23.29	0.0001
3	8	23.46	0.0028
4	12	26.37	0.0095
5	16	34.09	0.0053
6	20	35.06	0.0198
7	24	43.30	0.0092
8	28	44.79	0.0232
9	32	51.56	0.0157
10	36	58.37	0.0106
11	40	63.56	0.0103
12	44	64.87	0.0219

The following outputs show the forecasts of the average exchange rate for the next three months of 2006 are: 0.59273, 0.59261, 0.59261

Forecasts

Variable	Obs	Forecast	Standard Error	95% Confidence Limits	
end	145	0.59274	0.00810	0.57686	0.60863
	146	0.59270	0.01204	0.56911	0.61630
	147	0.59269	0.01530	0.56270	0.62268
avg	145	0.59273	0.00547	0.58201	0.60346
	146	0.59261	0.01102	0.57101	0.61421
	147	0.59261	0.01435	0.56448	0.62074

iii)

```
ODS LISTING CLOSE;
ODS HTML;
data LatDol;
infile 'latdol.txt' delimiter='09'x MISSOVER DSD lrecl=32767 ;
       informat year best32. ;
       informat month   best32. ;
       informat avg  best32. ;
       informat end  best32. ;
       format year best12. ;
       format month   best12. ;
       format avg  best12. ;
       format end  best12. ;
    input
                year
                month
                avg
                end
    ;
date = mdy(month,1,year);
format date year4.;
proc print data=LatDol;
proc timeplot data=LatDol;
plot avg;

proc arima data=LatDol;
identify var=end nlag=18;
estimate p=1;

identify var=avg(1) nlag=18;
estimate q=1 noint;

identify var=avg(1) crosscor=end nlag=18;
estimate q=1 input=(2 $ / (1) end) noint;

forecast lead=3 out=results;

run;

ODS HTML CLOSE;
ODS LISTING;
```

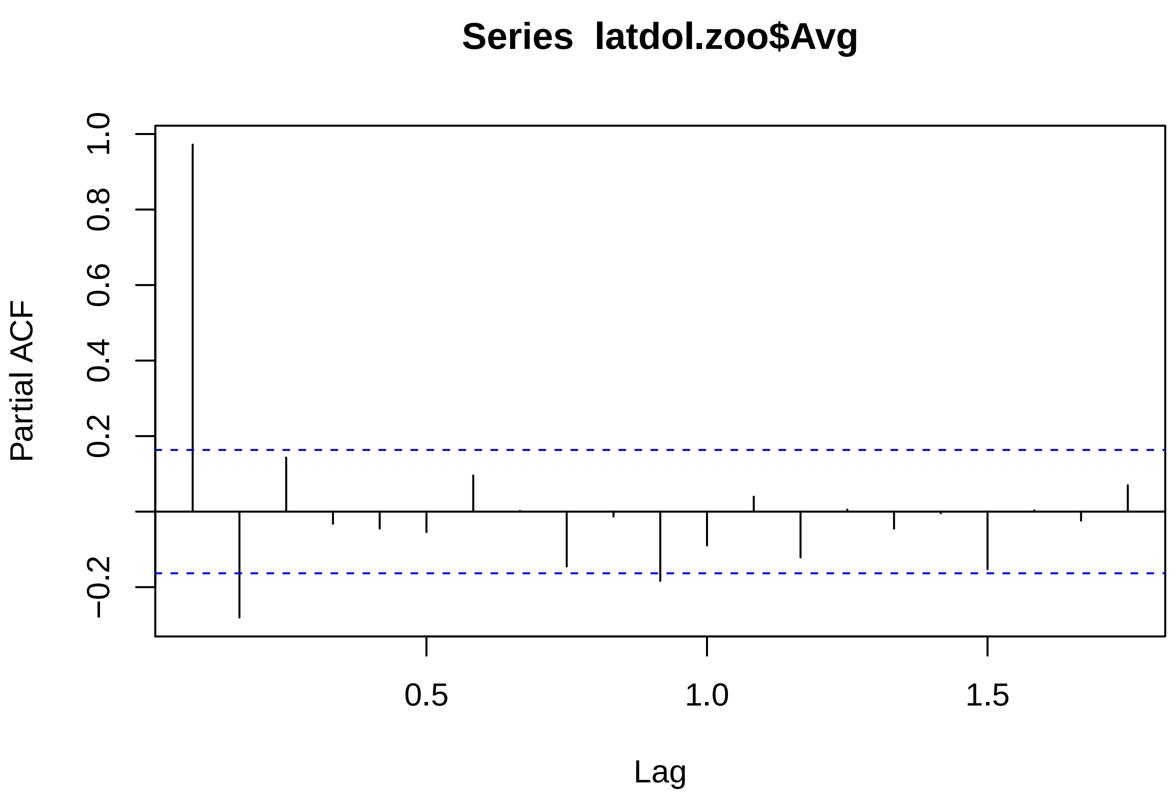
```r
library(zoo)
```

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

```r
library(forecast)
```

```
## Loading required package: timeDate
## This is forecast 5.4
```

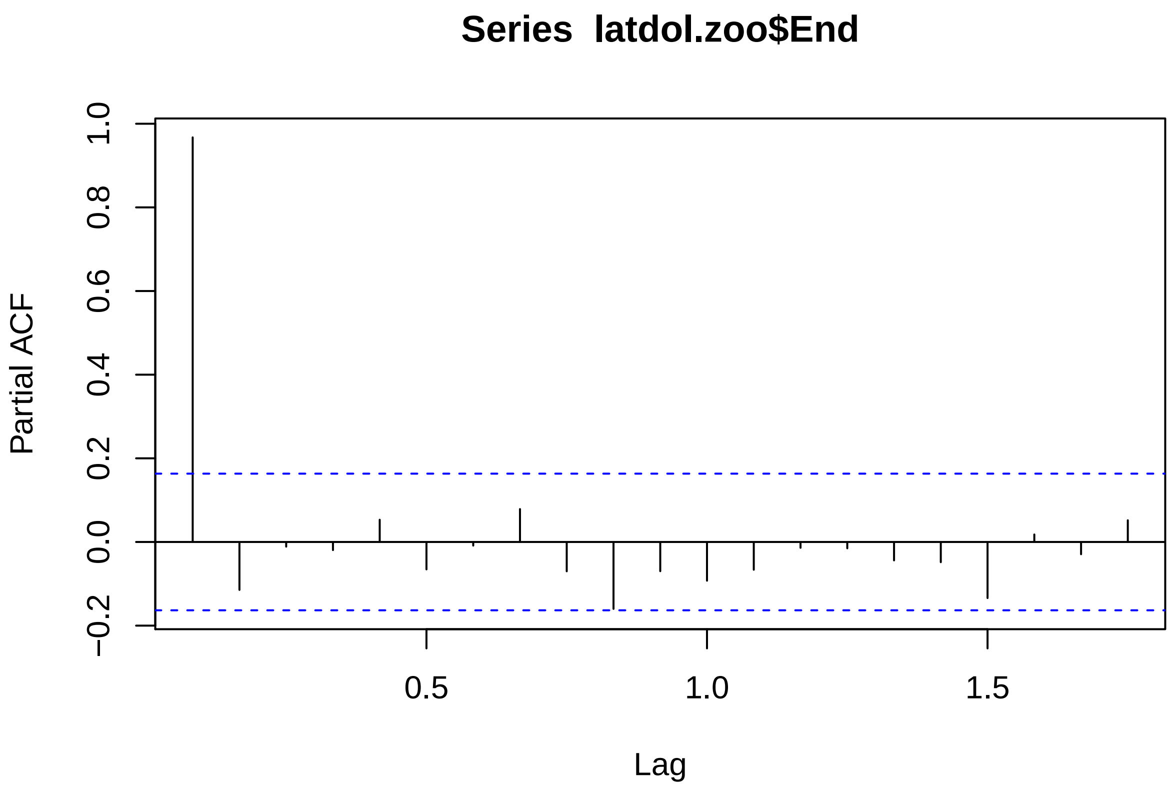
```r
latdol.zoo <- read.zoo("LatDol.dat",
                        index.column = 1:2,
                        FUN = function(year, month){ as.yearmon(paste(year, month, sep = "-"))})
colnames(latdol.zoo) = c("Avg", "End")

#plot(latdol.zoo)
#plot(diff(latdol.zoo))

#acf(latdol.zoo$Avg)
#acf(diff(latdol.zoo$Avg))
acf(latdol.zoo$Avg, type='partial') #!!!
```



```r
#fitAvg <- auto.arima(latdol.zoo$Avg)
#plot(forecast(fitAvg,h=20))
arima(latdol.zoo$Avg, order = c(0,1,1))
```

```
## Series: latdol.zoo$Avg
## ARIMA(0,1,1)
##
## Coefficients:
##          ma1
##       0.3672
## s.e.  0.0786
##
## sigma^2 estimated as 4.792e-05:  log likelihood=508.16
## AIC=-1012.32   AICc=-1012.24   BIC=-1006.4
```

```r
#acf(latdol.zoo$End)
#acf(diff(latdol.zoo$End))
acf(latdol.zoo$End, type='partial') #!!!
```

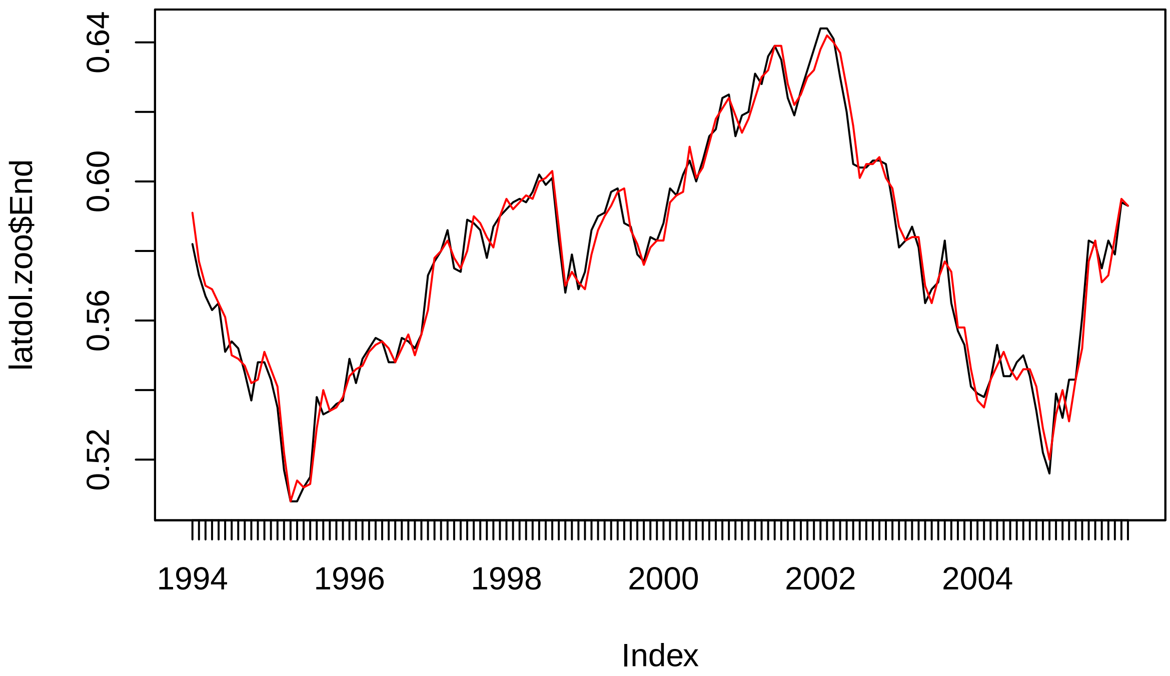



```r
#acf(diff(latdol.zoo$End), type='partial')

#fitEnd <- auto.arima(latdol.zoo$End)
#plot(forecast(fitEnd,h=20))
arima(latdol.zoo$End, order = c(1,0,0))
```

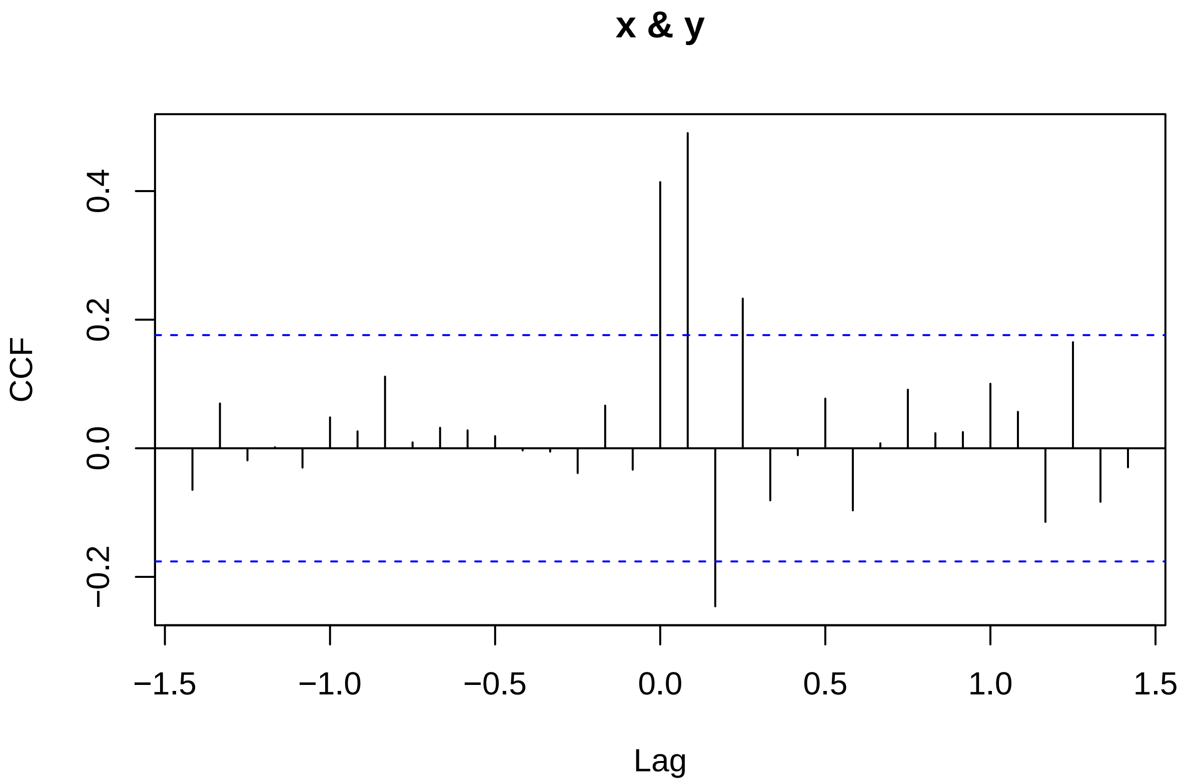
```
## Series: latdol.zoo$End
## ARIMA(1,0,0) with non-zero mean
```

```
##
## Coefficients:
##          ar1  intercept
##       0.9635     0.5796
## s.e.  0.0193     0.0157
##
## sigma^2 estimated as 6.451e-05:  log likelihood=489.06
## AIC=-972.12   AICc=-971.95   BIC=-963.21
```

```r
plot(latdol.zoo$End, ylim=range(latdol.zoo$End, latdol.zoo$Avg))
lines(latdol.zoo$Avg, col=2)
```




```r
prewhiten(latdol.zoo$Avg, latdol.zoo$End)
```




```r
ccf(latdol.zoo$Avg, latdol.zoo$End)
```