summary statistics

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In this tutorial, you get familiarised with the basic ideas of time series data, using Japanese financial data from Jan 1975 to Dec 1995. Dataset contains 10-year bond return (end of month), 3-month Tokyo Interbank Offerd Rate (TIBOR) and Collaterised overnight call rate (monthy average).

First, I import the libraries and dataset, and then compute the spread, which is the difference of 10-year bond return and 3-month TIBOR.

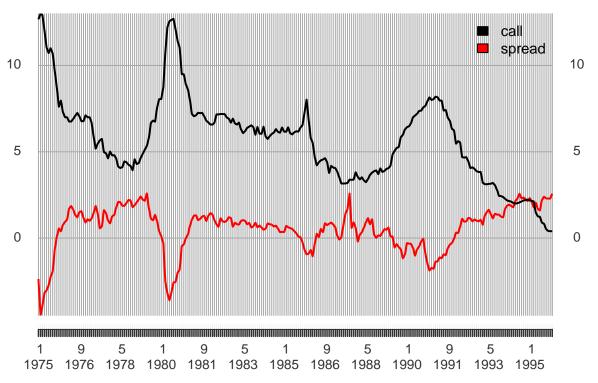
```
library(magrittr)
library(tidyverse)
library(xts)
dat<- read.csv("~/Documents/GitHub/Applied_TimeSeries_Analysis/dat/spreadCall.csv",</pre>
               header=F, skip=2, stringsAsFactors = F) %>%
  set_colnames(c('date','tenYearBond', 'TIBOR', 'call')) %>%
 mutate(spread=tenYearBond-TIBOR)
datXts \leftarrow xts(dat[,c(4,5)], order.by = as.yearmon(dat[,1], format="%Y/%m"))
first(datXts, "3 months")
##
             call spread
   1 1975 12.674 -2.37
    2 1975 13.000 -4.48
## 3 1975 12.920 -3.93
last(datXts, "3 months")
##
           call spread
## 10 1995 0.41
                  2.29
## 11 1995 0.40
                  2.29
## 12 1995 0.40
                  2.57
```

1. Basics of time series data

First thing to do is to vidualise the data.

```
plot.xts(datXts, legend.loc = 7)
```





The sample means of call and spread are

1.0000000 -0.7619003

```
colMeans(datXts)
```

call

```
## call spread
## 5.7216383 0.5613095
```

Next, variance covariance[correlation] matrix gives a bries idea of the data series.

To get the correlation matrix, we divide variance covariance matrix by the standard diviation matrix, which I call sdMat (Variances on diagonal and cross product of standard diviations on off-diagonal elements).

```
div<-scale(datXts, scale=F) # diviation from mean</pre>
vcov<-t(div)%*%div/(nrow(div)-1)
vcov
##
                call
                         spread
## call
            6.281399 -2.463163
## spread -2.463163 1.663924
sdCall<- sd(datXts$call)</pre>
sdSpread<- sd(datXts$spread)</pre>
sdMat<- matrix(c(sdCall^2, sdCall*sdSpread, sdCall*sdSpread, sdSpread^2),2)</pre>
sdMat
##
             [,1]
                       [,2]
## [1,] 6.281399 3.232920
## [2,] 3.232920 1.663924
corrMat<- vcov/sdMat</pre>
corrMat
##
                 call
                           spread
```

```
## spread -0.7619003 1.0000000
```

In addition to mean, variance and covariance, it is important to report autocovariance since time series data is characterised by its time-dependent order.

auto-variance covariance matrix is shown as follows where k represents the lag length.

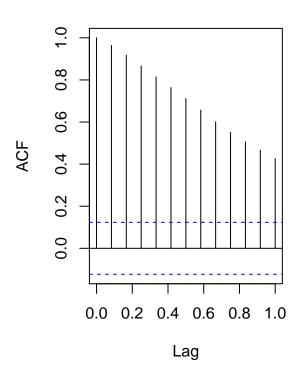
```
\begin{bmatrix} cov(spread_t, spread_{t-k}) & cov(spread_t, call_{t-k}) \\ cov(call_t, spread_{t-k}) & cov(call_t, call_{t-k}) \end{bmatrix}
```

As examples, I consider k=1 and k=12.

```
autoCov_k12<- t(div[13:nrow(datXts),]) %*% div[1:(nrow(datXts)-12),]/(nrow(div)-13) # k=12
autoCov_k1
##
             call
                    spread
## call
         6.078412 -2.365019
## spread -2.369980 1.560101
autoCov_k12
##
              call
                      spread
         2.8124375 -0.6140454
## call
## spread -0.2104592 0.1605558
autoCov_k1/sdMat
##
              call
                      spread
## call
         0.9676844 -0.7315429
## spread -0.7330772 0.9376037
autoCov_k12/sdMat
##
               call
                        spread
## call
         0.44774062 -0.18993526
## spread -0.06509881 0.09649227
The autocorrelation plot (correlogram) for call and spread are
par(mfrow=c(1,2))
acf(datXts$call,lag.max = 12)
acf(datXts$spread,lag.max = 12)
```

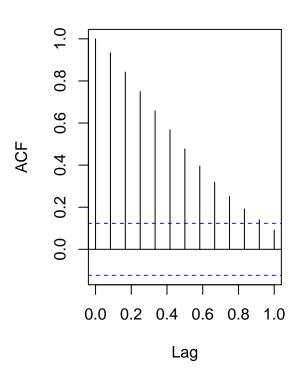
Series datXts\$call

Series datXts\$spread



##

data: datXts\$spread



Blue dotted line shows the critical value for the autocorrelation test. Under the null hypothesis of no autocorrelation, the test statistics (auto correlation function) follows standard normal distribution divided by the square root of the number of observations, i.e. $1.96/\sqrt{252} = 0.123$. As we see from the correlation matrix, the null hypothesis of no autocorrelation is rejected for all the abservations except 12-lag spread. Note however, that this test is only for a specic lag (imagin t-test).

Ljung-Box test offers a statistical way to examine if any of a group of autocorrelations of a time series data is different from zero. Null hypothesis therefore is that the autocorrelations for up to 12 lags are all zero $(\rho_1 = \rho_2 = ... = \rho_{12} = 0)$. We test for lag length of one, six and twelve (k=1, 6 and 12).

```
# Ljung-Box test
for (i in c(1,6,12)){
  print(Box.test(datXts$spread, lag=i, type='L'))
}
##
    Box-Ljung test
##
##
##
  data: datXts$spread
##
   X-squared = 222.4, df = 1, p-value < 2.2e-16
##
##
##
    Box-Ljung test
##
##
   data: datXts$spread
##
   X-squared = 802.52, df = 6, p-value < 2.2e-16
##
##
##
    Box-Ljung test
```

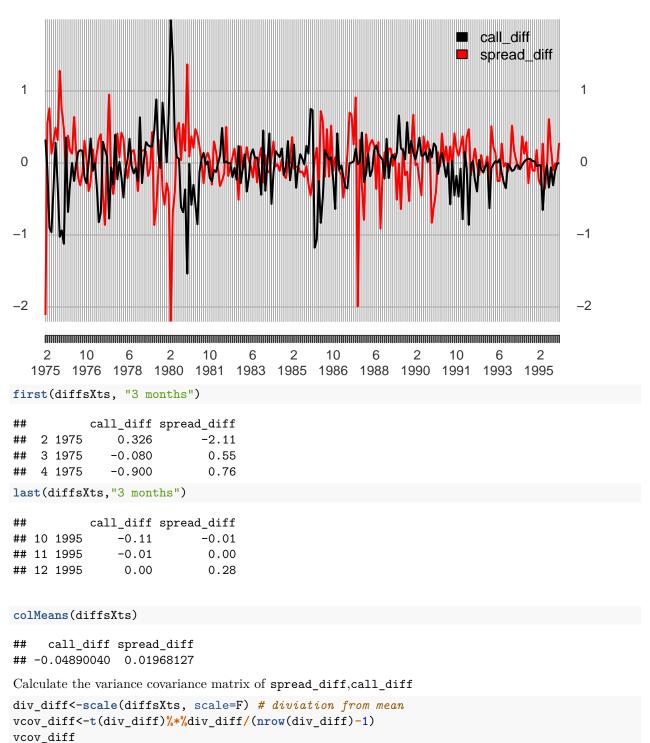
```
## X-squared = 903.72, df = 12, p-value < 2.2e-16
for (i in c(1,6,12)){
  print(Box.test(datXts$call, lag=i, type='L'))
}
##
##
    Box-Ljung test
##
## data: datXts$call
## X-squared = 236.9, df = 1, p-value < 2.2e-16
##
##
##
   Box-Ljung test
##
## data: datXts$call
## X-squared = 1099.3, df = 6, p-value < 2.2e-16
##
##
##
   Box-Ljung test
##
## data: datXts$call
## X-squared = 1560.4, df = 12, p-value < 2.2e-16
```

The result rejects the null hypothesis at all lags inspected, indicating call and spread indeed have autocorrelation.

Finally, I repeat the same steps, but this time for series of first order difference, which I call call_diff and spread_diff, respectively.

```
diffsXts<- diff.xts(datXts) %>%
    set_colnames(c("call_diff","spread_diff")) %>%
    na.omit
plot.xts(diffsXts,legend.loc = 7)
```

diffsXts 2 1975 / 12 1995



```
## call_diff spread_diff

## call_diff 0.14720440 -0.08578896

## spread_diff -0.08578896 0.17005830

sdCall_diff<- sd(diffsXts$call_diff)

sdSpread_diff<- sd(diffsXts$spread_diff)
```

```
sdMat_diff<- matrix(c(sdCall_diff^2, sdCall_diff*sdSpread_diff,</pre>
                sdCall_diff*sdSpread_diff, sdSpread_diff^2),2)
sdMat_diff
##
             [,1]
                      [,2]
## [1,] 0.1472044 0.1582192
## [2,] 0.1582192 0.1700583
corrMat_diff<- vcov_diff/sdMat_diff</pre>
corrMat_diff
##
               call_diff spread_diff
## call_diff
               1.0000000
                         -0.5422157
## spread_diff -0.5422157
                           1.0000000
Autocovariance and autocorrelation are;
autoCov_diff_k12<- t(div_diff[13:nrow(diffsXts),]) ** div_diff[1:(nrow(diffsXts)-12),]/(nrow(div_diff)
autoCov_diff_k1
##
                call_diff spread_diff
## call_diff
               0.05385098 -0.04883770
## spread_diff -0.04089622 0.01980912
autoCov_diff_k12
##
                call_diff spread_diff
## call_diff
              0.009660003 0.0032060610
## spread_diff 0.003012920 0.0005562539
Correlograms are;
par(mfrow=c(1,2))
acf(diffsXts$call_diff,lag.max = 12)
acf(diffsXts$spread_diff,lag.max = 12)
   Series diffsXts$call_diff
                     Series diffsXts$spread_diff
  0.
                    1.0
  0.8
                    0.8
                    9.0
  9.0
                  ACF
                    0.4
 0.4
  0.2
                    0.2
```

Critical value for autocorrelation test (dotted line) is $1.96/\sqrt{251} = 0.124$. Call_diff shows the sign of autocorrelation, but smaller than the level series. On the other hand, spread_diff doesn't have significant autocorrelation at any lags inspected.

Again, I conduct Ljung-Box test to examine the autocorrelation up to 12 lags.

0.0 0.2 0.4 0.6 0.8 1.0

Lag

```
for (i in c(1,6,12)){
  print(Box.test(diffsXts$call_diff, lag=i, type='L'))
}
```

##

0.0 0.2 0.4 0.6 0.8 1.0

Lag

```
## Box-Ljung test
##
## data: diffsXts$call_diff
## X-squared = 33.722, df = 1, p-value = 6.356e-09
##
##
##
   Box-Ljung test
##
## data: diffsXts$call_diff
## X-squared = 68.776, df = 6, p-value = 7.285e-13
##
##
##
   Box-Ljung test
##
## data: diffsXts$call_diff
## X-squared = 71.956, df = 12, p-value = 1.377e-10
for (i in c(1,6,12)){
  print(Box.test(diffsXts$spread_diff, lag=i, type='L'))
}
##
   Box-Ljung test
##
##
## data: diffsXts$spread_diff
## X-squared = 3.4191, df = 1, p-value = 0.06445
##
##
##
  Box-Ljung test
##
## data: diffsXts$spread_diff
## X-squared = 4.7598, df = 6, p-value = 0.575
##
##
##
   Box-Ljung test
##
## data: diffsXts$spread_diff
## X-squared = 6.7867, df = 12, p-value = 0.8714
spread_diff fails to reject the null hypothesis of no-autocorrelation at lag 1, 6 and 12, while call_diff
```

spread_diff fails to reject the null hypothesis of no-autocorrelation at lag 1, 6 and 12, while call_diff rejects the null at each lag inspected.