Financial Time Series Analysis using R

Interactive Brokers Webinar Series

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  - Click **here** for more info
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Agenda

- Intro to R and Financial Time Series
- Stationarity
- ARIMA Models
- Forecasting

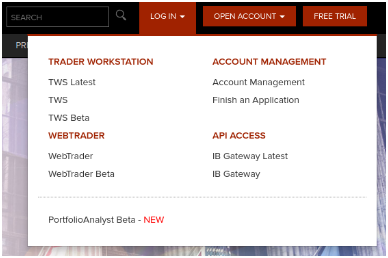
Suggested Readings and Resources

- The classic textbook on time series analysis
  - Hamilton, 1994
- Time series using R:
  1. Econometrics in R, Farnsworth, 2008
  2. An introduction to analysis of financial data with R, Tsay, 2014
  3. Manipulating time series in R, J. Ryan, 2017
- Advanced time series using R
  1. Analysis of integrated and cointegrated time series with R, Pfaff, 2008
  2. Multivariate time series analysis, Tsay, 2013

Introduction

Getting Started

- R
  - The R base system - https://cran.r-project.org/
  - RStudio - https://www.rstudio.com/products/rstudio/
- Interactive Brokers - https://www.interactivebrokers.com
  - Trader Workstation (TWS)
  - or IB Gateway



Time Series in R

- The xts package, (J. A. Ryan & Ulrich, 2014), provides efficient ways to manipulate time series[1]

```
> library(xts)
> library(lubridate)
> n <- 100
> set.seed(13)
> x <- rnorm(n)
> names(x) <- as.character(date(today()) - 0:(n-1))
> x <- as.xts(x)
> x[today(),]
```

```
                [,1]
2017-06-08 0.5543269
```

[1] lubridate package, (Grolemund & Wickham, 2011), makes date format handling much easier

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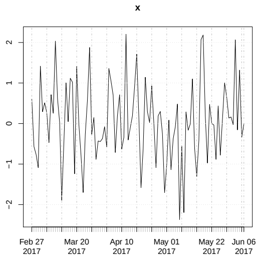
```
                  [,1]
2017-06-08 0.5543269
```

```
# it is easy to plot an xts object
> plot(x)
```



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Time Series in R II

- We can also look at x as a data frame instead

```
> x <- data.frame(Date = date(x), x = x[,1])
> rownames(x) <- NULL
> summary(x)

      Date                      x
 Min.   :2017-03-01   Min.   :-2.02704
 1st Qu.:2017-03-25   1st Qu.:-0.75623
 Median :2017-04-19   Median :-0.07927
 Mean   :2017-04-19   Mean   :-0.06183
 3rd Qu.:2017-05-14   3rd Qu.: 0.55737
 Max.   :2017-06-08   Max.   : 1.83616

> # add year and month variables
> x$Y <- year(x$Date); x$M <- month(x$Date);
```

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> # add year and month variables
> x$Y <- year(x$Date); x$M <- month(x$Date);
```

- The package plyr, (Wickham, 2011), provides efficient data split summary

```
> library(plyr)
> max_month_x <- ddply(x,c("Y","M"),function(z) max(z[,"x"]))
> max_month_x # max value over month

     Y M       V1
1 2017 3 1.745427
2 2017 4 1.614479
3 2017 5 1.836163
4 2017 6 1.775163
```

IB API

- The IBrokers package, J. A. Ryan, 2014, provides access to IB Trader Workstation (TWS) API
- The package also allows users to automate trades and receive real-time data[2]

[2] See the recent Webinar presentation by Anil Yadav here.

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```
> library(IBrokers)
> tws <- twsConnect()
> isConnected(tws) # should be true
> ac <- reqAccountUpdates(tws) # requests account details
> security <- twsSTK("SPY") # choose security of interest
> is.twsContract(security) # make sure it is identified
> P <- reqHistoricalData(tws,security, barSize = '5 mins',duration = "1 Y")

TWS Message: 2 -1 2100 API client has been unsubscribed from account data.
waiting for TWS reply on SPY .... done.
```

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waiting for TWS reply on SPY .... done.

> P[c(1,nrow(P))] # look at first and last data points

                    SPY.Open SPY.High SPY.Low SPY.Close SPY.Volume SPY.WAP
2016-06-09 09:30:00   211.51   211.62  211.37    211.41      26766 211.501
2017-06-08 15:55:00   243.77   243.86  243.68    243.76      30984 243.772
                    SPY.hasGaps SPY.Count
2016-06-09 09:30:00           0      8378
2017-06-08 15:55:00           0      8952
```

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Stationarity

Basic Concepts

- Let y_t denote a time series observed over $t = 1, .., T$ periods
- y_t is called **weakly stationary**, if

$$\mathbb{E}[y_t] = \mu \text{ and } \mathbb{V}[y_t] = \sigma^2, \forall t \qquad (1)$$

i.e. expectation and variance of y are time invariant

[3] See for instance Tsay, 2005

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  i.e. expectation and variance of y are time invariant

- Also, y_t is called **strictly stationary**, if

$$f\left(y_{t_1}, ..., y_{t_m}\right) = f\left(y_{t_1+j}, ..., y_{t_m+j}\right) \tag{2}$$

  where m, j, and $(t_1, ..., t_m)$ are arbitrary positive integers[3]

[3] See for instance Tsay, 2005

Linearity

- In this presentation, we focus on linear time series
- Let us consider an AR(1) process in the form of

$$y_t = c + \phi y_{t-1} + \epsilon_t, \tag{3}$$

where $\epsilon_t \sim D(0, \sigma_\epsilon^2)$ is iid

- Intuitively, ϕ denotes the serial correlation of y_t

$$\phi = cor(y_t, y_{t-1}) \tag{4}$$

- The larger the magnitude of $| \phi | \rightarrow 1$, the more persistent the process is

Unit Root

- Weak stationarity holds true if $\mathbb{E}[y_t] = \mu < \infty$ for all t, such that

$$\mu = c + \phi\mu \Rightarrow \mu = \frac{c}{1-\phi} \tag{5}$$

- The same applies to $\mathbb{V}[y_t] = \sigma^2 < \infty, \forall t$:

$$\sigma^2 = \phi^2\sigma^2 + \sigma_\epsilon^2 \Rightarrow \sigma^2 = \frac{\sigma_\epsilon^2}{1-\phi^2} \tag{6}$$

- A necessary condition for weak stationarity implies $\mid \phi \mid < 1$

Unit Root

If $\phi = 1$, the process y_t is a unit root

Problems with Non-Stationarity

- Non-stationary data cannot be modeled or forecasted
- Results based on non-stationarity can be spurious
  - e.g. false serial correlation in stock prices

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- Non-stationary data cannot be modeled or forecasted
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- If y_t has a unit root (non-stationary), i.e. $\phi = 1$, with $c = 0$, then

$$y_t = y_{t-1} + \epsilon_t \tag{7}$$

$$y_{t-1} = y_{t-2} + \epsilon_{t-1} \tag{8}$$

$$\Rightarrow y_t = \sum_{s=0}^{t} \epsilon_s \tag{9}$$

  where $y_0 = \epsilon_0$
- The process in (7) is unstable in nature,
  - the initial shock, ϵ_0, does not dissipate over time

Transformation and Integrated Process

- In linear time series, transformation takes the form of a first difference

$$\Delta y_t = y_t - y_{t-1} \tag{10}$$

- Taking the first difference of (7), we have

$$\Delta y_t = \epsilon_t \tag{11}$$

- The process in (11) is stationary and does not depend on previous shocks

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$$\Delta y_t = \epsilon_t \tag{11}$$

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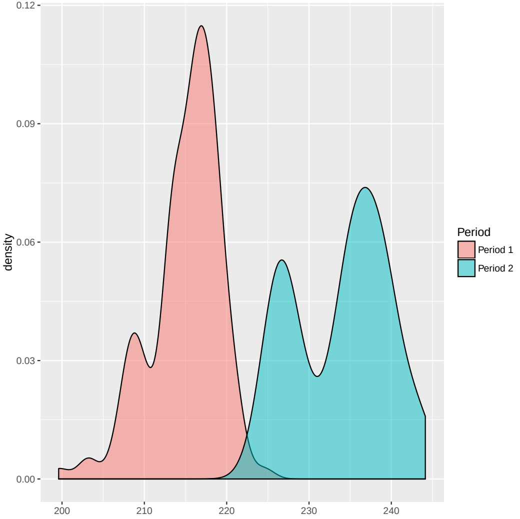
Integrated Process

If y_t has a unit root (non-stationary), while $\Delta y_t = y_t - y_{t-1}$ is stationary, then y_t is called integrated of first order, $I(1)$.

Example I: SPY ETF Stationarity

Figure: SPY ETF - Violation of Weak Stationarity

Figure: SPY ETF - Violation of Strict Stationarity



- Let P_t denote the price of the SPY ETF at time t and

$$p_t = \log(P_t) \tag{12}$$

- If p_t is $I(1)$, then Δp_t should be stationary, where

$$\Delta p_t = p_t - p_{t-1} = \log\left(\frac{P_t}{P_{t-1}}\right) \approx r_t \tag{13}$$

denotes the return on the asset between $t-1$ and t

Figure: SPY ETF Returns - Weak Stationarity

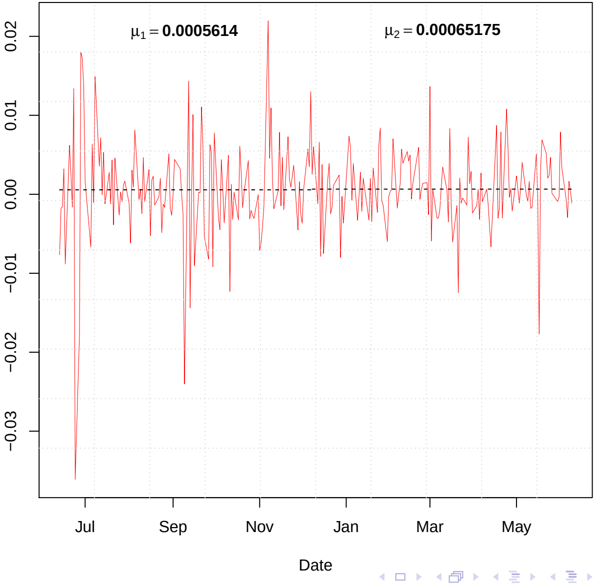
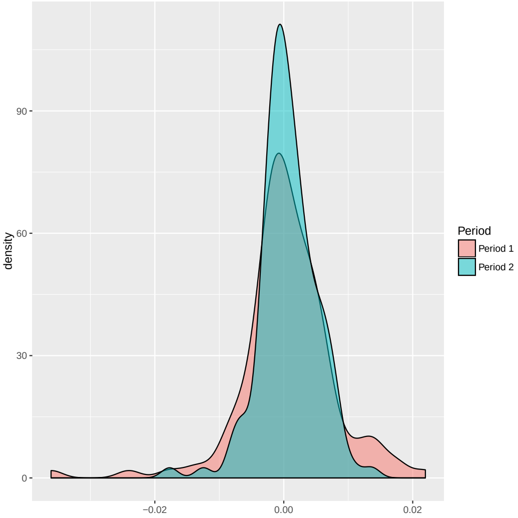


Figure: SPY ETF Returns - Strict Stationarity



- Let's take a look at the serial correlation of the prices
- We will focus on the closing price

```
> find.close <- grep("Close",names(P))
> P_daily <- apply.daily(P[,find.close],function(x) x[nrow(x),])
> dim(P_daily)
```

```
[1] 252   1
```

```
> cor(P_daily[-1],lag(P_daily)[-1])
```

```
           SPY.Close
SPY.Close    0.99238
```

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> dim(P_daily)

[1] 252   1

> cor(P_daily[-1],lag(P_daily)[-1])

           SPY.Close
SPY.Close   0.99238
```

- On the other hand, the corresponding statistic for returns is

```
> R_daily <- P_daily[-1]/lag(P_daily)[-1] - 1
> cor(R_daily[-1],lag(R_daily)[-1])

           SPY.Close
SPY.Close -0.06828564
```

Test for Unit Root

- It is important to plot the time series before running any tests of unit root
- It is recommended to use reasoning where the non-stationarity might come from
    - In the case of stock prices, time is one major factor
- Assuming that a time series has a unit root when it does not can bias inference

Test for Unit Root

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- Assuming that a time series has a unit root when it does not can bias inference

Augmented Dickey-Fuller Test

- A common test for unit root is the Augmented Dickey-Fuller (**ADF**) test
- It tests the null hypothesis whether a unit root is present in the time series
  - The more negative the statistic is the more likely to reject the null

ADF Test in R

- To test for unit root, we can use the adf.test function from the 'tseries' package, (Trapletti & Hornik, 2017)
- We look again at the daily prices and returns from Example I

```
> library(tseries)
> adf.test(P_daily);adf.test(R_daily)

        Augmented Dickey-Fuller Test

data:  P_daily
Dickey-Fuller = -2.3667, Lag order = 6, p-value = 0.4214
alternative hypothesis: stationary

        Augmented Dickey-Fuller Test

data:  R_daily
Dickey-Fuller = -6.3752, Lag order = 6, p-value = 0.01
alternative hypothesis: stationary
```

ARIMA Models

(Autoregressive Integrated Moving Average)

ARIMA Models

- Let y_t follow an ARIMA(p, d, q) model, where
  1. p is the order of autoregressive (AR) model
  2. d is the order of differencing to yield a $I(0)$ process
  3. q is the order of the moving average (MA) model

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- For instance,

$$\text{AR}(p) = \text{ARIMA}(p, 0, 0) \tag{14}$$

$$\text{MA}(q) = \text{ARIMA}(0, 0, q) \tag{15}$$

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- For instance,

$$\text{AR}(p) = \text{ARIMA}(p, 0, 0) \tag{14}$$

$$\text{MA}(q) = \text{ARIMA}(0, 0, q) \tag{15}$$

Special Case

- If y_t has a unit root, i.e. $I(1)$, then first difference, Δy_t, yields a stationary process
- Also, if Δy_t follows an AR(1) process, then we conclude that y_t has an ARIMA$(1, 1, 0)$ process

ARIMA Identification

- Identification of ARIMA can be facilitated as follows
  1. Find the order of integration $I(d)$ of the time series
     - e.g. most stock prices are integrated of order 1, $d = 1$
  2. Look at indicators in the data for AR and MA orders
     - A common approach is to refer to the **PACF** and **ACF**, respectively[4]
  3. Consider an information criteria, e.g. AIC (Sakamoto, Ishiguro, & Kitagawa, 1986)
  4. Finally, test whether the residuals of the identified model follow a white noise process

[4] See this **discussion** for further reading.

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Ljung-Box Statistic

- This statistic is useful to test whether residuals are serially correlated
- A value around zero (large p.value) implies a good fit

[4] See this **discussion** for further reading.

Example II: Identifying ARIMA Models

- We consider a simulated time series from a given ARIMA model
- Specifically, we consider an ARIMA(3,1,2) process

```
> N <- 10^3
> set.seed(13)
> y <- arima.sim(N,model = list(order = c(3,1,2), ar = c(0.8, -0.5,0.4),
+ ma = c(0.5,-0.3))) + 200
# Note that y is a ts object rather than xts
```

Step 1: Plot and Test for Unit Root

```
> plot(y);
> ADF <- adf.test(y); ADF$p.value

[1] 0.4148301

# lag on ts object should be assigned as -1
> delta_y <- na.omit(y - lag(y,-1) )
> plot(delta_y);
> ADF2 <- adf.test(delta_y); ADF2$p.value

[1] 0.01
```

- Step 1 tells us that $d = 1$, i.e. y_t follows an ARIMA$(p, 1, q)$
- We need to identify p and q

Step 2: Identify p and q using the AIC information criterion

```
> p.seq <- 0:4
> q.seq <- 0:4
> pq.seq <- expand.grid(p.seq,q.seq)
> AIC.list <- lapply(1:nrow(pq.seq),function(i)
+ AIC(arima(y,c(pq.seq[i,1],1,pq.seq[i,2]))))
> AIC.matrix <- matrix(unlist(AIC.list),length(p.seq))
> rownames(AIC.matrix) <- p.seq
> colnames(AIC.matrix) <- q.seq
```

AIC.matrix

$p \setminus q$	0	1	2	3	4
0	3973.32	3075.67	2923.06	2914.88	2916.86
1	3542.07	2983.22	2916.50	2916.88	2883.02
2	3407.54	2949.70	2912.02	2907.37	2866.26
3	3053.10	2851.96	2844.42	2846.41	2848.31
4	2987.36	2845.46	2846.41	2847.81	2850.41

- It follows from Step 2 that the optimal combination is $(p = 3, q = 2)$
- Alternatively, we can use the auto.arima function

```
> identify.arima <- auto.arima(y)
> identify.arima


Series: y
ARIMA(3,1,2)

Coefficients:
         ar1      ar2     ar3     ma1      ma2
      0.7758  -0.4821  0.3875  0.5376  -0.2752
s.e.  0.0785   0.0448  0.0315  0.0836   0.0796

sigma^2 estimated as 0.9965:  log likelihood=-1416.21
AIC=2844.42   AICc=2844.5   BIC=2873.87
```

- In either case, we get consistent results indicating that the model is ARIMA(3,1,2)

- Finally, we look at the residuals of the fitted model

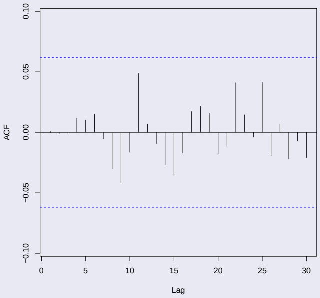
Step 3: check residuals

```
> Box.test(residuals(identify.arima),type = "Ljung-Box")

        Box-Ljung test

data:  residuals(identify.arima)
X-squared = 0.00087004, df = 1, p-value = 0.9765

> library(forecast)
> Acf(residuals(identify.arima),main = "")
```



Forecasting

Forecasting

- So far, we learned how to identify a time series model
- For application, we are interested in forecasting future values of the time series
- Such decision will be based on a history of T periods
  - T periods to fit the model
  - and a number of lags to serve as forecast inputs

- Hence, our decision will be based on the quality of
  1. the data
  2. the fitted model

Rolling Window

- We will use a rolling window approach to perform and evaluate forecasts

- Set $t = 150$ and perform the following steps
  1. Standing at the end of day t
  2. Use $T = 150$ historic days of data (including day t) to fit an ARIMA model
  3. Make a forecast for next period, i.e. $t + 1$
  4. Set $t \to t + 1$ and go back to Step 1
- The above steps are repeated until $t + 1$ becomes the last observation in the time series

Example III: Forecast the SPY ETF

- In total we have 252 days of closing prices for the SPY ETF
- To avoid price non-stationary, we focus on returns alone
- This leaves us with 101 days to test our forecasts[5]
- We consider three models for forecast
  1. Dynamically fitted ARIMA(p,0,q) model
  2. Dynamically fitted AR(1) model
  3. Plain moving average (momentum)

```
> library(forecast)
> T. <- 150
> arma.list <- numeric()
> ar1.list <- numeric()
> ma.list <- numeric()

> for(i in T.:(length(R_daily)-1) ) {
+   arma.list[i] <- list(auto.arima(R_daily[(i-T.+1):i])) # ARIMA(p,0,q)
+   ar1.list[i] <- list(arima(R_daily[(i-T.+1):i],c(1,0,0))) # AR(1)
+   ma.list[i] <- list(mean(R_daily[(i-T.+1):i])) # momentum
+   }
```

[5] The experiment relies on the forecast package, Hyndman, 2017

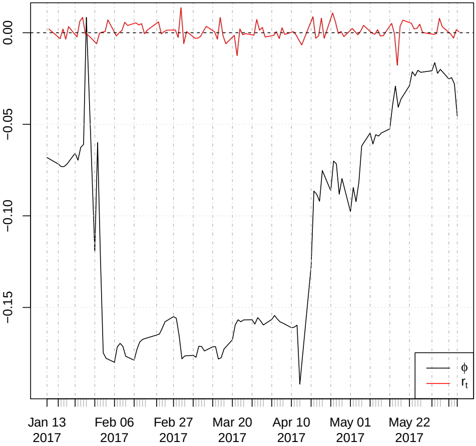
```
> y_hat <- sapply(arma.list[T.:length(arma.list)],
+                 function(x) forecast(x,1)[[4]] )
> y_hat2 <- sapply(ar1.list[T.:length(ar1.list)],
+                  function(x) forecast(x,1)[[4]] )
> y_hat3 <- sign(unlist(ma.list))
> forecast_accuracy <- cbind(mean(sign(y_hat) == sign(y)),
+ mean(sign(y_hat2) == sign(y)),
+ mean(sign(y_hat3) == sign(y)))
```

- Finally, summarize the forecast accuracy in a table

	ARIMA	AR(1)	Momentum
Accuracy	55.45%	53.47%	52.48%

- Among the three, ARIMA performs the best
  - Could be attributed to more flexibility in fitting the model over time

- While AR(1) is a constrained ARIMA model, note that the autoregressive coefficient still changes dramatically over time
  - Red line denotes the SPY ETF daily return
  - Black line denotes the estimated AR(1) coefficient over time, i.e. ϕ



Summary

- Importance of stationarity
- Non-stationary models could imply spurious results
- Plots are always insightful
- Use tests carefully
- Consider multiple time series to form forecasts
    - Hence the idea of multivariate time series analysis

Good Luck!

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