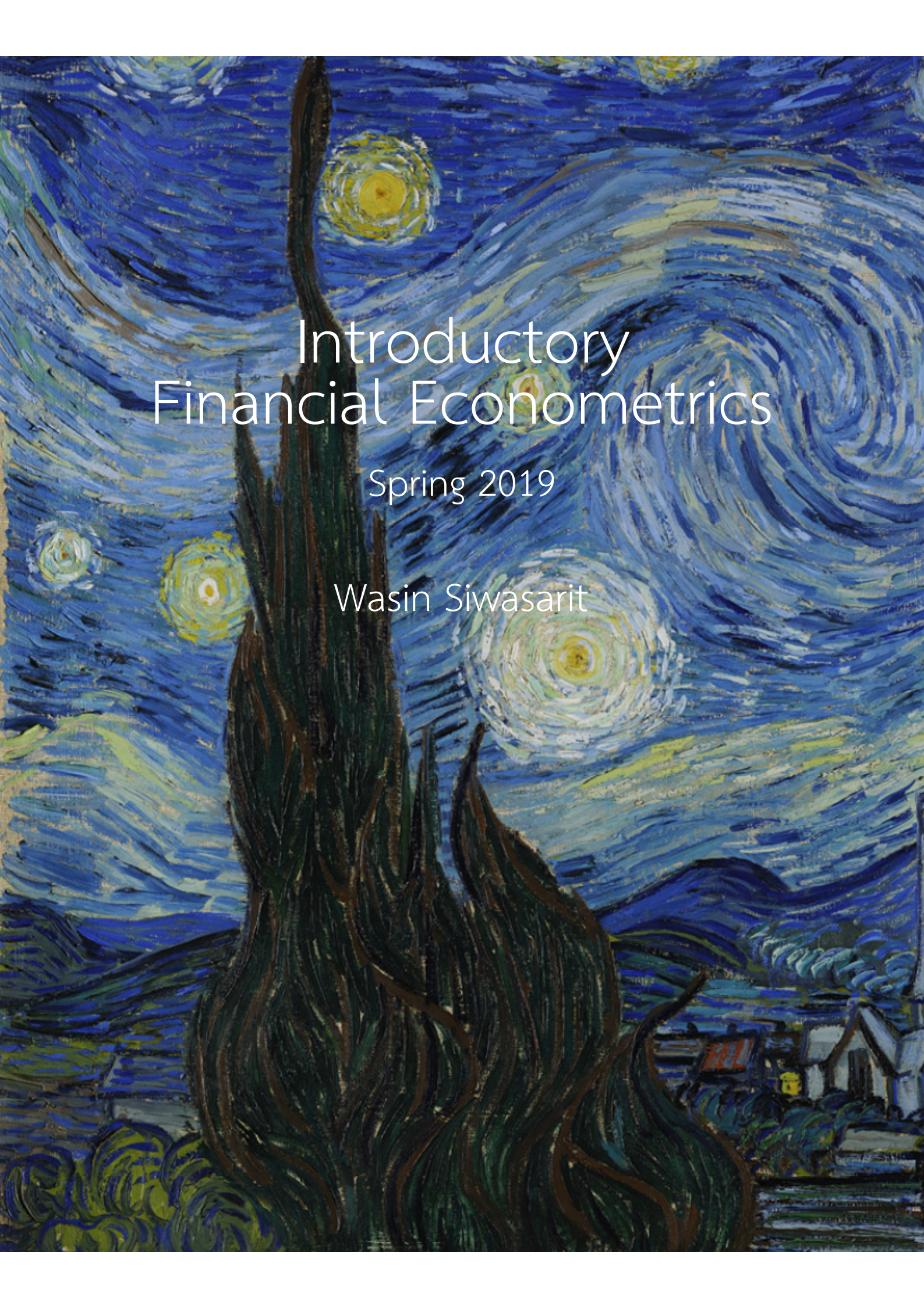


The background of the slide is a reproduction of the painting 'The Starry Night' by J.M.W. Turner. It features a turbulent, swirling blue sky filled with bright, glowing stars and a large, dark, silhouetted cypress tree in the foreground. In the lower right, a small village with white houses and a church spire is visible on a hillside.

# Introductory Financial Econometrics

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Road Map of this class:



## 1. Financial Time Series and Their Characteristics

Financial time series (FTS) analysis

Financial time series (FTS) analysis is concerned with theory and practice of asset valuation over time.

What is the difference, if any, from traditional time series analysis?

Two topics are highly related, but FTS has added uncertainty, because it must deal with the ever-changing business & economic environment and the fact that volatility is not directly observed.

### 1.1 The Objectives of this chapter

1. to access financial data online and to process the embedded information
2. to provide basic knowledge of FTS data such as skewness, heavy tails, and measure of dependence between asset returns
3. to introduce statistical tools econometric models useful for analyzing these series.
4. to gain experience in analyzing FTS

## 1.2 Examples of financial time series

1. Daily log returns of Apple stock: 2007 to 2018 (12 years). Data downloaded using quantmod

2. The VIX index.

3. CDS spreads: Daily 3-year CDS spreads of JP Morgan from July 20, 2004 to September 19, 2018.

4. Quarterly earnings of Coca-Cola Company: 1983-2009 Seasonal time series useful in

- earning forecasts
- pricing weather related derivatives (e.g. energy)
- modeling intraday behavior of asset returns

5. US monthly interest rates (3m & 6m Treasury bills)

Relations between the two asset returns? Term structure of interest rates.

6. Exchange rate between US Dollar vs Euro Fixed income, hedging, carry trade.

7. Size of insurance claims.

8. High-frequency financial data:

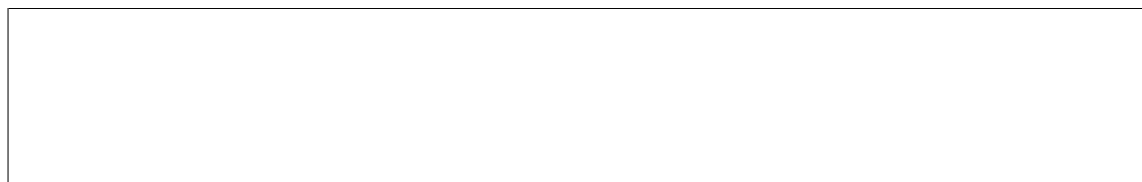
Tick-by-tick data of Caterpillars stock: January 04, 2010.

## 1.3 Asset Returns

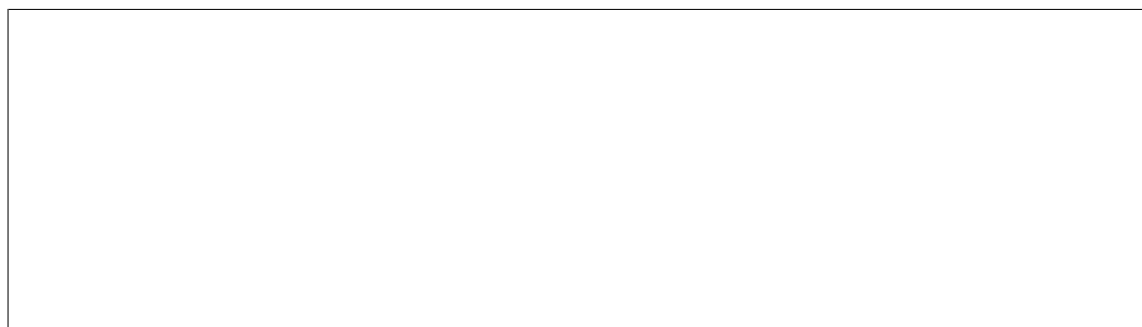
Let  $P_t$  be the price of an asset at time  $t$ , and assume no dividend. One-period simple return: Gross return

$$1 + R_t = \frac{P_t}{P_{t-1}}$$

One-Period Simple Net Return or Simple Return:



Multiperiod simple return: Gross return)



Example: Table below gives 5 daily prices of Apple stock in January 2020.

**Apple Inc. (AAPL)**  
 NasdaqGS - NasdaqGS Real Time Price. Currency in USD

**310.33** +0.70 (+0.23%)  
 At close: January 10 4:00PM EST

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[Summary](#) [Company Outlook](#) [Chart](#) [Conversations](#) [Statistics](#) **[Historical Data](#)** [Profile](#) [Financials](#) [Analysis](#) [Options](#)

Time Period: [Jan 12, 2019 - Jan 12, 2020](#) Show: [Historical Prices](#) Frequency: [Daily](#) [Apply](#)

Currency in USD [Download Data](#)

| Date         | Open   | High   | Low    | Close* | Adj Close** | Volume     |
|--------------|--------|--------|--------|--------|-------------|------------|
| Jan 10, 2020 | 310.60 | 312.67 | 308.25 | 310.33 | 310.33      | 35,217,272 |
| Jan 09, 2020 | 307.24 | 310.43 | 306.20 | 309.63 | 309.63      | 42,527,100 |
| Jan 08, 2020 | 297.16 | 304.44 | 297.16 | 303.19 | 303.19      | 33,019,800 |
| Jan 07, 2020 | 299.84 | 300.90 | 297.48 | 298.39 | 298.39      | 27,218,000 |
| Jan 06, 2020 | 293.79 | 299.96 | 292.75 | 299.80 | 299.80      | 29,596,800 |

what is one-day gross return of holding the stock from 01/06 to 12/07 and the daily simple return?

what is one-day log return of holding the stock from 01/09 to 01/10 ?

Time interval is important! Default is one year. Annualized (average) return:

Besides the simple return, we can also compute the continuously compounding interest rate where  $r$  is the interest rate per annum,  $C$  is the initial capital,  $n$  is the number of years, and  $\exp$  is the exponential function.

$$A = C \times \exp(r \times n)$$

Continuously compounded (or log) return

$$r_t = \ln(1 + R_t) = \ln \frac{P_t}{P_{t-1}} = p_t - p_{t-1}$$

where  $p_t = \ln(P_t)$

Multiperiod log return:

Continuously compounding: Illustration of the power of compounding (int. rate 10 % per annum)

| Type         | #(payment) | Int.              | Net       |
|--------------|------------|-------------------|-----------|
| Annual       | 1          | 0.1               | \$1.10000 |
| Semi-Annual  | 2          | 0.05              | \$1.10250 |
| Quarterly    | 4          | 0.025             | \$1.10381 |
| Monthly      | 12         | 0.0083            | \$1.10471 |
| Weekly       | 52         | $\frac{0.1}{52}$  | \$1.10506 |
| Daily        | 365        | $\frac{0.1}{365}$ | \$1.10516 |
| Continuously | $\infty$   |                   | \$1.10517 |

Portfolio return: N assets

Dividend payment:

Excess Returns (adjusting for risk)

Remarks:

Example If the monthly log returns of an asset are 4.46 %, −7.34 % and 10.77 %, then what is the corresponding quarterly log return?

Example If the monthly simple returns of an asset are 4.46 %, −7.34 %, and 10.77 %, then what is the corresponding quarterly simple return?

### 1.4 Distributional Properties of Returns

What is the distribution of  $r_{it}$  where  $i = 1, \dots, N$ ; and  $t = 1, \dots, T$

Some theoretical properties:

Moments of a random variable  $X$  with density  $f(x)$ :  $l$ -th moment

$$m'_l = E(X^l) = \int_{-\infty}^{\infty} x^l f(x) dx$$

First Moment: mean or expectation of  $X$ .

$l$ -th central moment

$$m_l = E[(X - \mu_x)^l] = \int_{-\infty}^{\infty} (x - \mu_x)^l f(x) dx$$

2nd central moment.

Standard deviation: square-root of variance

Skewness (Symmetry)

$$S(x) = E \left[ \frac{(X - \mu_x)^3}{\sigma_x^3} \right]$$

Kurtosis (Fat-tails)

$$K(x) = E \left[ \frac{(X - \mu_x)^4}{\sigma_x^4} \right]$$

Q1: Why study the mean and variance of returns?

They are concerned with long-term return and risk, respectively.

Q2: Why is symmetry important?

Symmetry has important implications in holding short or long financial positions and in risk management.

Q3: Why is kurtosis important?

Related to volatility forecasting, efficiency in estimation and tests High kurtosis implies heavy (or long) tails in distribution.

Estimation

Sample mean, Sample Variance, Sample Skewness and Sample Kurtosis



**1.5 Hypothesis Testing**

A random variable under the normal distribution

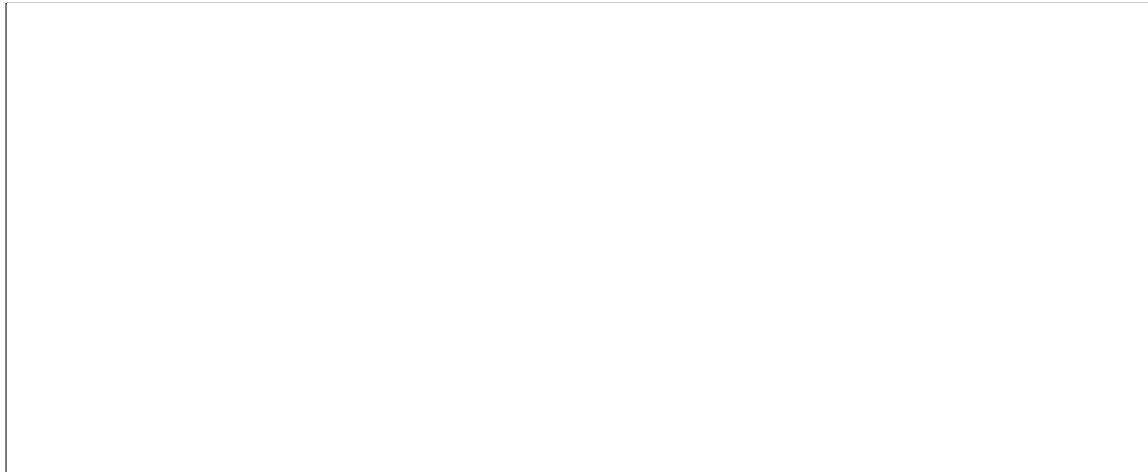
$$\widehat{S(x)} \sim N(0, \frac{6}{T})$$

$$\widehat{K(x)} - 3 \sim N(0, \frac{24}{T})$$

Test for symmetry

Test for tail thickness

Test for normality :(Jarque-Bera test)



## 1.6 Empirical work using R program

FE code

```
#EE435 Wasin Siwasarit Lecture1 Spring/2019
setwd("/Users/wasin_siwasarit/Desktop/EE435")
cat(rep("\n",50)) #clear R Console
#install.packages("quantmod")
#install.packages("fBasics")
#install.packages("sn")
#install.packages("PerformanceAnalytics")
#install.packages("car")
#install.packages("tseries")
#install.packages("forecast")
library(quantmod)
library(fBasics)
library(sn)
library(PerformanceAnalytics)
library(car)
library(tseries)
library(forecast)

getSymbols("^GSPC",from="2000-01-03",to="2020-01-10")
dim(GSPC)
head(GSPC)
tail(GSPC)
da=GSPC
chartSeries(GSPC,theme="white")
price=da[,6]
plot(price,type='l')
```

```

logprice=log(price)
plot(logprice,type='l')
logreturn=diff(log(price))
simplereturn <-exp(logreturn)-1
#1 Plot the series of log return and simple return

par(mfrow=c(1,1))
plot(logreturn,type='l')
plot(simplereturn)

newlogreturn <- logreturn[2:nrow(logreturn),]
newsimplereturn <- simplereturn[2:nrow(logreturn),]

#2 Histogram and sample statistics
hist(logreturn, breaks=100, col="slateblue")
chart.Histogram(logreturn,methods = c("add.normal"))
table.Stats(logreturn)

#3 QQ-plots and tests for normality
#
# use qqnorm function
par(mfrow=c(1,1))
qqnorm(newlogreturn)
qqline(newlogreturn, col = 2)
jarque.bera.test(newlogreturn)

```

### FE Print out

```

> #install.packages("quantmod")
> #install.packages("fBasics")
> #install.packages("sn")
> #install.packages("PerformanceAnalytics")
> #install.packages("car")
> #install.packages("tseries")
> #install.packages("forecast")
> library(quantmod)
> library(fBasics)
> library(sn)
> library(PerformanceAnalytics)
> library(car)
> library(tseries)
> library(forecast)
> getSymbols("^GSPC",from="2000-01-03",to="2020-01-10")
[1] "GSPC"
> dim(GSPC)
[1] 5037    6

```

```

> head(GSPC)
GSPC.Open GSPC.High GSPC.Low GSPC.Close GSPC.Volume GSPC.Adjusted
2000-01-03 1469.25 1478.00 1438.36 1455.22 931800000 1455.22
2000-01-04 1455.22 1455.22 1397.43 1399.42 1009000000 1399.42
2000-01-05 1399.42 1413.27 1377.68 1402.11 1085500000 1402.11
2000-01-06 1402.11 1411.90 1392.10 1403.45 1092300000 1403.45
2000-01-07 1403.45 1441.47 1400.73 1441.47 1225200000 1441.47
2000-01-10 1441.47 1464.36 1441.47 1457.60 1064800000 1457.60
> tail(GSPC)
GSPC.Open GSPC.High GSPC.Low GSPC.Close GSPC.Volume GSPC.Adjusted
2020-01-02 3244.67 3258.14 3235.53 3257.85 3458250000 3257.85
2020-01-03 3226.36 3246.15 3222.34 3234.85 3461290000 3234.85
2020-01-06 3217.55 3246.84 3214.64 3246.28 3674070000 3246.28
2020-01-07 3241.86 3244.91 3232.43 3237.18 3420380000 3237.18
2020-01-08 3238.59 3267.07 3236.67 3253.05 3720890000 3253.05
2020-01-09 3266.03 3275.58 3263.67 3274.70 3638390000 3274.70
> da=GSPC
> chartSeries(GSPC,theme="white")
> price=da[,6]
> plot(price,type='l')
> logprice=log(price)
> plot(logprice,type='l')
> logreturn=diff(log(price))
> simplereturn <-exp(logreturn)-1
> par(mfrow=c(1,1))
> plot(logreturn,type='l')
> plot(simplereturn)
> newlogreturn <- logreturn[2:nrow(logreturn),]
> newsimplereturn <- simplereturn[2:nrow(logreturn),]
> #2 Histogram and sample statistics
> hist(logreturn, breaks=100, col="slateblue")
> chart.Histogram(logreturn,methods = c("add.normal"))
> table.Stats(logreturn)
GSPC.Adjusted
Observations      5036.0000
NAs                1.0000
Minimum           -0.0947
Quartile 1        -0.0047
Median            0.0006
Arithmetic Mean   0.0002
Geometric Mean    0.0001
Quartile 3        0.0057
Maximum           0.1096
SE Mean           0.0002
LCL Mean (0.95)   -0.0002
UCL Mean (0.95)   0.0005

```

```
Variance          0.0001
Stdev              0.0119
Skewness           -0.2302
Kurtosis           8.6521
> #3 QQ-plots and tests for normality
> #
> # use qqnorm function
> par(mfrow=c(1,1))
> qqnorm(newlogreturn)
> qqline(newlogreturn, col = 2)
> jarque.bera.test(newlogreturn)

Jarque Bera Test

data:  newlogreturn
X-squared = 15752, df = 2, p-value < 2.2e-16
```

#### FE code (Cont.)

```
#4 Test mean = 0
t.test(newlogreturn)

#5 Test Skewness = 0
T=length(newlogreturn)
s3=skewness(newlogreturn)
tst = s3/sqrt(6/T)
tst
pv = 2*pnorm(tst)
pv

#6 Test excess kurtosis =0
k4 = kurtosis(newlogreturn)
tst = k4/sqrt(24/T)
tst
pv = 2*(1-pnorm(tst))
pv
```

## FE Print out (Cont.)

```
> t.test(newlogreturn)
```

```
One Sample t-test
```

```
data: newlogreturn
```

```
t = 0.96103, df = 5035, p-value = 0.3366
```

```
alternative hypothesis: true mean is not equal to 0
```

```
95 percent confidence interval:
```

```
-0.0001674840  0.0004895925
```

```
sample estimates:
```

```
mean of x
```

```
0.0001610542
```

```
> #5 Test Skewness = 0
```

```
> T=length(newlogreturn)
```

```
> s3=skewness(newlogreturn)
```

```
> s3
```

```
[1] -0.230244
```

```
> tst = s3/sqrt(6/T)
```

```
> tst
```

```
[1] -6.670456
```

```
> pv = 2*pnorm(tst)
```

```
> pv
```

```
[1] 2.550093e-11
```

```
> #6 Test excess kurtosis =0
```

```
> k4 = kurtosis(newlogreturn)
```

```
> k4
```

```
[1] 8.652073
```

```
> tst = k4/sqrt(24/T)
```

```
> tst
```

```
[1] 125.3307
```

```
> pv = 2*(1-pnorm(tst))
```

```
> pv
```

```
[1] 0
```

