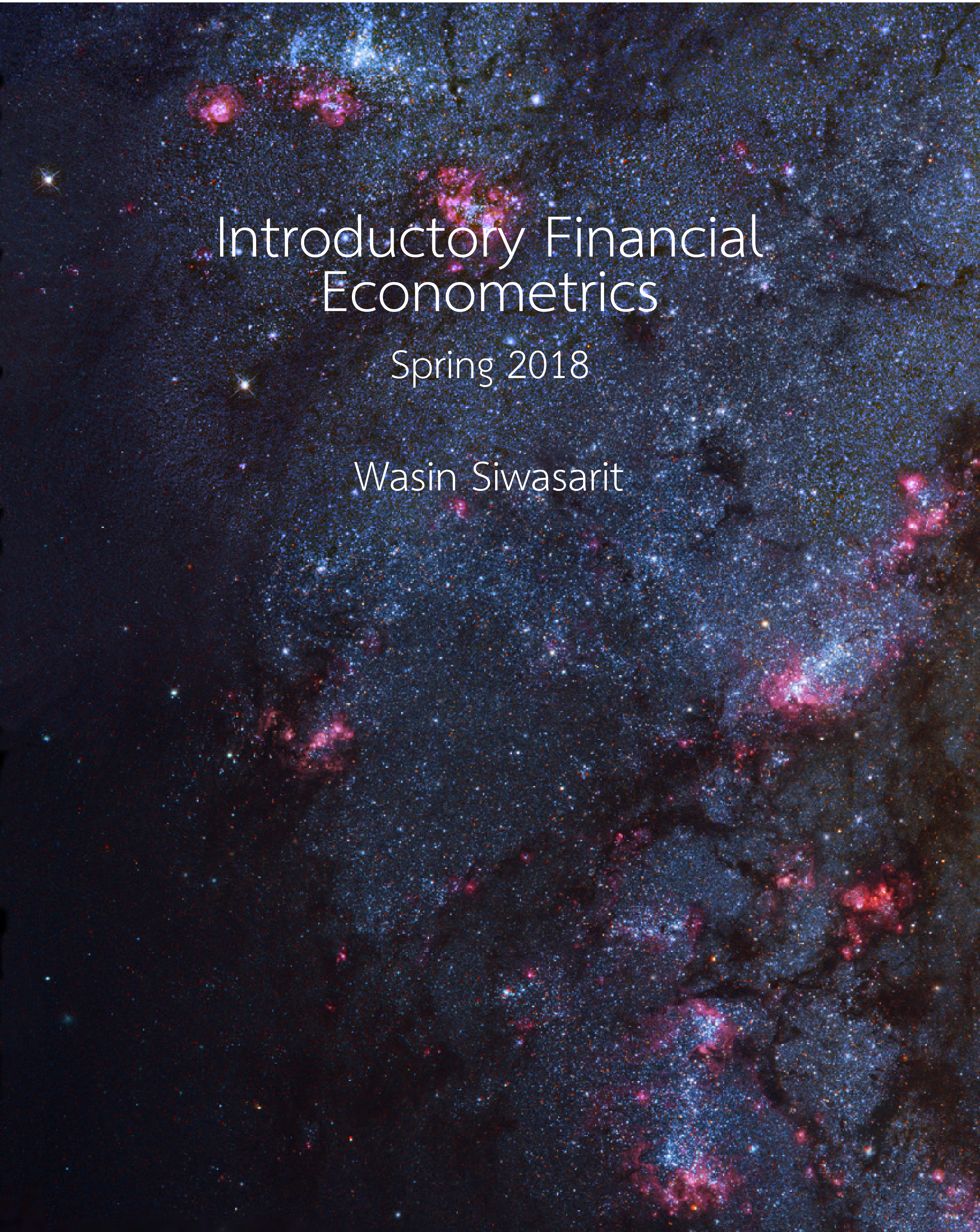

Introductory Financial Econometrics

Spring 2018

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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 six daily (adjusted) closing prices of Apple stock in December 2015.

Date	Price
12/23	108.02
12/24	107.45
12/28	106.24
12/29	108.15
12/30	106.74
12/31	104.69

what is one-day gross return of holding the stock from 12/28 to 12/29 and the daily simple return?

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	∞		\$1.10517

Portfolio return: N assets

Dividend payment:

Excess Returns (adjusting for risk)

Example

1. Whai is the log return from 12/23 to 12/24?

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 $i = 1, ..., N$; and $t = 1, ..., T$

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 (Symmestry)

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

Kurtosis (Fat-taills)

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

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

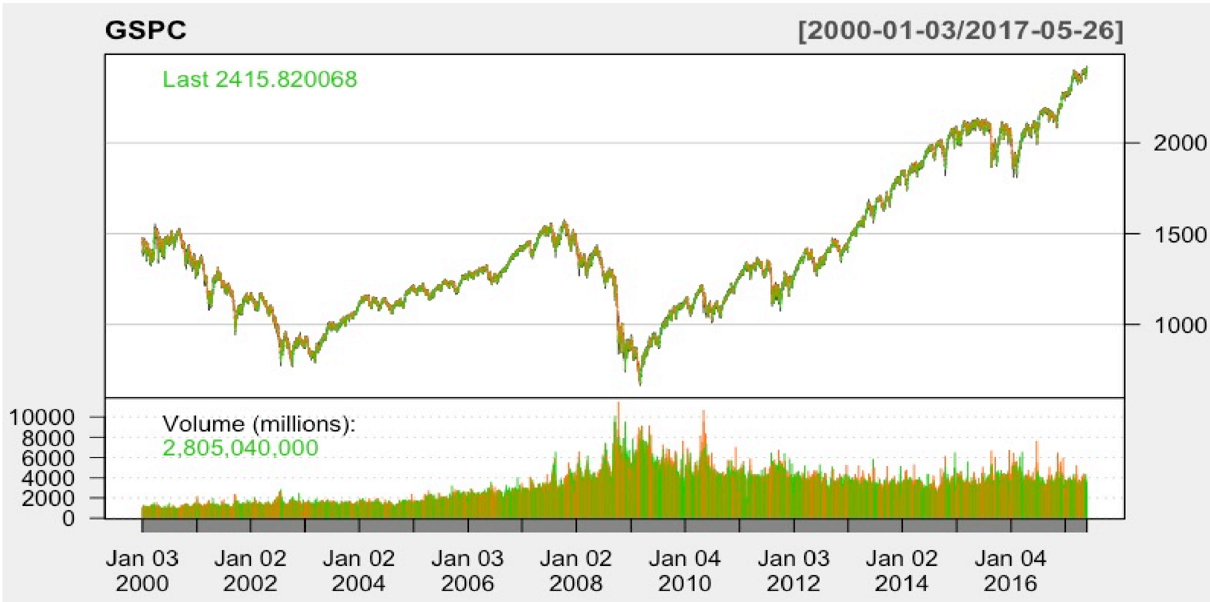
FE Toolbox

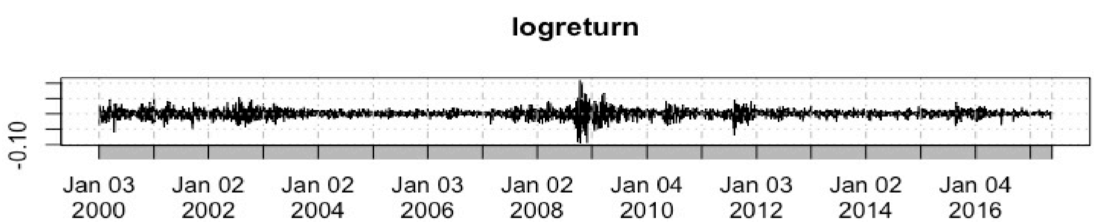
```
   #EE435 Wasin Siwasarit  Lecture1  Spring/2018
setwd("/Users/wasinsiwasarit/Desktop/EE435")
cat(rep("\n",50))  #clear R Console
#install.packages("quantmod")
#install.packages("fBasics")
#install.packages("sn")
#install.packages("PerformanceAnalytics")
#install.packages("car")
#install.packages("tseries")
#install.packages("forecast")
library(quantmod)
library(fBasics)
library(sn)
library(PerformanceAnalytics)
library(car)
library(tseries)
library(forecast)

getSymbols("^GSPC",from="2000-01-03",to="2017-01-28")
dim(GSPC)
head(GSPC)
tail(GSPC)
da=GSPC
chartSeries(GSPC,theme="white")
price=da[,6]
plot(price,type='l')
```

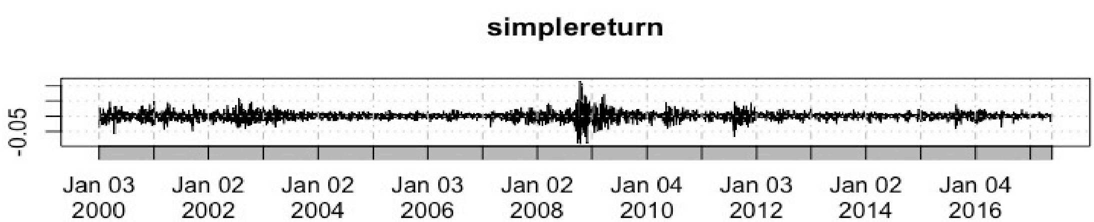
```
logprice=log(price)
plot(logprice,type='l')
logreturn=diff(log(price))
simplereturn <-exp(logreturn)-1
#1 Plot the series of log return and simple return

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)
```

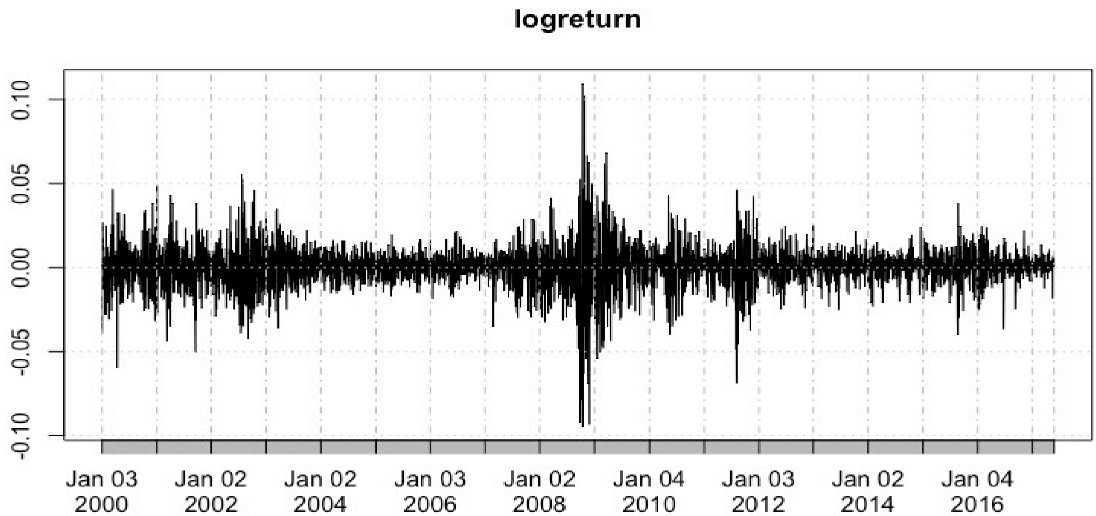
FE Analysis

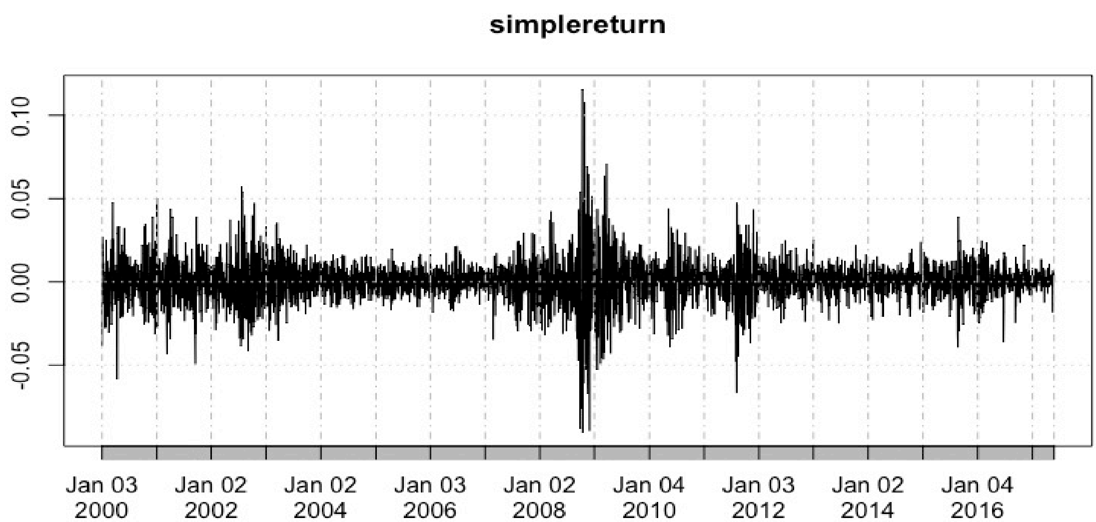
```
> table.Stats(logreturn)
                GSPC.Adjusted
Observations        4377.0000
NAs                    1.0000
Minimum               -0.0947
Quartile 1            -0.0051
Median                 0.0005
Arithmetic Mean        0.0001
Geometric Mean         0.0000
Quartile 3             0.0058
Maximum                0.1096
SE Mean                0.0002
LCL Mean (0.95)       -0.0002
UCL Mean (0.95)        0.0005
Variance               0.0002
Stdev                  0.0123
Skewness              -0.1989
Kurtosis               8.3611
> par(mfrow=c(1,1))
> qqnorm(newlogreturn)
> qqline(newlogreturn, col = 2)
> jarque.bera.test(newlogreturn)

        Jarque Bera Test

data:  newlogreturn
X-squared = 12778, df = 2, p-value < 2.2e-16
```

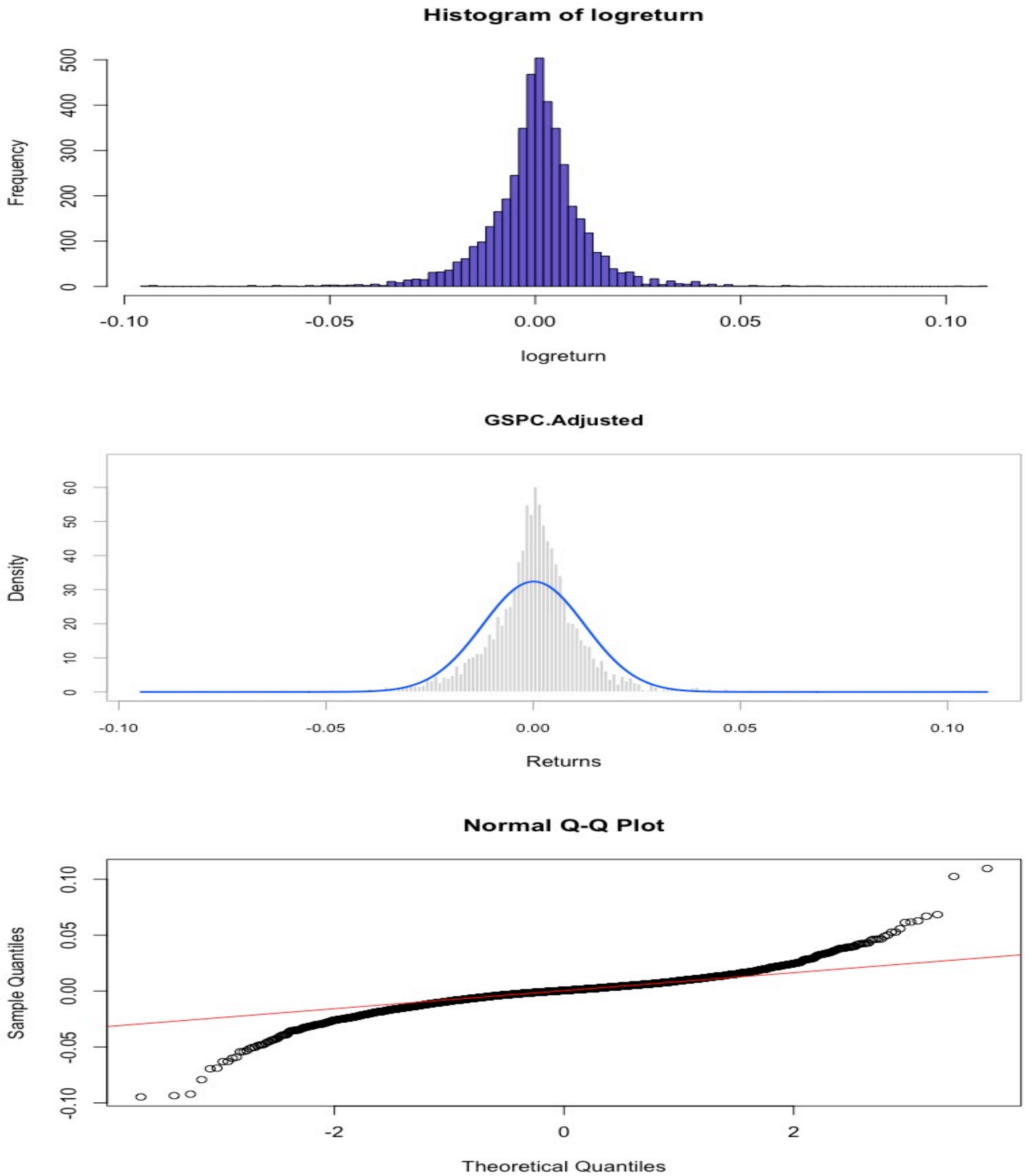

GSPC
[2000-01-03/2017-05-26]
Last 2415.820068
2000
1500
1000
Volume (millions):
2,805,040,000
10000
8000
6000
4000
2000
0
Jan 03 2000
Jan 02 2002
Jan 02 2004
Jan 03 2006
Jan 02 2008
Jan 04 2010
Jan 03 2012
Jan 02 2014
Jan 04 2016


logreturn
-0.10
Jan 03 2000
Jan 02 2002
Jan 02 2004
Jan 03 2006
Jan 02 2008
Jan 04 2010
Jan 03 2012
Jan 02 2014
Jan 04 2016


simplereturn
-0.05
Jan 03 2000
Jan 02 2002
Jan 02 2004
Jan 03 2006
Jan 02 2008
Jan 04 2010
Jan 03 2012
Jan 02 2014
Jan 04 2016


logreturn
0.10
0.05
0.00
-0.05
-0.10
Jan 03 2000
Jan 02 2002
Jan 02 2004
Jan 03 2006
Jan 02 2008
Jan 04 2010
Jan 03 2012
Jan 02 2014
Jan 04 2016


simplereturn
0.10
0.05
0.00
-0.05
Jan 03 2000
Jan 02 2002
Jan 02 2004
Jan 03 2006
Jan 02 2008
Jan 04 2010
Jan 03 2012
Jan 02 2014
Jan 04 2016


Histogram of logreturn
Frequency
logreturn
GSPC.Adjusted
Density
Returns
Normal Q-Q Plot
Sample Quantiles
Theoretical Quantiles

FE toolbox (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 Analysis (Cont.)

```
> t.test(newlogreturn)

        One Sample t-test

data:  newlogreturn
t = 0.62168, df = 4376, p-value = 0.5342
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 -0.0002493954  0.0004810069
sample estimates:
   mean of x
0.0001158057

> T=length(newlogreturn)
> s3=skewness(newlogreturn)
> tst = s3/sqrt(6/T)
> tst
[1] -5.370912
> pv = 2*pnorm(tst)
> pv
[1] 7.833935e-08
> k4 = kurtosis(newlogreturn)
> tst = k4/sqrt(24/T)
> tst
```

```
[1] 112.913
> pv = 2*(1-pnorm(tst))
> pv
[1] 0
>
```