

,

2019-09-16

Contents

1		5
1.1	5
2		11

Chapter 1

1.1

Stata. R Python,

R > R - ,
R RStudio.

RStudio Mac OS Windows.

RStudio Windows / Mac OS:

1. R .
 - Windows: “Download R for Windows” “base” “Download R 3.x.x for Windows”.
 - Mac OS: “Download R for (Mac) OS X” “Latest Release” “R 3.x.x”.
2. RStudio (.

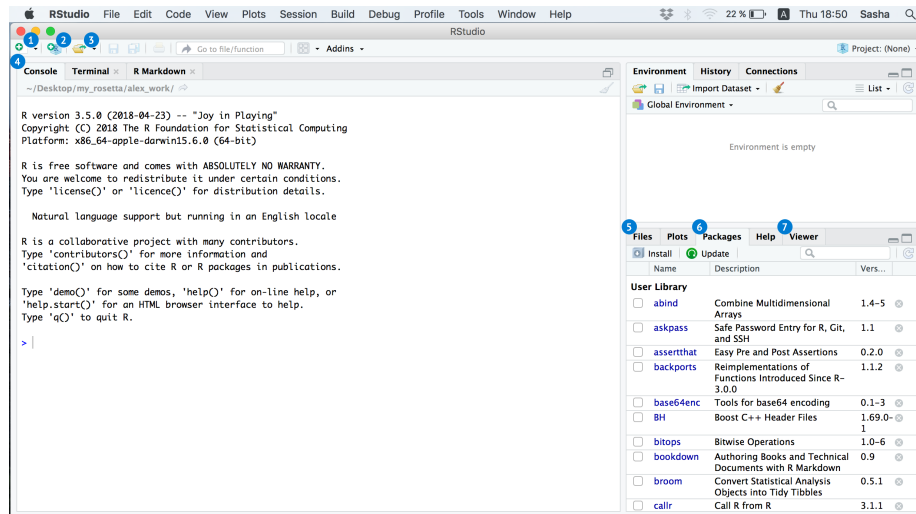
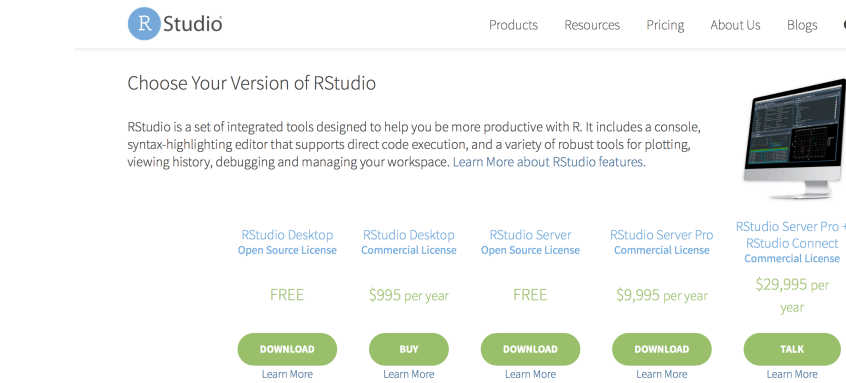


Figure 1.1:



```

, RStudio
#####

```

1. **New file** - `newFile()`.
2. **New project** - `newProject()`.
3. **Open file** - `openFile()`.
4. **Console** - `console()`, `console.log()`.
5. **Files** - `files()`, `files.openFile()`.
6. **Packages** - `packages()`, `packages.install()`, `installed.packages()`.

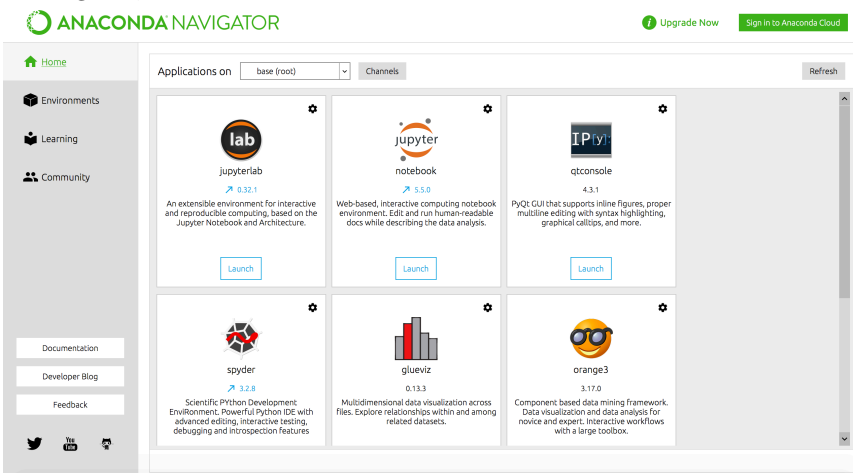
7. Viewer - .

Python > Python - Python , Jupyter Notebook.

#####

1. Anaconda .

2. Anaconda Navigator,



Jupyter Notebook. Navigator.bb

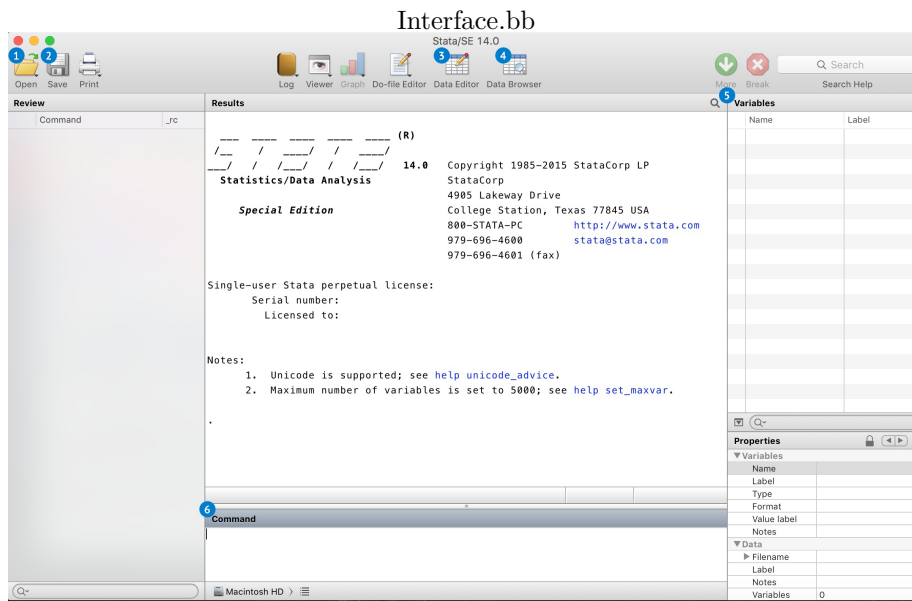
#####

Jupyter Notebook, , “New” “Notebook: Python 3”. File in Jupyter.bb

The image shows the JupyterLab interface. At the top, there's a header with the Jupyter logo, the text "jupyter", and buttons for "Quit" and "Logout". Below the header, there are tabs for "Files", "Running", and "Clusters". The "Files" tab is active, showing a file browser. A dropdown menu is open, showing options for "Notebook: Python 3" and "Other: Text File, Folder, Terminal". The file browser lists various folders and files, including "anaconda3", "Applications", "Desktop", "Documents", "Downloads", "Dropbox", "ml_fse_course", "Movies", "Music", "Pictures", "probability_hse_exams", and "Public".

Below the file browser, there's a code cell. The code cell has a prompt "In [1]:" followed by the code `print("Hello world")`. The output of the code is "Hello world". Below the code cell, there's another prompt "In []:" followed by a cursor.

At the bottom of the interface, there's a footer with the text "Test 1 (autosaved)" and a "Logout" button.

Figure 1.2: *Stata*

```
### STATA > Stata, R Python, ,
.
##### :
Stata - Stata SE,
Stata MP.
##### :
1. Open File - .
2. Save - .
3. Data Editor - .
4. Data Browser - .
5. Variables - .
6. Command - , .
```


Chapter 2

R

```
library(tidyverse) #
library(skimr) #      summary
library(rio) #      .dta
library(car) #
library(tseries) #
library(sjPlot) #
```

```
df = import("us-return.dta")
```

```
# skim_with(numeric = list(hist = NULL, p25 = NULL, p75 = NULL)) #
skim(df) #
```

Skim summary statistics

n obs: 2664

n variables: 22

```
-- Variable type:character -----
variable missing complete    n min max empty n_unique
      B         0      2664 2664   0   6  2544         31
```

```
-- Variable type:numeric -----
variable missing complete    n  mean    sd    p0    p25    p50
      A    2544      120 2664 60.5   34.79    1   30.75   60.5
    BOISE    2544      120 2664 0.017   0.097  -0.27  -0.045   0.015
```

CITCRP	2544	120	2664	0.012	0.081	-0.28	-0.037	0.011
CONED	2544	120	2664	0.019	0.05	-0.14	-0.012	0.019
CONTIL	2544	120	2664	-0.0011	0.15	-0.6	-0.051	0
DATGEN	2544	120	2664	0.0075	0.13	-0.34	-0.072	0.017
DEC	2544	120	2664	0.02	0.099	-0.36	-0.051	0.024
DELTA	2544	120	2664	0.012	0.096	-0.26	-0.053	0.013
GENMIL	2544	120	2664	0.017	0.065	-0.15	-0.026	0.011
GERBER	2544	120	2664	0.016	0.088	-0.29	-0.036	0.015
IBM	2544	120	2664	0.0096	0.059	-0.19	-0.029	0.002
MARKET	2544	120	2664	0.014	0.068	-0.26	-0.013	0.012
MOBIL	2544	120	2664	0.016	0.08	-0.18	-0.032	0.013
MOTOR	2544	120	2664	0.018	0.097	-0.33	-0.053	0.017
PANAM	2544	120	2664	0.0035	0.13	-0.31	-0.065	0
PSNH	2544	120	2664	-0.0042	0.11	-0.48	-0.049	0
rkfree	2544	120	2664	0.0068	0.0022	0.0021	0.0052	0.0066
RKFREE	2544	120	2664	0.0068	0.0022	0.0021	0.0052	0.0066
TANDY	2544	120	2664	0.025	0.13	-0.25	-0.058	0.022
TEXACO	2544	120	2664	0.012	0.08	-0.19	-0.037	0.01
WEYER	2544	120	2664	0.0096	0.085	-0.27	-0.049	-0.002
p75	p100	hist						
90.25	120							
0.07	0.38							
0.064	0.32							
0.045	0.15							
0.058	0.97							
0.078	0.53							
0.075	0.39							
0.063	0.29							
0.06	0.19							
0.065	0.23							
0.05	0.15							
0.062	0.15							
0.057	0.37							
0.084	0.27							
0.074	0.41							
0.043	0.32							
0.0078	0.013							
0.0078	0.013							
0.094	0.45							
0.048	0.4							
0.06	0.27							

```
df = rename(df, n = A, date = B) #
```

```
df = na.omit(df) #
```

CAPM :)

MOTOR.

,

-

```

MOTOR
#
df = mutate(df, y = MOTOR - RKFREE, x = MARKET - RKFREE)

```

```

ols = lm(y ~ x, data = df)
summary(ols)

```

```

Call:
lm(formula = y ~ x, data = df)

```

```

Residuals:
    Min       1Q   Median       3Q      Max
-0.168421 -0.059381 -0.003399  0.061373  0.182991

```

```

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.005253   0.007200   0.730   0.467
x             0.848150   0.104814   8.092 5.91e-13 ***
---

```

```

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

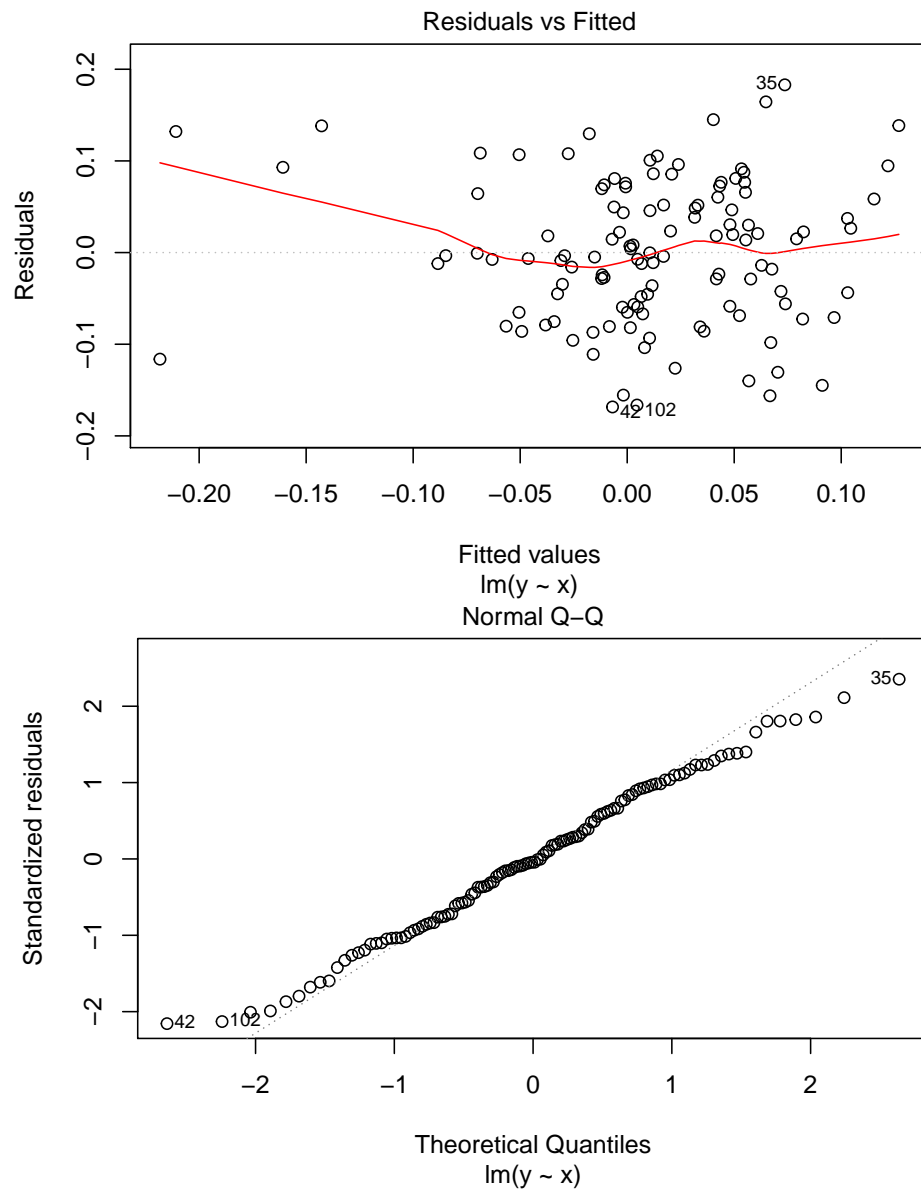
Residual standard error: 0.07844 on 118 degrees of freedom
Multiple R-squared:  0.3569,    Adjusted R-squared:  0.3514
F-statistic: 65.48 on 1 and 118 DF,  p-value: 5.913e-13

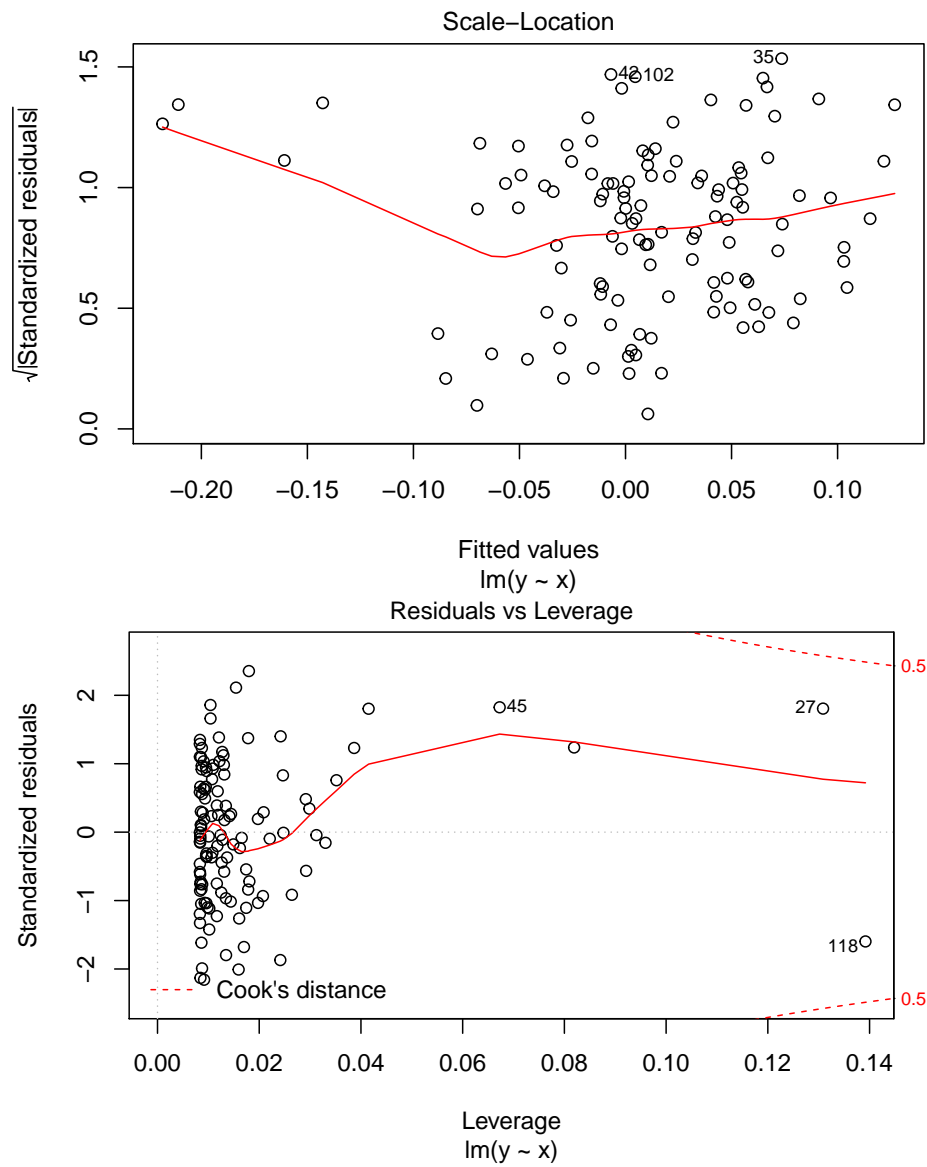
```

```

plot(ols)

```





```
est = cbind(Estimate = coef(ols), confint(ols))
```

```
linearHypothesis(ols, c("x = 1"))
```

Linear hypothesis test

Hypothesis:

$x = 1$

Model 1: restricted model

Model 2: $y \sim x$

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	119	0.73900				
2	118	0.72608	1	0.012915	2.0989	0.1501

:)

$$H_0 : S = 0, K = 3,$$

S —

(Skewness), K —

(Kurtosis)

```
jarque.bera.test(resid(ols))
```

Jarque Bera Test

data: resid(ols)

X-squared = 1.7803, df = 2, p-value = 0.4106

$$H_0 : \epsilon_i \sim N(\mu, \sigma^2)$$

```
shapiro.test(resid(ols))
```

Shapiro-Wilk normality test

data: resid(ols)

W = 0.99021, p-value = 0.5531

```
set.seed(7)
```

```
newData = df
```

```
newData = mutate(newData, x = x + rnorm(n = n())) #
```

```
yhat = predict(ols, newdata = newData, se = TRUE)
```

2.0.0.1

use us-return.dta

end of do-file

```
summarize
ren A n
ren B date
```

Variable	Obs	Mean	Std. Dev.	Min	Max
-----+-----					
A	120	60.5	34.78505	1	120
B	0				
MOBIL	120	.0161917	.0803075	-.178	.366
TEXACO	120	.0119417	.0797036	-.194	.399
IBM	120	.0096167	.059024	-.187	.15
-----+-----					
DEC	120	.01975	.0991438	-.364	.385
DATGEN	120	.0074833	.1275399	-.342	.528
CONED	120	.0185083	.0502719	-.139	.151
PSNH	120	-.0042167	.1094712	-.485	.318
WEYER	120	.0096333	.0850664	-.271	.27
-----+-----					
BOISE	120	.016675	.0974882	-.274	.379
MOTOR	120	.0181583	.0972656	-.331	.27
TANDY	120	.0250083	.127566	-.246	.454
PANAM	120	.0035167	.1318054	-.313	.406
DELTA	120	.0116917	.0959317	-.26	.289
-----+-----					
CONTIL	120	-.0011	.1506992	-.6	.974
CITCRP	120	.0118583	.0809719	-.282	.318
GERBER	120	.0164	.0877379	-.288	.234
GENMIL	120	.0165833	.0650403	-.148	.19
MARKET	120	.0139917	.0683532	-.26	.148
-----+-----					
RKFREE	120	.0068386	.0021869	.00207	.01255
rkfree	120	.0068386	.0021869	.00207	.01255

```
drop if n == .
gen y = MOTOR - RKFREE
gen x = MARKET - RKFREE
(2,544 observations deleted)
```

```
reg y x
```

Source	SS	df	MS	Number of obs	=	120
--------	----	----	----	---------------	---	-----

-----+-----				F(1, 118)	=	65.48
Model		.402913404	1	.402913404	Prob > F	= 0.0000
Residual		.726081541	118	.006153233	R-squared	= 0.3569
-----+-----				Adj R-squared	=	0.3514
Total		1.12899494	119	.009487352	Root MSE	= .07844

-----+-----						
y		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----						
x		.8481496	.1048138	8.09	0.000	.6405898 1.055709
_cons		.0052529	.0071999	0.73	0.467	-.009005 .0195107
-----+-----						

```
test x = 1
```

```
( 1)  x = 1
```

```
      F( 1, 118) =    2.10
      Prob > F =    0.1501
```

```
predict u_hat, resid
predict y_hat
```

```
(option xb assumed; fitted values)
```

Stata

<https://www.stata.com/manuals13/rsktest.pdf>

```
sktest u_hat
```

Skewness/Kurtosis tests for Normality

		----- joint -----				
Variable		Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
-----+-----						
u_hat		120	0.8841	0.1027	2.74	0.2539
-----+-----						
R.						

```
swilk u_hat
```

Shapiro-Wilk W test for normal data

Variable		Obs	W	V	z	Prob>z
-----+-----						
u_hat		120	0.99021	0.942	-0.133	0.55310

QQ -

qnorm u_hat

```
```stata
rvfplot, yline(0)
```
```

- (R).

lvr2plot

“““

```
predict D, cooksd
predict standard, rstandard
```

```
graph twoway scatter standard y_hat [aweight=D], msymbol(oh) yline(0)
```

```
set seed 7
```

```
set obs 120
gen x_new = x+ 0.5 *rnormal()
gen y_hat_new = .8481496 * x_new+ .0052529
number of observations (_N) was 120, now 120
```

2.0.0.2 python

Statsmodels.

```
import pandas as pd #
import numpy as np # ,
import matplotlib.pyplot as plt #
import statsmodels.api as sm
import statsmodels.formula.api as smf
import statsmodels.graphics.gofplots as gf
from statsmodels.stats.outliers_influence import summary_table
import seaborn as sns #
from scipy.stats import shapiro #
import statsmodels.discrete.discrete_model
```

```

        ,
        :)

plt.style.use('seaborn')
plt.rc('font', size=14)
plt.rc('figure', titlesize=15)
plt.rc('axes', labelsz=15)
plt.rc('axes', titlesize=15)

df = pd.read_stata('us-return.dta')

df.dropna(inplace=True) ## (
df.reset_index(drop=True, inplace=True)

df = df.rename(columns={'A': 'n', 'B': 'date'})

df['y'] = df['MOTOR'] - df['RKFREE']
df['x'] = df['MARKET'] - df['RKFREE']

:)

regr = smf.ols('y~x', data = df).fit()
regr.summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                        OLS Regression Results
=====
Dep. Variable:          y      R-squared:          0.357
Model:                  OLS    Adj. R-squared:      0.351
Method:                 Least Squares  F-statistic:      65.48
Date:                   , 16   2019  Prob (F-statistic):  5.91e-13
Time:                   10:46:25  Log-Likelihood:      136.18
No. Observations:       120      AIC:              -268.4
Df Residuals:           118      BIC:              -262.8
Df Model:                1
Covariance Type:        nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept      0.0053      0.007      0.730      0.467      -0.009      0.020
x              0.8481      0.105      8.092      0.000      0.641      1.056
=====
Omnibus:                2.684    Durbin-Watson:          2.030
Prob(Omnibus):          0.261    Jarque-Bera (JB):        1.780

```

| | | | |
|-----------|--------|-----------|-------|
| Skew: | -0.031 | Prob(JB): | 0.411 |
| Kurtosis: | 2.406 | Cond. No. | 14.6 |

=====

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 """

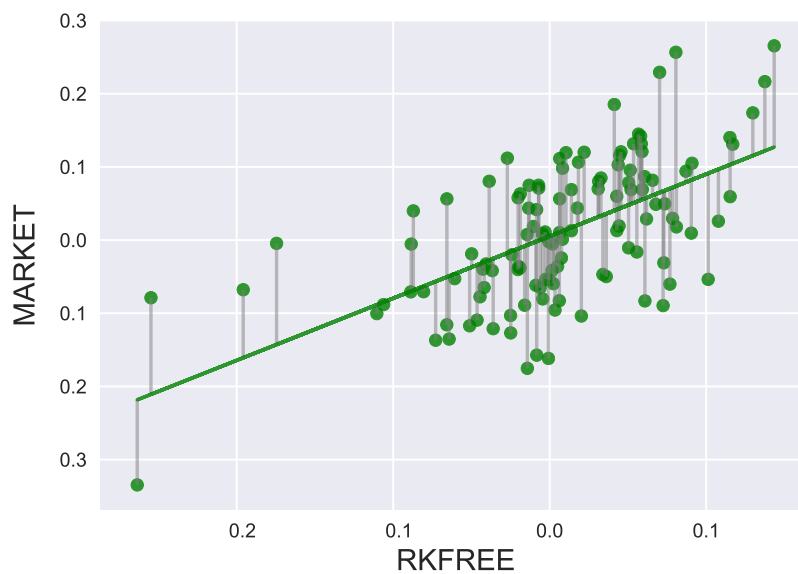
```
df['yhat'] = regr.fittedvalues
```

```

    , R,
    :)

fig, ax = plt.subplots()
ax.plot(df['x'],regr.fittedvalues, color='g', alpha =0.8)
ax.scatter(df['x'],regr.fittedvalues+regr.resid, color = 'g', alpha = 0.8, s = 40)
ax.vlines(df['x'],regr.fittedvalues,regr.fittedvalues+regr.resid, color = 'gray', alpha = 0.5)
plt.title('')
plt.xlabel('RKFREE')
plt.ylabel('MARKET')
plt.show()

```



```
regr.conf_int()
```

```

              0      1
Intercept -0.009005  0.019511
x          0.640590  1.055709

```

F-test.

```

hypotheses = '(x = 1)'
regr.f_test(r_matrix = hypotheses)

```

```

<class 'statsmodels.stats.contrast.ContrastResults'>
<F test: F=array([[2.09891771]]), p=0.1500556415866233, df_denom=118, df_num=1>

```

. , R.

```

W, p_value = shapiro(regr.resid)
#pd.DataFrame(data = {'W': [round(W,3)], 'p_value': [round(p_value,3)]})

```

```

import random
random.seed(7)

```

```

newData = df['x'] + 0.5*np.random.normal(len(df))
prediction = regr.predict(newData)

```

! , autoplot R.

```
fig_1 = plt.figure(1)
```

```

fig_1.axes[0] = sns.residplot(df['x'], df['y'],
                             lowess=True,
                             scatter_kws={'alpha': 0.6},
                             line_kws={'color': 'red', 'lw': 2, 'alpha': 0.8})

```

```

fig_1.axes[0].set_title('Residuals vs Fitted')
fig_1.axes[0].set_xlabel('Fitted values')
fig_1.axes[0].set_ylabel('Residuals')

```

```

#
abs_resid = abs(regr.resid).sort_values(ascending=False)
abs_resid_top3 = abs_resid[:3]

```

```

for i in abs_resid_top3.index:
    fig_1.axes[0].annotate(i,
                           xy=(regr.fittedvalues[i],
                                regr.resid[i]))

```



```

norm_residuals = regr.get_influence().resid_studentized_internal #

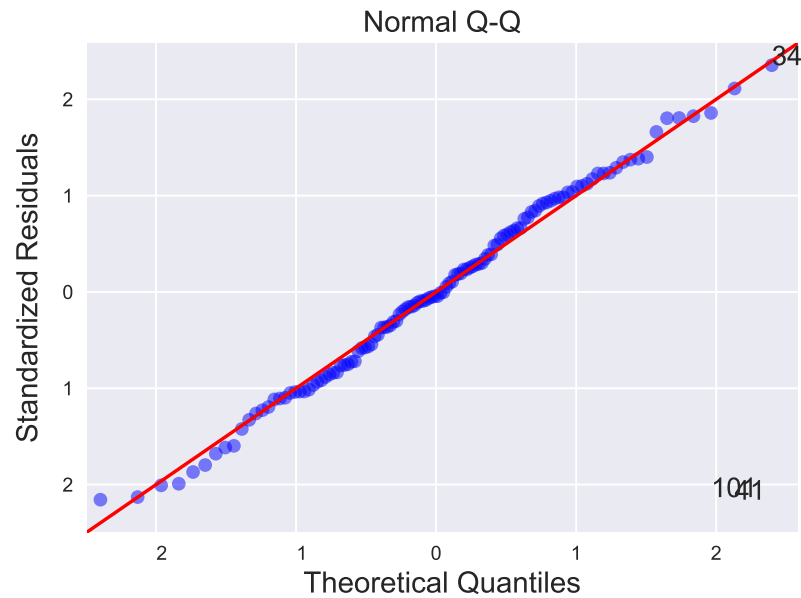
QQ = gf.ProbPlot(norm_residuals)
fig_2 = QQ.qqplot(line='45', alpha=0.5, color='b', lw=1)

fig_2.axes[0].set_title('Normal Q-Q')
fig_2.axes[0].set_xlabel('Theoretical Quantiles')
fig_2.axes[0].set_ylabel('Standardized Residuals');

#
abs_norm_resid = np.flip(np.argsort(abs(norm_residuals)), 0)
abs_norm_resid_top3 = abs_norm_resid[:3]

for r, i in enumerate(abs_norm_resid_top3):
    fig_2.axes[0].annotate(i,
                           xy=(np.flip(QQ.theoretical_quantiles, 0)[r],
                               norm_residuals[i]))

```

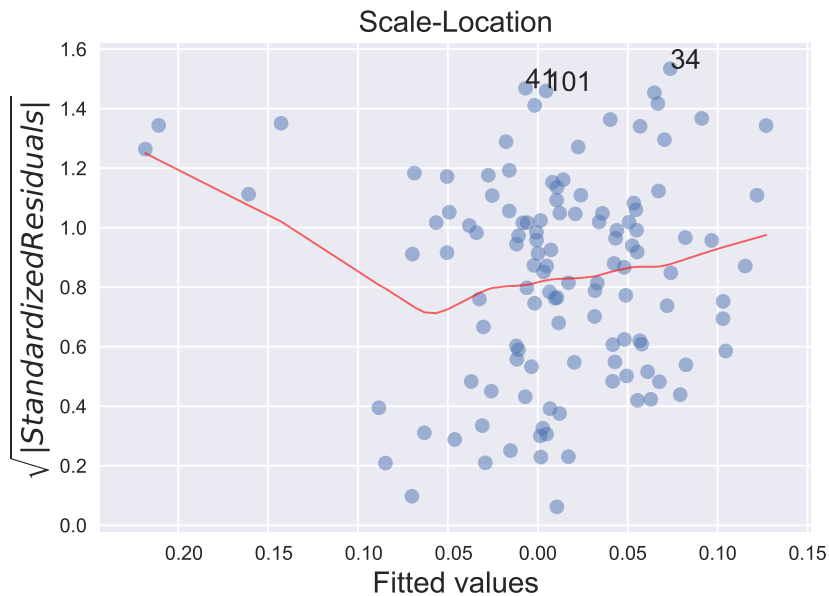


```
fig_3 = plt.figure(3)

plt.scatter(regr.fittedvalues, np.sqrt(abs(norm_residuals)), alpha=0.5)
sns.regplot(regr.fittedvalues, np.sqrt(abs(norm_residuals)),
            scatter=False,
            ci=False,
            lowess=True,
            line_kws={'color': 'red', 'lw': 1, 'alpha': 0.6})

fig_3.axes[0].set_title('Scale-Location')
fig_3.axes[0].set_xlabel('Fitted values')
fig_3.axes[0].set_ylabel('$\sqrt{|Standardized Residuals|}$')

# !)
```

```
leverage = regr.get_influence().hat_matrix_diag #
cook_dist = regr.get_influence().cooks_distance[0] #

fig_4 = plt.figure(4)

plt.scatter(leverage, norm_residuals, alpha=0.5)
sns.regplot(leverage, norm_residuals,
            scatter=False,
            ci=False,
            lowess=True,
            line_kws={'color': 'red', 'lw': 1, 'alpha': 0.8})

fig_4.axes[0].set_xlim(0, 0.20)

(0, 0.2)

fig_4.axes[0].set_ylim(-3, 5)

(-3, 5)

fig_4.axes[0].set_title('Residuals vs Leverage')
fig_4.axes[0].set_xlabel('Leverage')
fig_4.axes[0].set_ylabel('Standardized Residuals')

leverage_top3 = np.flip(np.argsort(cook_dist), 0)[:3]
```

```
for i in leverage_top3:
    fig_4.axes[0].annotate(i,
                           xy=(leverage[i],
                               norm_residuals[i]))
plt.show()
```

