

## Questions

This test exercise is of an applied nature and uses data that are available in the data file TestExer3. We consider the so-called Taylor rule for setting the (nominal) interest rate. This model describes the level of the nominal interest rate that the central bank sets as a function of equilibrium real interest rate and inflation, and considers the current level of inflation and production. Taylor (1993) considers the model:

$$i_t = r^* + \pi_t + 0.5(\pi_t - \pi^*) + 0.5g_t$$

with  $i_t$  the Federal funds target interest rate at time  $t$ ,  $r^*$  the equilibrium real federal funds rate,  $\pi_t$  a measure of inflation,  $\pi^*$  the target inflation rate and  $g_t$  the output gap (how much actual output deviates from potential output). We simplify the Taylor rule in two manners. First, we avoid determining  $r^*$  and  $\pi^*$  and simply add an intercept to the model to capture these two variables (and any other deviations in the means). Second, we consider production  $y_t$  rather than the output gap. In this form the Taylor rule is

$$i_t = \beta_1 + \beta_2\pi_t + \beta_3y_t + \varepsilon_t$$

Monthly data are available for the USA over the period 1960 through 2014 for the following variables:

- INTRATE: Federal funds interest rate
- INFL: Inflation
- PROD: Production • UNEMPL: Unemployment
- COMMPRI: Commodity prices
- PCE: Personal consumption expenditure
- PERSINC: Personal income
- HOUST: Housing starts

(a) Use general-to-specific to come to a model. Start by regressing the federal funds rate on the other 7 variables and eliminate 1 variable at a time.

In [1]:

```
%matplotlib inline
import sys
sys.path.append('/Users/CJ/Documents/bitbucket/xforex_v1/xforex_v3')
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime
from xforex.BackTesting.econometrics_tools import Econometrics_Tool
import numpy as np

dat = pd.read_csv(
    '/Users/CJ/Documents/bitbucket/xforex_v1/xforex_v3/training/econometric
s/week3-model-specifiction/TestExer3-TaylorRule-round1.txt',
    sep='\t').drop(['Unnamed: 9', 'Unnamed: 10', 'Unnamed: 11', 'Unnamed:
12', 'Unnamed: 13'], axis = 1)
dat.describe()
g2s_model = \
Econometrics_Tool().iter_linear_fit(dat[['PROD', 'INFL', 'UNEMPL', 'COMMPRI', 'PCE',
ERSINC', 'HOUST']], \
    dat['INTRATE'])
print g2s_model.summary()
```

eliminate column: UNEMPL  
eliminate column: PROD

# OLS Regression Results

```
=====
=====
Dep. Variable:          INTRATE    R-squared:
      0.637
Model:                OLS    Adj. R-squared:
      0.635
Method:              Least Squares    F-statistic:
      229.9
Date:                Tue, 13 Sep 2016    Prob (F-statistic):
      2.03e-141
Time:                15:45:59    Log-Likelihood:
      -1450.2
No. Observations:      660    AIC:
      2912.
Df Residuals:          654    BIC:
      2939.
Df Model:              5
```

Covariance Type: nonrobust

```
=====
=====
               coef      std err          t      P>|t|      [95.0% C
onf. Int.]
-----
const         -0.2401      0.230      -1.042      0.298      -0.692
      0.212
INFL           0.7175      0.057     12.555      0.000      0.605
      0.830
COMMPRI        -0.0075      0.003     -2.841      0.005     -0.013
      -0.002
PCE            0.3405      0.059      5.756      0.000      0.224
      0.457
PERSINC         0.2402      0.059      4.048      0.000      0.124
      0.357
HOUST          -0.0205      0.004     -4.678      0.000     -0.029
      -0.012
=====
=====
```

```
Omnibus:          23.848    Durbin-Watson:
      0.100
Prob(Omnibus):      0.000    Jarque-Bera (JB):
      31.255
Skew:              0.354    Prob(JB):
      1.63e-07
Kurtosis:          3.797    Cond. No.
      94.1
=====
=====
```

## Warnings:

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

(b) Use specific-to-general to come to a model. Start by regressing the federal funds rate on only a constant and add 1 variable at a time. Is the model the same as in (a)?

**ans:** below code shows to add 1 variable at a time and find the best combinations of variables. And the model seems the same as (a)

In [2]:

```
s2g_model = Econometrics_Tool().global_iter_linear_fit_aic(dat[['PROD',  
'INFL','UNEMPL','COMMPRI','PCE','PERSINC','HOUST']], \  
                dat['INTRATE'])
```

\*\*\*\*\*

Final model:

## OLS Regression Results

```

=====
=====
Dep. Variable:                INTRATE    R-squared:
    0.637
Model:                      OLS    Adj. R-squared:
    0.635
Method:                    Least Squares    F-statistic:
    229.9
Date:                Tue, 13 Sep 2016    Prob (F-statistic):
    2.03e-141
Time:                15:45:59    Log-Likelihood:
    -1450.2
No. Observations:                660    AIC:
    2912.
Df Residuals:                654    BIC:
    2939.
Df Model:                5

```

Covariance Type: nonrobust

```

=====
=====

```

	coef	std err	t	P> t	[95.0% C
onf. Int.]					
-----					
const	-0.2401	0.230	-1.042	0.298	-0.692
0.212					
INFL	0.7175	0.057	12.555	0.000	0.605
0.830					
COMMPRI	-0.0075	0.003	-2.841	0.005	-0.013
-0.002					
PCE	0.3405	0.059	5.756	0.000	0.224
0.457					
PERSINC	0.2402	0.059	4.048	0.000	0.124
0.357					
HOUST	-0.0205	0.004	-4.678	0.000	-0.029
-0.012					

```

=====
=====

```

```

=====
=====
Omnibus:                23.848    Durbin-Watson:
    0.100
Prob(Omnibus):                0.000    Jarque-Bera (JB):
    31.255
Skew:                0.354    Prob(JB):
    1.63e-07
Kurtosis:                3.797    Cond. No.
    94.1
=====
=====

```

## Warnings:

```

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

```

\*\*\*\*\*



In [3]:

```
from tabulate import tabulate
print '|specific to general model:'
print tabulate(pd.DataFrame(s2g_model.params), headers='keys', tablefmt='psql')

print '\n|general to specific model:'
print tabulate(pd.DataFrame(g2s_model.params), headers='keys', tablefmt='psql')
```

|specific to general model:

	0
const	-0.240119
INFL	0.717527
COMMPRI	-0.00750067
PCE	0.340525
PERSINC	0.240242
HOUST	-0.0205297

|general to specific model:

	0
const	-0.240119
INFL	0.717527
COMMPRI	-0.00750067
PCE	0.340525
PERSINC	0.240242
HOUST	-0.0205297

(c) Compare your model from (a) and the Taylor rule of equation (1). Consider  $R^2$ , AIC and BIC. Which of the models do you prefer? **ans:** Taylor rule:

$$federalFundsRate_t = const + b1 * inflation + b2 * production + \varepsilon_t$$

Please change below for the model comparison results. Model from (a) are better when comparing  $R^2$ , AIC and BIC



In [4]:

```
taylor_model = Econometrics_Tool().linear_fit(dat[['PROD', 'INFL']], \
                                             dat['INTRATE'])

df_compare = pd.DataFrame(index=['r-square', 'aic', 'bic'])

df_compare['taylor'] = [taylor_model.rsquared, taylor_model.aic, taylor_model.bic]
df_compare['general_to_specific'] = [g2s_model.rsquared, g2s_model.aic, g2s_model.bic]
print tabulate(df_compare, headers='keys', tablefmt='psql')
```

	taylor	general_to_specific
r-square	0.574701	0.637361
aic	3011.62	2912.42
bic	3025.09	2939.38

(d) Test the Taylor rule of equation (1) using the RESET test, Chow break and forecast test (with in both tests as break date January 1980) and a Jarque-Bera test. What do you conclude?

**ans:**

(1) In RESET Test, p value is 0.11. null assumption cannot be rejected at 5% level. (2) In Chow break and forecast test, p value is 7.62693e-74 and 0.0647282, which suggests the possible instability of the taylor. (3) In Jarque-Bera test, p value is 0.00198523, null assumption is rejected at 5% level, which suggests non-normality of error terms

In [5]:

```
# after 1980 model test
from scipy import stats
from statsmodels.stats.outliers_influence import reset_ramsey
from datetime import datetime

dat.index = dat.OBS.map(lambda x: datetime.strptime(x, '%Y:%m'))

df_stat = pd.DataFrame(index=['jarque_bera test', 'RESET', 'Chow-break', 'Chow-f
orcast'])
model =taylor_model

# RESET TEST: for higher degree dependency
RESET_test = [str(reset_ramsey(model, degree=2)).split(",")[0], \
               str(reset_ramsey(model, degree=2)).split(",")[1].split("=")[1]]

# chow break: stability
# dat.index = dat['Year']
chow_break = Econometrics_Tool().chow_break(dat[['PROD', 'INFL']],
dat['INTRATE'], datetime(1980,1,1))

# chow forecast:

# dat.index = dat['Year']
chow_forecast = Econometrics_Tool().chow_forecast(dat[['PROD', 'INFL']], dat['INTR
ATE'], 0.2)

df_stat['stat'] = [stats.jarque_bera(model.resid)[0], RESET_test[0] , chow_break[
] ,chow_forecast[0]]
df_stat['p-value'] = [stats.jarque_bera(model.resid)[1], RESET_test[1], chow_bre
ak[1] ,chow_forecast[1]]

print tabulate(df_stat, headers='keys', tablefmt='psql')
```





## OLS Regression Results

```

=====
=====
Dep. Variable:          INTRATE    R-squared:
      0.856
Model:                OLS    Adj. R-squared:
      0.856
Method:             Least Squares    F-statistic:
      1961.
Date:                Tue, 13 Sep 2016    Prob (F-statistic):
      6.08e-278
Time:                15:45:59    Log-Likelihood:
      -1527.1
No. Observations:          660    AIC:
      3058.
Df Residuals:            658    BIC:
      3067.
Df Model:                  2

Covariance Type:          nonrobust

```

```

=====
=====
              coef      std err          t      P>|t|      [95.0% C
onf. Int.]
-----
PROD          0.1596      0.018       8.819      0.000      0.124
      0.195
INFL          1.1583      0.021     55.658      0.000      1.117
      1.199
=====
=====
Omnibus:                3.527    Durbin-Watson:
      0.069
Prob(Omnibus):          0.171    Jarque-Bera (JB):
      3.597
Skew:                   0.165    Prob(JB):
      0.166
Kurtosis:               2.851    Cond. No.
      1.45
=====
=====

```

## Warnings:

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

## OBS

```

1980-02-01    14.13
1980-03-01    17.19
1980-04-01    17.61
1980-05-01    10.98
1980-06-01     9.47

```

Name: INTRATE, dtype: float64

## OLS Regression Results

```

=====
=====
Dep. Variable:          INTRATE    R-squared:
      0.954

```

```

Model:                                OLS    Adj. R-squared:
      0.954
Method:                            Least Squares    F-statistic:
      2504.
Date:                                Tue, 13 Sep 2016    Prob (F-statistic):
      5.00e-161
Time:                                15:45:59    Log-Likelihood:
      -412.38
No. Observations:                    241    AIC:
      828.8
Df Residuals:                        239    BIC:
      835.7
Df Model:                            2

```

Covariance Type: nonrobust

```

=====
=====
              coef      std err          t      P>|t|      [95.0% C
onf. Int.]
-----
PROD          0.1997      0.014      14.727      0.000      0.173
      0.226
INFL          0.9588      0.016      59.867      0.000      0.927
      0.990
=====
=====
Omnibus:                4.345    Durbin-Watson:
      0.144
Prob(Omnibus):          0.114    Jarque-Bera (JB):
      4.179
Skew:                   -0.322    Prob(JB):
      0.124
Kurtosis:               3.046    Cond. No.
      1.49
=====
=====

```

#### Warnings:

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

#### OLS Regression Results

```

=====
=====
Dep. Variable:            INTRATE    R-squared:
      0.837
Model:                    OLS    Adj. R-squared:
      0.836
Method:                    Least Squares    F-statistic:
      1069.
Date:                      Tue, 13 Sep 2016    Prob (F-statistic):
      6.83e-165
Time:                      15:45:59    Log-Likelihood:
      -1002.7
No. Observations:          419    AIC:
      2009.
Df Residuals:              417    BIC:
      2017.
Df Model:                  2

```

Covariance Type: nonrobust

```

=====
=====
              coef      std err          t      P>|t|      [95.0% C
onf. Int.]
-----
PROD          0.1239      0.029      4.296      0.000      0.067
      0.181
INFL          1.3650      0.032     42.444      0.000      1.302
      1.428
=====
=====
Omnibus:              7.009   Durbin-Watson:
      0.081
Prob(Omnibus):        0.030   Jarque-Bera (JB):
      7.091
Skew:                -0.318   Prob(JB):
      0.0289
Kurtosis:            2.980   Cond. No.
      1.40
=====
=====

```

## Warnings:

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

n2: 132

## OLS Regression Results

```

=====
=====
Dep. Variable:          INTRATE   R-squared:
      0.887
Model:                  OLS       Adj. R-squared:
      0.886
Method:                 Least Squares   F-statistic:
      2059.
Date:                  Tue, 13 Sep 2016   Prob (F-statistic):
      1.75e-249
Time:                  15:45:59   Log-Likelihood:
      -1210.0
No. Observations:      528   AIC:
      2424.
Df Residuals:          526   BIC:
      2432.
Df Model:              2

```

Covariance Type: nonrobust

```

=====
=====
              coef      std err          t      P>|t|      [95.0% C
onf. Int.]
-----
PROD          0.2152      0.019     11.105      0.000      0.177
      0.253
INFL          1.1803      0.021     56.269      0.000      1.139

```

1.222

```

=====
=====
Omnibus:                4.033    Durbin-Watson:
    0.074
Prob(Omnibus):          0.133    Jarque-Bera (JB):
    3.883
Skew:                   0.167    Prob(JB):
    0.143
Kurtosis:              3.254    Cond. No.
    1.41
=====
=====

```

## Warnings:

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

## OLS Regression Results

```

=====
=====
Dep. Variable:          INTRATE    R-squared:
    0.545
Model:                 OLS        Adj. R-squared:
    0.538
Method:               Least Squares    F-statistic:
    77.87
Date:                 Tue, 13 Sep 2016    Prob (F-statistic):
    5.87e-23
Time:                 15:45:59    Log-Likelihood:
    -255.11
No. Observations:      132    AIC:
    514.2
Df Residuals:          130    BIC:
    520.0
Df Model:              2

```

Covariance Type: nonrobust

```

=====
=====
               coef      std err          t      P>|t|      [95.0% C
onf. Int.]
-----
PROD          -0.0411      0.032      -1.294      0.198      -0.104
    0.022
INFL           0.7037      0.060      11.740      0.000      0.585
    0.822
=====
=====

```

```

=====
=====
Omnibus:                16.983    Durbin-Watson:
    0.052
Prob(Omnibus):          0.000    Jarque-Bera (JB):
    20.201
Skew:                   0.957    Prob(JB):
    4.11e-05
Kurtosis:              3.094    Cond. No.
    2.24
=====
=====

```



## Warnings:

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

	stat	p-value
jarque_bera test	12.4440433084	0.00198523
RESET	<F test: F=array([[ 2.53711954]])	0.111679
Chow-break	220.016340507	7.62693e-74
Chow-forecast	1.22281217974	0.0647282