

Project 5 - Equilibrium Foreign Exchange in Python

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1 Objectives

The project is aimed at explanation of macroeconomic factors influence on FX evolution.

1.1 Definitions

1. **Cointegration** is an econometric technique for testing the correlation between non-stationary time series variables. If two or more series are themselves non-stationary, but a linear combination of them is stationary, then the series are said to be cointegrated.

2. The **equilibrium foreign exchange** represents the foreign exchange indicated by macroeconomic indicators (basically the results of a regression in our case)

1.2 Algorithm

- Choose macroeconomic factors
- Implement a regression
- Analyze how accurate are regression results

2 Data

- For the project USD/JPY currency pair was chosen.
- Macroeconomic factors:
 - Consumer Price Index
 - 10-Year Treasury Constant Maturity Rate (I will call it just Interest Rate)

2.1 Data Source

The historical data of CPI is downloaded from the [FRED](#)

3 Implementation Details

Python code in the project is fairly not so difficult, so I do not pay big attention to it here.

3.1 Data Download

As was mentioned before the data was downloaded from FRED using **python pandas_datereader** package:

```
from pandas_datereader import data as pdr
pdr.DataReader()
```

I decided to analyze data for 30 last months. Moreover, as a first parameter I consider a fraction: $\frac{CPI_USA}{CPI_JPN}$, the second parameter is mentioned USA interest rate.

3.2 Regression in Python

To implement a regression in python `statsmodels` package can be used:

```
import statsmodels.api as sm
sm.add_constant()
model = sm.OLS()
model.fit()
```

4 Results

OLS Regression Results

Dep. Variable:	EXJPUS	R-squared:	0.315			
Model:	OLS	Adj. R-squared:	0.291			
Method:	Least Squares	F-statistic:	12.88			
Date:	Tue, 13 Feb 2018	Prob (F-statistic):	0.00125			
Time:	01:33:16	Log-Likelihood:	48.954			
No. Observations:	30	AIC:	-93.91			
Df Residuals:	28	BIC:	-91.10			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

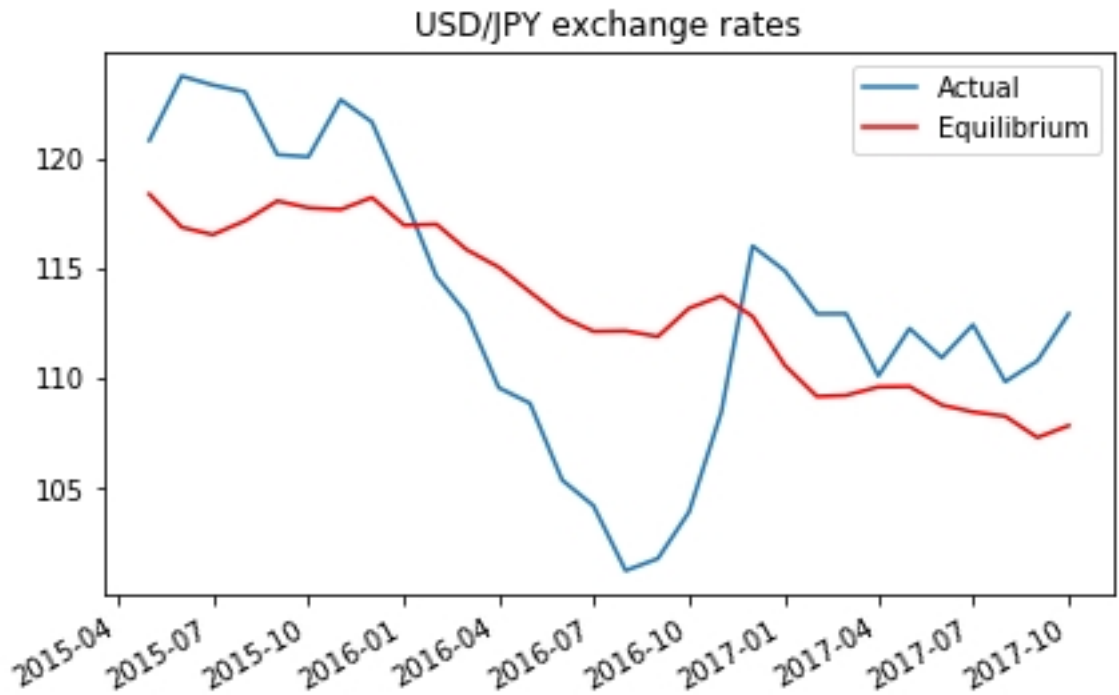
const	4.9046	0.050	98.483	0.000	4.803	5.007
0	-2.7399	0.764	-3.588	0.001	-4.304	-1.176
=====						
Omnibus:	4.434	Durbin-Watson:	0.240			
Prob(Omnibus):	0.109	Jarque-Bera (JB):	3.964			
Skew:	-0.827	Prob(JB):	0.138			
Kurtosis:	2.338	Cond. No.	85.7			
=====						

As we can see both coefficients are significant, moreover, we can see that increase in $\frac{CPI_{USA}}{CPI_{JPN}}$ ratio leads to appreciation of JPY (decrease in ratio $\frac{USD}{JPY}$). This works as expected, however $R^2 = 0.315$ that means that approximately 30% are explained by the model. The result of the model fairly is not reliable.

We can be even more precise. Log-level regression coefficients (except of the intercept) may be interpreted as a percentage. (see [this link](#))

As a result we can conclude that change in CPI ratio by 1% leads to 2.74% change in exchange rate.

However, when we use 2 factors the result is really great! All coefficients are significant and $R^2 = 0.892$ that means that approximately 90% changes in exchange rate can be explained by this model! The interpretation above (with percentage) may be applied here as well.



As we can see on the graph our modeling is not so accurate.

OLS Regression Results

=====						
Dep. Variable:	EXJPUS	R-squared:	0.892			
Model:	OLS	Adj. R-squared:	0.884			
Method:	Least Squares	F-statistic:	111.3			
Date:	Tue, 13 Feb 2018	Prob (F-statistic):	9.13e-14			
Time:	01:33:16	Log-Likelihood:	76.639			
No. Observations:	30	AIC:	-147.3			
Df Residuals:	27	BIC:	-143.1			
Df Model:	2					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	4.6234	0.031	149.599	0.000	4.560	4.687
0	-3.4491	0.315	-10.964	0.000	-4.095	-2.804
USACPIALLMINMEI	0.1553	0.013	11.999	0.000	0.129	0.182
=====						
Omnibus:	4.870	Durbin-Watson:	0.746			
Prob(Omnibus):	0.088	Jarque-Bera (JB):	3.269			
Skew:	-0.742	Prob(JB):	0.195			
Kurtosis:	3.643	Cond. No.	204.			
=====						

Graph shows how actually close model results and actual data are.

