# 19) Mean Reversion on Futures

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### Reference

Tables, Graphics, and Figures from

https://www.quantopian.com/lectures

Lecture 53 Mean Reversion on Futures

#### Random Walk

$$P_t = \mu + P_{t-1} + \epsilon_t$$

$$r_t = P_t - P_{t-1} = \mu + \epsilon_t$$

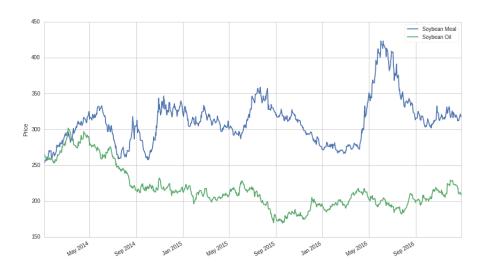
```
import numpy as np
import pandas as pd
import statsmodels.api as sm
from statsmodels.tsa.stattools import coint, adfuller
```

import matplotlib.pyplot as plt
from quantopian.research.experimental import continuous\_future, history

### Soybean Crush

```
soy meal mult = symbols('SMF17').multiplier
soy oil mult = symbols('BOF17').multiplier
soybean mult = symbols('SYF17').multiplier
sm future = continuous future('SM', offset=0,
            roll='calendar', adjustment='mul')
sm price = history(sm future,
         'price','2014-01-01', '2017-01-01','daily')
bo future = continuous future('BO',
         offset=0, roll='calendar', adjustment='mul')
bo price = history(bo future,
     'price', '2014-01-01', '2017-01-01', 'daily')
sm price.plot()
bo price.multiply(soy oil mult//soy meal mult).plot()
plt.vlabel('Price')
plt.legend(['Soybean Meal', 'Soybean Oil']);
```

## Soybean Meal vs Soybean Oil



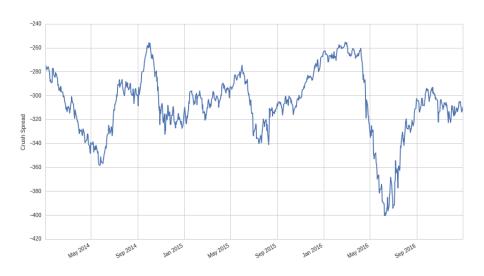
### **Augmented Dickey-Fuller Test**

```
print 'p-value: ', coint(sm price, bo price)[1]
p-value:
         0.228842012164
sm future = continuous future('SM', offset=1, roll='calendar', adjustment='mul')
sm price = history(sm future, 'price', '2014-01-01', '2017-01-01', 'daily')
bo future = continuous future('BO', offset=1, roll='calendar', adjustment='mul')
bo price = history(bo future, 'price', '2014-01-01', '2017-01-01', 'daily')
sy future = continuous future('SY', offset=0, roll='calendar', adjustment='mul')
sy price = history(sy future, 'price', '2014-01-01', '2017-01-01', 'daily')
crush = sy price - (sm price + bo price)
crush.plot()
plt.ylabel('Crush Spread');
```

print 'p-value for stationarity: ', adfuller(crush)[1]

p-value for stationarity: 0.0253387237046

### **Crush Spread**



## **Examples of Economically-Linked Futures**

## Profitability of Oil Refining

**3:2:1 Crack Spread**: Buy three crude oil, sell two gasoline, Sell one heating oil

## **Fattening Feeder Cattle**

**8:4:3 Cattle Crush**: Buy 8 October live-cattle, Sell 4 May feeder cattle, Sell 3 July corn

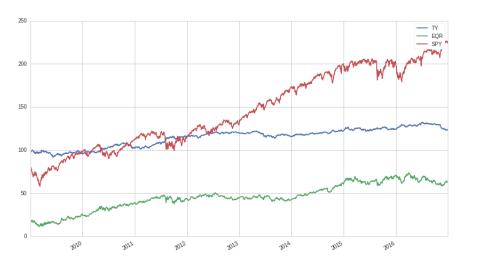
### Potential relationships between Futures and Stocks

- Crude oil futures and oil stocks
- Gold futures and gold mining stocks
- Crude oil futures and airline stocks
- Currency futures and exporters
- Interest rate futures and utilities
- Interest rate futures and Real Estate Investment Trusts (REITs)
- Corn futures and agricultural processing companies

### **Futures and Stocks**

```
ty future = continuous future('TY', offset=0, roll='calendar',
                              adjustment='mul')
ty prices = history(ty future, 'price', '2009-01-01', '2017-01-01', 'daily')
ty prices.name = ty future.root symbol
equities = symbols(['EQR', 'SPY'])
equity prices = get pricing(equities, fields='price',
                            start date='2009-01-01', end date='2017-01-01')
equity prices.columns = map(lambda x: x.symbol, equity prices.columns)
data = pd.concat([ty prices, equity prices], axis=1)
data = data.dropna()
data.plot()
plt.legend();
print 'Cointegration test p-value: ', coint(data['TY'], data['EQR'])[1]
Cointegration test p-value: 0.0299261276671
```

### **EQR (REIT)** and **Ten-Year Interest Rate Futures**



### **Crude Oil Futures and Oil Company Stocks**

data['futures lag diff'] = data['futures ret'].shift(1)

#Compute lagged futures returns

data = data[2:].dropna()

```
cl future = continuous future('CL', offset=0, roll='calendar', adjustment='mul')
cl prices = history(cl future, 'price', '2007-01-01', '2017-04-06', 'daily')
cl prices.name = cl future.root symbol
equities = symbols(['XOM', 'SPY'])
equity prices = get pricing(equities, fields='price', start date='2007-01-01',
                           end date='2017-04-06')
equity prices.columns = map(lambda x: x.symbol, equity prices.columns)
data = pd.concat([cl prices, equity prices],axis=1)
data = data.dropna()
data['stock ret'] = np.log(data['XOM']).diff()
data['spy ret'] = np.log(data['SPY']).diff()
data['futures ret'] = np.log(data['CL']).diff()
# Compute excess returns in excess of SPY
data['stock excess'] = data['stock ret'] - data['spy ret']
```

### **Data Table**

	CL	хом	SPY	stock_ret	futures_ret	spy_ret	stock_excess	futures_lag	futures_lag_diff
2017-03-31 00:00:00+00:00	50.85	82.00	235.72	-0.020281	0.010279	-0.002331	-0.017950	0.014610	0.014610
2017-04-03 00:00:00+00:00	50.25	82.08	235.37	0.000975	-0.011870	-0.001486	0.002461	0.010279	0.010279
2017-04-04 00:00:00+00:00	51.13	82.35	235.50	0.003284	0.017361	0.000552	0.002732	-0.011870	-0.011870
2017-04-05 00:00:00+00:00	50.82	82.53	234.77	0.002183	-0.006081	-0.003105	0.005288	0.017361	0.017361
2017-04-06 00:00:00+00:00	51.74	83.02	235.39	0.005920	0.017941	0.002637	0.003282	-0.006081	-0.006081

### **Contemporaneous and Lagged Correlation**

```
contemp_corr = data['stock_excess'].shift(1).corr(data['futures_lag_diff'])
#Compute correlation of excess stock returns with lagged futures returns
lagged_corr = data['stock_excess'].corr(data['futures_lag_diff'])
print 'Contemporaneous correlation: ', contemp_corr
print 'Lagged correlation: ', lagged_corr
Contemporaneous correlation: 0.257312975324
```

```
Contemporaneous correlation: 0.257312975324
Lagged correlation: -0.0519203748947
```

### **OLS** Result

Model:	OLS	Adj. R-squared:	0.002	
Dependent Variable:	stock_excess	AIC:	-16587.6204	
Date:	2017-04-25 18:21	BIC:	-16575.9124	
No. Observations:	2576	Log-Likelihood:	8295.8	
Df Model:	1	F-statistic:	6.958	
Df Residuals:	2574	Prob (F-statistic):	0.00840	
R-squared:	0.003	Scale:	9.3463e-05	

	Coef.	Std.Err.	t	P> t	[0.025	0.975]
const	-0.0001	0.0002	-0.6881	0.4914	-0.0005	0.0002
futures_lag_diff	-0.0216	0.0082	-2.6377	0.0084	-0.0377	-0.0055

### **Futures Lag Diff and Stock Excess**

data['futures\_lag\_diff'].plot(alpha=0.50, legend=True)
data['stock\_excess'].plot(alpha=0.50, legend=True);

