

# Pairs Trading Optimization using Q learning: A Cointegration Approach

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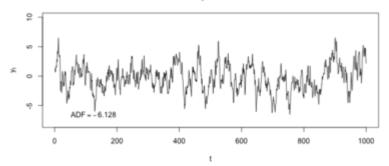
# Stationarity

A time series X(t) is weakly stationary if it satisfies:

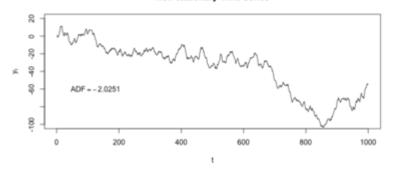
$$egin{aligned} \mathbb{E}[x(t)] &= m_x(t) = m_x(t+ au) \ ext{ for all } au \in \mathbb{R} \ \\ \mathbb{E}[(x(t_1) - m_x(t_1))(x(t_2) - m_x(t_2))] &= C_x(t_1, t_2) \end{aligned}$$

- Implication:
  - A stationary process never drift too far away from mean m
  - The spread of a stationary process is limited by its autocovariance

### Stationary Time Series



#### Non-stationary Time Series



Stationary Process vs Non-Stationary Proces. Wikipedia.

# AR(1) Process

AR(1) process follows:

$$X_t = \alpha + \phi X_{t-1} + \epsilon_t$$
  
$$\epsilon_t = N(0, \sigma^2)$$

- Characteristics
  - Mean:  $E(X_t) = \mu$
  - Variance:  $Var(X_t) = \frac{\sigma^2}{(1-\phi^2)}$
  - Covariance:  $Cov(X_t, X_{t+h}) = \phi^h \frac{\sigma^2}{(1-\phi^2)}$
  - Rate of Change:  $E(X_t|X_0=x) = \mu + \phi^{\tau}(x-\mu)$
- General Autoregressive Model:

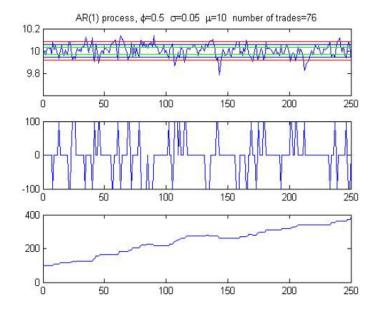
$$X_t = c + \sum_{i=1}^p arphi_i X_{t-i} + arepsilon_t$$

### Mean Reversion

- Prices have a tendency to "mean-revert" Engle (1987), Engle and Granger (1993)
- How To Trade an asset following AR(1):

• 
$$s = \left| \frac{X_t - \mu}{\sigma_X} \right|$$
 s-score

- Trade Entry:
  - 1.If  $\frac{X_t \mu}{C}$  < -1(lower threshold), long asset;
  - 2.if  $\frac{X_t \mu}{\sigma_X}$  > 1(upper threshold), short asset
- Trade Exit:
  - 1. If s < 0.5 closing
  - 2. If s > 1.5 stop loss
- Parameters to adjust: Estimation Window, Threshold, stop-loss level and trading window
- Prices are rarely stationary



Trade Execution on Simulated AR(1) process Top to Bottom: Prices, Positions, Wealth

# Pair Trading

- Objective: Many economic time series are non-stationary with an ascending or descending random trend, it is possible that a linear combination of these time series will always be stationary in a long run. Our objective is to identify two assets such that their linear combination produces a mean-reverting spread and thus they are identified as being co-integrated.
- For multivariate scenario: cointegration is defined as

$$e_t = \beta'_C Y_t \qquad e_t \sim I(0)$$
  
=  $\pm \beta_1 y_{1,t} \pm \beta_2 y_{2,t} \pm \cdots \pm \beta_n y_{n,t}$ 

- Hypothesis:
  - Given two asset X and Y, y = aX + bY can be a stationary process with long term mean relative mispricing persists. The "true long-term price" of combination of two assets X and Y being m, price difference m-y(t)
  - Pricing inefficiencies are identifiable with statistical models
- Cointegration exists where there is a correction of error in y from the equilibrium, and is therefore not a forecasting problem.

# Cointegration

Define two Time Series Xt and Yt

$$\begin{split} X_t &= \gamma_o + \gamma_1 Z_t + \epsilon_t \sim I(1) \\ Y_t &= \delta_o + \delta_1 Z_t + \eta_t \sim I(1) \\ Z_t &\sim I(1) \\ \epsilon_t, \eta_t &\sim I(0) \end{split}$$

- $\delta_1 X_t \gamma_1 Y_t(0)$  is stationary
- Cointegration assumes common I(1) processes shared (Ψ)

$$X_{1,t} = \alpha_1 + \gamma_1 Z_{1,t} + \gamma_2 Z_{2,t} + \dots + \gamma_p Z_{p,t} + \epsilon_{1,t}$$

$$X_{2,t} = \alpha_2 + \phi_1 Z_{1,t} + \phi_2 Z_{2,t} + \dots + \phi_p Z_{p,t} + \epsilon_{2,t}$$

$$\dots$$

$$X_{m,t} = \alpha_m + \psi_1 Z_{1,t} + \psi_2 Z_{2,t} + \dots + \psi_p Z_{p,t} + \epsilon_{m,t}$$

- Defines k = m p as number of independent linear combinations
  - p = m: k =0, no cointegration
  - 0<p<m: cointegrated</li>
  - p=0: all time series stationary

# Cointegration: Continued

- Obtain residuals e from the long-run (equilibrium) relationship
  - $\hat{e} = y_t bx_t a$  (OLS regression)test it for the unit root.
  - If unit root does not exist, then process e is stationary.
- Plug e into ECM model to obtain  $\beta_1$  and  $\alpha$

$$\Delta y_t = \beta_1 \Delta x_t - (1 - \alpha)e_{t-1} + \epsilon_t$$

# Cointegration: Continued

### Start with VAR model:

$$y_t = a_{11}y_{t-1} + a_{12}z_{t-1} + \varepsilon_{yt}$$
  
 $z_t = a_{21}y_{t-1} + a_{12}z_{t-1} + \varepsilon_{zt}$ 

### End With ECM

$$\Delta y_t = a_y (y_{t-1} - \beta z_{t-1}) + \varepsilon_{yt}$$
  

$$\Delta z_t = a_z (y_{t-1} - \beta z_{t-1}) + \varepsilon_{zt}$$

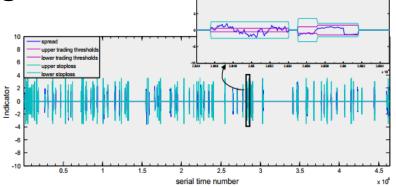
Long term mean

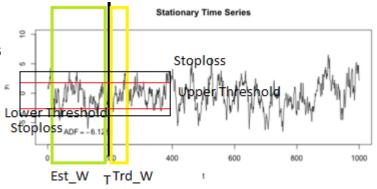
$$A_{t-1} - \beta B_{t-1} + \rho = \mu + \varepsilon_t$$

- Johansen Procedure (For multivariate scenario)
  - •Test the rank of Cointegration Matrix (Johansen Test) and obtain β
  - Use cointegration vector from 2 to estimate other
     VECM parameters ( speed of correction, intercept)

Q-learning: Decision Variables

- Estimation Window:
  - run cointegration test
  - re-estimate spread equations
- Trading Window:
  - Parameters from Estimation Window still apply
- Trading Threshold:
  - Threshold above and below spread
- Stop-loss:
  - Wider window than trading threshold to prevent loss





# Q-learning: Objective Value

- Sortino Ratio
  - $S = \frac{R-T}{DR}, \qquad DR = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Min(0, Xi-T))^2}$
  - Measure the return under downward volatilities.
  - Reward upward volatility but discourage downward volatility
  - Alternatives include: pure return, Sharpe ratio

# Q-learning: Model

- Multi-Arm Bandit Model with each arm
- SARSA

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$$

```
Initialize Q(s, a), \forall s \in S, a \in A(s), arbitrarily, and Q(terminal - state, .) = 0

Repeat (for each episode):

Initialize S

Choose A from S using policy derived from Q(e.g., \epsilon - greedy)

Repeat (for each step of episode):

Take action A, observe R, S'

Choose A' from S' using policy derived from Q(e.g., \epsilon - greedy)

Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma Q(S', A') - Q(S, A)]

S \leftarrow S'; A \leftarrow A';
```

until S is terminal

#### Input: Stock A, Stock B

- Initialization:
  - a. action space<sub>n×4</sub> ← [δ<sub>n×1</sub>, stoploss<sub>n×1</sub>, estimation window<sub>n×1</sub>, trading window<sub>n×1</sub>]
  - b.  $number of iteration \leftarrow max number of iteration$
- For episode ← 1 to number of iteration
- 3. action ← choose action based on the epsilon greedy policy
- reward ← perform action (action, A, B)
- action update (action, reward)
- 6. End
- 7. Return Sortino ratio

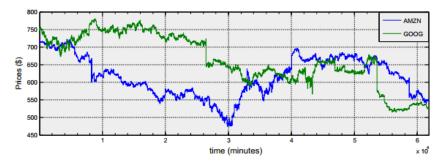
Output: Sortino Ratio

### Simulation

- Data
  - 60000 mins of intraday min-level price data of Amazon and Google
- Decision Space
  - Estimation Window is from 60 to 600 minutes with increment of 5 mins
  - Trading Window is from 5 to 120 minutes with increment of 5 mins
  - Trading thresholds between 0 and 3 with increment of 0.5
  - Stop loss varies between 0 and 5 with increment of 0.5
- Parameter

■ 75% in-sample data and 25% out of sample data, Q-agent set  $\alpha = 1$ ,  $\epsilon = 1$  for training phase and

 $\alpha = 0.3, \epsilon = 0.3$  for testing



## Performance

Q-learning vs Static Optimization

	CPM		RLM	
Test and estimation window size (min)	380		Dynamic [60,600]	
Trading window size (min)	80		Dynamic [5,120]	
Δ (standard deviation)	1.5		Dynamic [0.5,3]	
Stop-loss (standard deviation)	3		Dynamic [1,5]	
	In-sample	Out-sample	In-sample	Out-sample
Return (%)	15.8	11.3	91.5	46.6
Downside volatility	0.51	0.18	0.61	0.12
Annualized return (%)	31.6	67.8	183	279.6
Sortino ratio	0.27	0.52	1.46	3.72
Number of trades	265	180	586	388
Average return per trade (%)	0.06	0.06	0.16	0.12
Average time per trade (min)	185.4	91	83.8	42.2

- STEP 1:
- Regression

$$\Delta Y_t = \sum_{k=1}^{p-1} \Gamma_k \Delta Y_{t-k} + R_{0t}$$

$$Y_{t-1} = \sum_{k=1}^{p-1} \Gamma_k \Delta Y_{t-k} + R_{kt}$$

Concentrated Model

$$R_{0t} = \alpha \beta' R_{kt} + u_t$$

$$\Delta \widetilde{Y}_t = \alpha \beta' \widetilde{Y}_t + u_t$$

$$S_{ij} = \frac{1}{T} \sum_{t=1}^{T} R_{it} R'_{jt}, \quad i, j = [0, k]$$

$$\Delta Y_t = \Pi Y_{t-p} + \sum_{k=1}^{p-1} \Gamma_k \Delta Y_{t-k} + \epsilon_t$$

$$\Pi = I - \sum_{k=1}^{p} A_k, \quad \Gamma_k = \sum_{i=1}^{k} A_i - I.$$

STEP 2:

$$\mathbf{S}_{00} = \frac{1}{T}\mathbf{R}_{0t}\mathbf{R}_{0t}' \quad \mathbf{S}_{kk} = \frac{1}{T}\mathbf{R}_{kt}\mathbf{R}_{kt}' \quad \mathbf{S}_{k0} = \frac{1}{T}\mathbf{R}_{kt}\mathbf{R}_{0t}' \quad \mathbf{S}_{0k} = \frac{1}{T}\mathbf{R}_{0t}\mathbf{R}_{kt}'$$

Solve

$$(S_{k0}S_{00}^{-1}S_{0k} - \lambda S_{kk})\beta = 0$$
$$|\lambda S_{kk} - S_{k0}S_{00}^{-1}S_{0k}| = 0$$
$$S_{kk}^{-1}S_{k0}S_{00}^{-1}S_{0k}\beta_{i} = \lambda_{i}\beta_{i}$$

STEP 3:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \log(1 - \lambda_i)$$

$$\lambda_{max} = -T\log(1 - \lambda_{r+1})$$

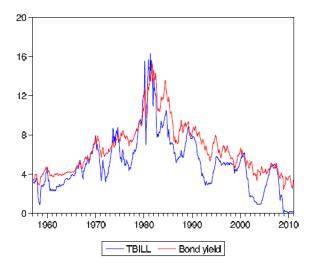
- Trace Test
- H0: K = K0
- H0: K > K0
- Set K0 =0 representing no cointegration and test whether it can be rejected so that there is at least one cointegration relationship
- Maximum Eigenvalue Test
- H0: K = K0
- H0: K = K0+1
- Set K0 = 0,rejecting null hypothesis indicates there is 1 combination of stationary possible that leads to a stationary, less power than trace test. Increment K value.

Step 4

$$\Delta Y_t = \hat{\alpha} \widetilde{\beta}' Y_{t-1} + \sum_{k=1}^{p-1} \Gamma_k \Delta Y_{t-k} + \epsilon_t$$

$$\widehat{Y}_{T+h} = \widehat{\Pi}^h Y_T + \sum_{i=0}^{h-1} \widehat{\Pi}^i C$$

### **Historic US Interest Rates**



### Johansen Test

```
Sample (adjusted): 1957M04 2011M01
Included observations: 646 after adjustments
Trend assumption: No deterministic trend (restricted constant)
Series: Y R
Lags interval (in first differences): 1 to 2
                                          0.05
Hypothesized
                             Trace
No. of CE(s) Eigenvalue
                           Statistic Critical Value Prob.**
               0.033251 24.33360
                                        20.26184
                                                    0.0130
   None
               0.003845
                            2.488511
  At most 1
                                         9.164546
No. of CE(s) Eigenvalue
                           Statistic Critical Value Prob.**
  None
               0.033251
                            21.84509
                                        15.89210
                                                    0.0051
               0.003845
                            2.488511
                                         9.164546
  At most 1
                                                    0.6798
```

Fit VCEM Model

$$\Delta y_t = 0.38 \Delta y_{t-1} - 0.08 \Delta r_{t-1} - 0.016 e_{t-1} + \epsilon_t$$
$$\Delta r_t = 0.53 \Delta y_{t-1} - 0.14 \Delta r_{t-1} - 0.047 e_{t-1} + \epsilon_t$$

=======================================	=========	========
Error Correction:	D(Y)	D(R)
CointEq1	-0.016142 (0.00861) [-1.87572]	0.047416 (0.01450) [ 3.26980]
D(Y(-1))	0.380541 (0.04554) [ 8.35696]	0.526983 (0.07673) [ 6.86787]
D(R(-1))	-0.076016 (0.02650) [-2.86868]	0.137130 (0.04465) [ 3.07103]

Cointegration

$$e_{t-1} = (y_{t-1} - 0.94 r_{t-1} - 0.0159)$$

```
Sample (adjusted): 1957M03 2011M01
Included observations: 647 after adjustments
Standard errors in ( ) & t-statistics in [ ]
Cointegrating Eq:
                      CointEq1
       Y(-1)
                      1.000000
       R(-1)
                     -0.940823
                      (0.07272)
                      [-12.9369]
                     -0.015868
                       (0.00423)
                      [-3.75153]
```