

# **Introduction to pair trading**

## **-Based on cointegration-**

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# Topics

1. What is pair trading?
2. What is cointegration?
3. Idea of pair trading based on cointegration
4. Simulation by R language
5. Summary & concluding remarks

# **1. What is pair trading?**

# **Pair trading was pioneered by ...**

- **Gerry Bamberger and Nunzio Tartaglia**
- **Quantitative group at Morgan Stanley**
- **Around 1980s**
- **D.E. Shaw & Co. is famous for this strategy**

**Pair trading is ...**

**Market neutral trading strategy**

**Pair trading belongs to ...**

*Physics, Information theory  
PCA, ICA, Autoregression  
Neural Net  
Pattern Recognition*

# **Basic idea of pair trading ...**

**Select two stocks  
which move similarly**

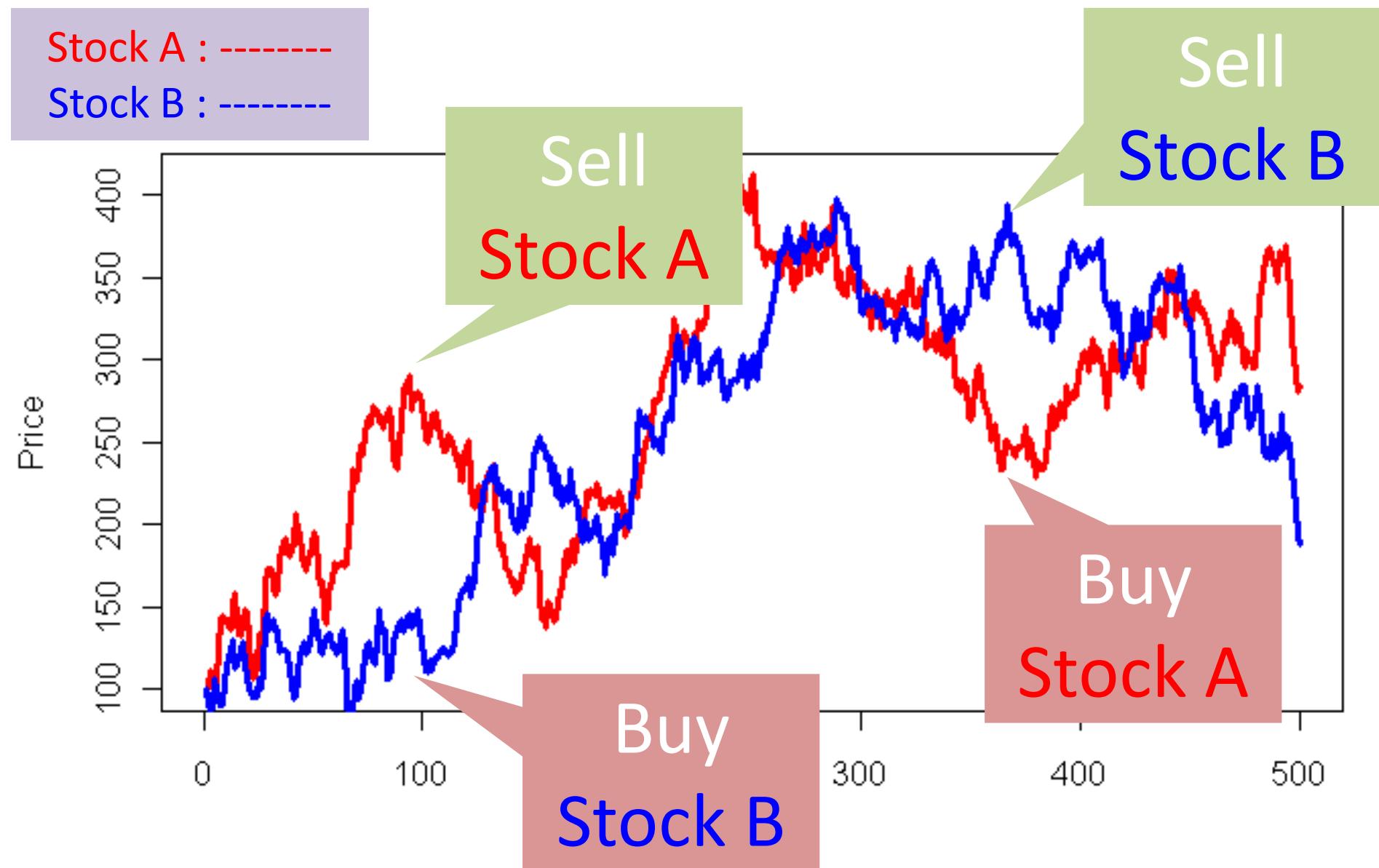
# **Basic idea of pair trading ...**

**Sell high priced stock**

**Buy low priced stock**

# Basic idea of pair trading ...

Stock A : -----  
Stock B : -----



# **Basic idea of pair trading ...**

**Usually, monitor  
the difference  
between two stock prices**

# Basic idea of pair trading ...

the difference between two stock prices



## **2. What is cointegration?**

# Cointegration is ...

- Pioneered by Engle and Granger
- Statistical property of time series
- Around 1990s

**Cointegration is ...**

**Not correlation**

# Cointegration and correlation

- **Correlation**

- Specify co-movement of **return**
  - **Short term** relationship

- **Cointegration**

- Specify co-movement of **price**
  - **Long term** relationship

# (weak) Stationary time series

Not depend on time

- $E(X_t) = \mu$
- $\text{var}(X_t) = \sigma^2$
- $\text{cov}(X_t, X_{t-s}) = \gamma(s)$

# Example of stationary time series

## White noise

- $E(\varepsilon_t) = 0$
- $\text{var}(\varepsilon_t) = \sigma^2$
- $\text{cov}(\varepsilon_t, \varepsilon_s) = 0, t \neq s$

# Non stationary time series

Depend on time

- $E(X_t) = \mu_t$
- $\text{var}(X_t) = \sigma_t^2$
- $\text{cov}(X_t, X_{t-s}) = \gamma(t, s)$

# Example of non stationary time series

## Brownian motion

- $E(W_t) = 0$
- $\text{var}(W_t) = t$
- $\text{cov}(W_t, W_{t-s}) = t - s$

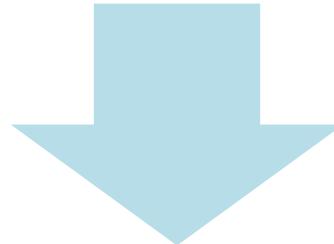
# Lag operator $L$

- $LX_t = X_{t-1}$
- $(1 - L)X_t = X_t - X_{t-1} = \Delta X_t$

# Integrated of order P

$X_t$  : non stationary

$(1 - L)^p X_t$  : stationary



$X_t \sim I(p)$

# Example of “integrate”

$Z_t = Z_{t-1} + \varepsilon_t$  : Random walk

$\varepsilon_t$  : White noise

Calculate difference

$\Delta Z_t = Z_t - Z_{t-1} = \varepsilon_t$  : Stationary

$\therefore Z_t \sim I(1)$

**$X_t$  and  $Y_t$  are cointegrated if ...**

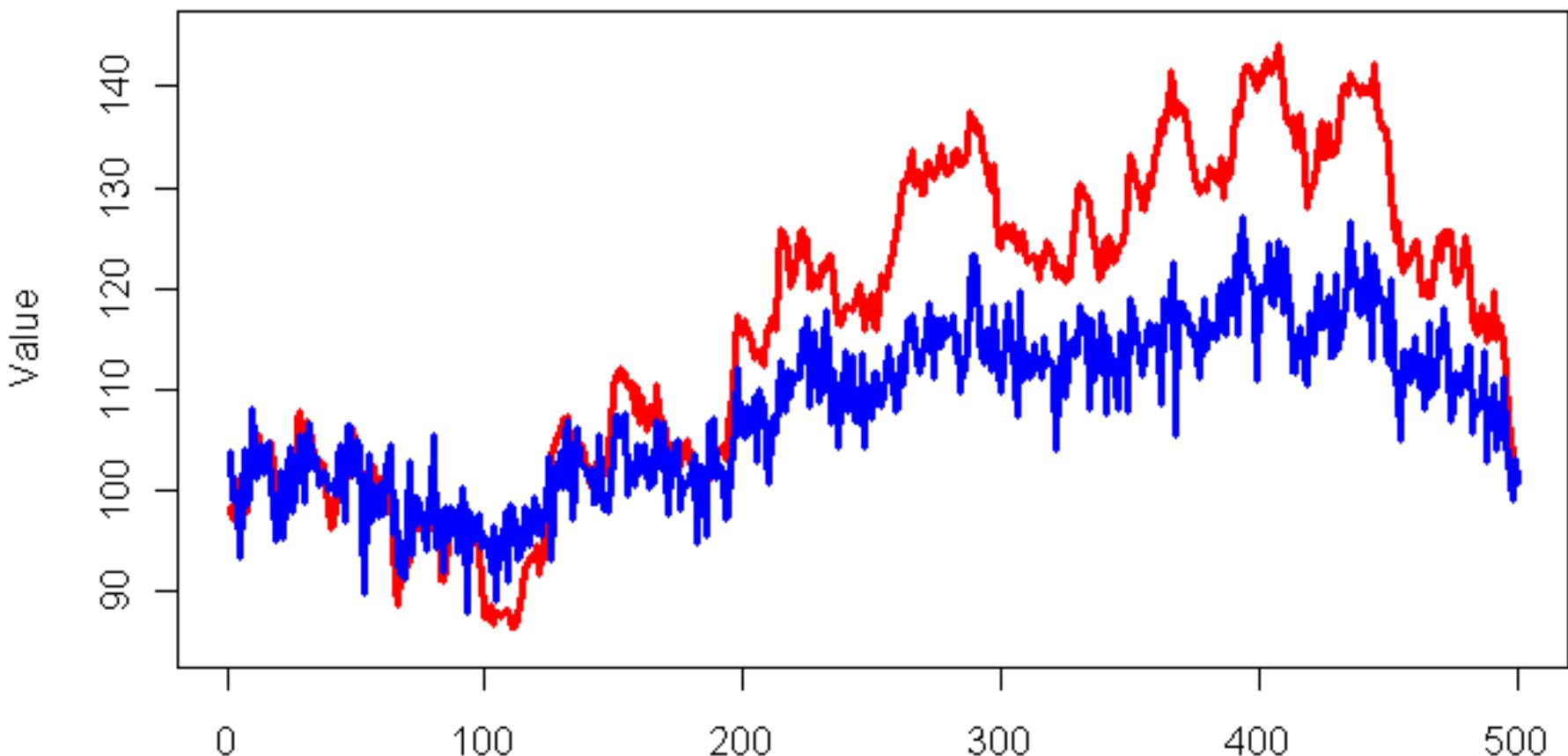
$$u_t = Y_t - (\alpha + \beta X_t)$$

$$u_t : \sim I(0), \boxed{\text{stationary process}}$$

$$X_t, Y_t : \sim I(1)$$

\*This is a special version of general cointegration for  $I(1)$

# Example of cointegrated time series



$X_t$  : -----

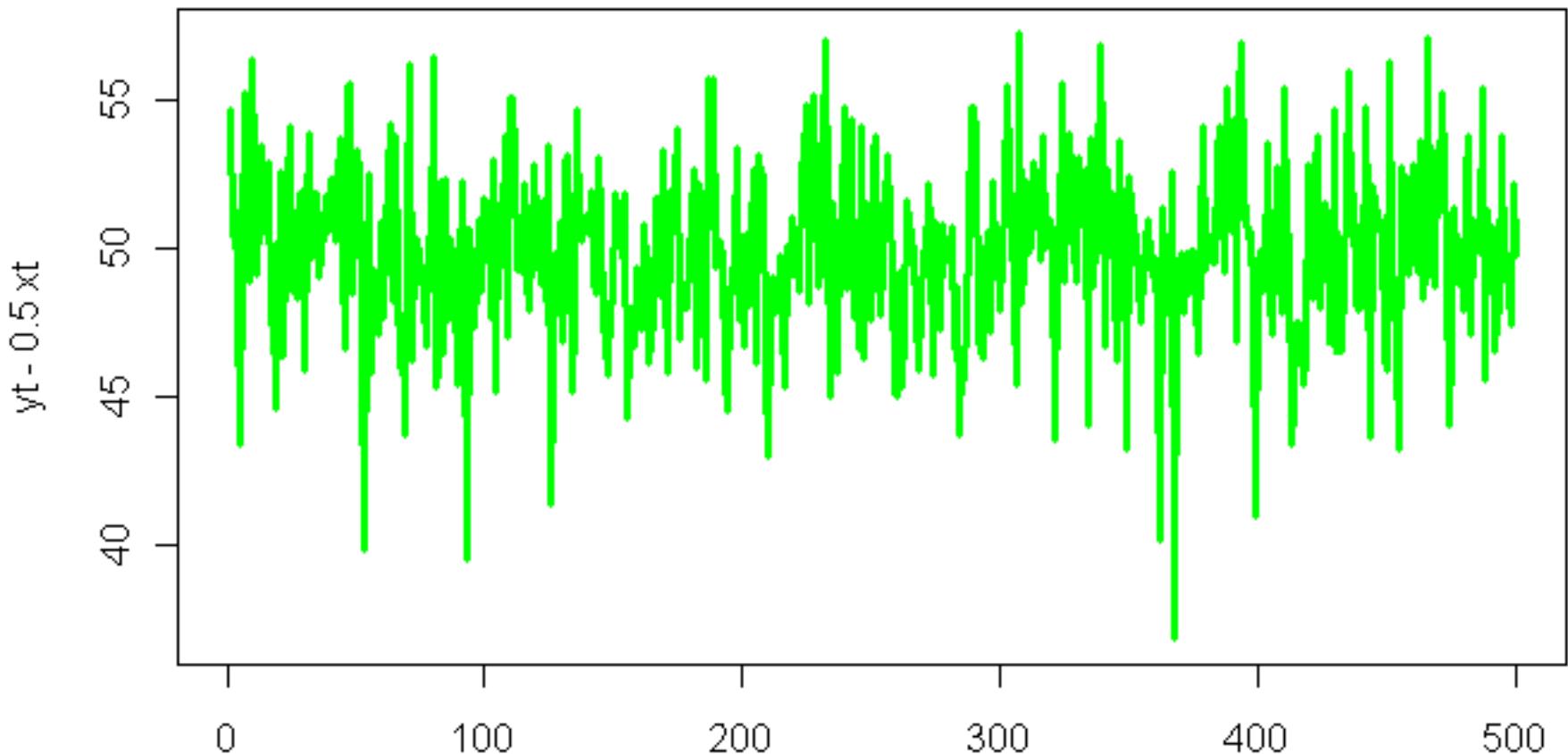
$Y_t$  : -----

$$Y_t = 50 + 0.5X_t + u_t$$

$X_t$  :  $100 + 2 \times$  Normal brownian motion

$u_t$  :  $3 \times$  Gaussian noise

# Example of cointegrated time series



Plot :  $u_t = Y_t - 0.5 X_t$

ut seems to be...

**Stationary**

**&**

**Mean reversion**

# Question

Can we apply this idea  
to trading strategy?

# **3. Idea of pair trading based on cointegration**

# Geometric brownian motion

The most widely used model of stock price

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t$$

$S_t$  : Stock price

$\mu$  : Average return

$\sigma$  : Volatility

$W_t$  : Brownian motion

# From Ito's lemma

$$d \log(S_t) = \left( \mu - \frac{\sigma^2}{2} \right) dt + \sigma dW_t$$

**Log price follow Brownian motion**

# Brownian motion(log price) is ...

I(1)

\* Random walk can be considered as discretization of Brownian motion

**Then, we can apply**

**Cointegration idea  
to log stock price**

**Log price spread(\*) is...**

**Stationary**

**&**

**Mean reversion**

※ $Spread_t := \log(Y_t) - (\alpha + \beta \log(X_t))$ ,  $X_t, Y_t$ : stock price

# Simple trading idea

if  $Spread_t >$  very high : Buy  $X_t$ , Sell  $Y_t$

if  $Spread_t <$  very low : Buy  $Y_t$ , Sell  $X_t$

$$Spread_t = \log(Y_t) - (\alpha + \beta \log(X_t))$$

$X_t, Y_t$  : stock price

# **4. Simulation by R language**

# Process

1. Find two likely cointegrated stocks
2. Estimate spreads
3. Check stationarity
4. Create trading signal
5. Run back-test

# 1. Find two likely cointegrated stocks

```
> library(PairTrading)  
> #load sample stock price data  
> data(stock.price)  
> #select 2 stocks  
> price.pair <- stock.price[,1:2]["2008-12-31::"]  
> head(price.pair)
```

7201 7203

2009-01-05 333 3010

2009-01-06 341 3050

2009-01-07 374 3200

2009-01-08 361 3140

\* Just load sample data in this case....

## 2. Estimate spreads

```
> reg <- EstimateParameters(price.pair, method = lm)
> str(reg)
List of 3
$ spread    :An 'xts' object from 2008-12-30 to 2011-08-05 containing:
  Data: num [1:635, 1] -0.08544 -0.0539 -0.04306 -0.00426 -0.01966 ...
  - attr(*, "dimnames")=List of 2
    ..$ : NULL
    ..$ : chr "B"
  Indexed by objects of class: [Date] TZ:
  xts Attributes:
  NULL
$ hedge.ratio: num 0.0997
$ premium   : num 7.48
```

## 2. Estimate spreads

```
> plot(reg$spread, main = "Spread")
```



$$Spread_t = \log(Y_t) - (\alpha + \beta \log(X_t)), X_t, Y_t : \text{stock price}$$

### 3. Check stationarity

```
> PP.test(as.numeric(reg$spread))
```

Phillips-Perron Unit Root Test

```
data: as.numeric(reg$spread)
```

```
Dickey-Fuller = -3.2299, Truncation lag parameter = 6, p-value  
= 0.08278
```

```
> adf.test(as.numeric(reg$spread))
```

Augmented Dickey-Fuller Test

```
data: as.numeric(reg$spread)
```

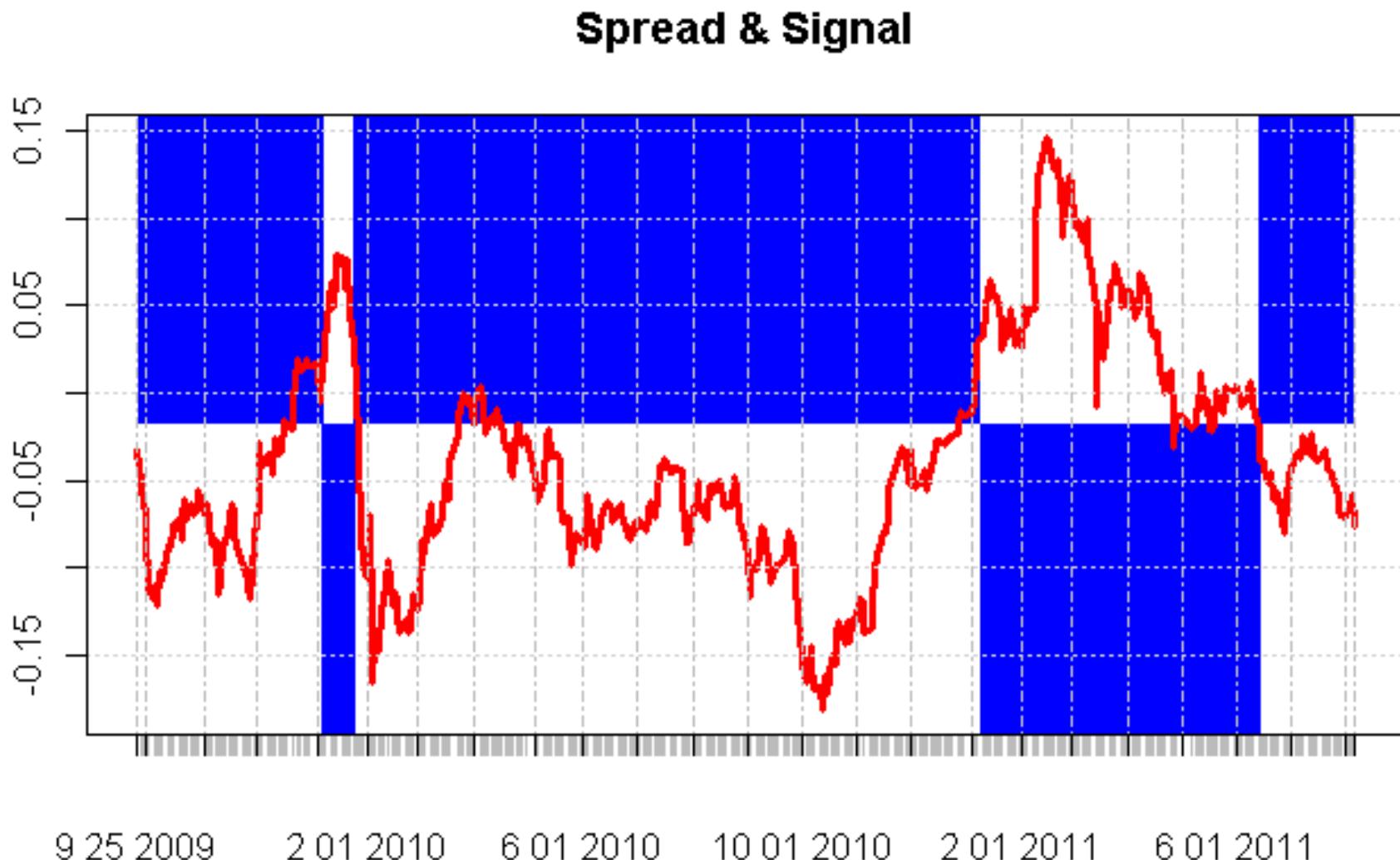
```
Dickey-Fuller = -3.6462, Lag order = 8, p-value = 0.02825
```

alternative hypothesis: stationary

## 4. Create trading signal

```
> params <-  
  EstimateParametersHistorically(price.pair,  
  period = 180)  
  
> signal <- Simple(params$spread, 0.05)  
  
> barplot(signal,col="blue",space = 0, border =  
  "blue",xaxt="n",yaxt="n",xlab="",ylab "")  
  
> par(new=TRUE)  
  
> plot(params$spread, type="l", col = "red",  
  lwd = 3, main = "Spread & Signal")
```

# 4. Create trading signal



9 25 2009    2 01 2010    6 01 2010    10 01 2010    2 01 2011    6 01 2011

## 5. Run back-test

```
> return.pairtrading <-  
  Return(price.pair, lag(signal),  
         lag(params$hedge.ratio))  
  
> plot(100 * cumprod(1 +  
  return.pairtrading), main =  
  "Performance of pair trading")
```

# 5. Run back-test

**Performance of pair trading**



# **5. Summary & concluding remarks**

# Summary & concluding remarks

- Pair trading is simple quantitative trading strategy
- Cointegration is long term relation ship of time series
- Idea of cointegration may give a chance to make a profit from financial market by pair trading
- Next step ....
  - Sophisticate parameter estimation & trading rule
  - Make a simulation close to real

# Reference

- Pairs trade([http://en.wikipedia.org/wiki/Pairs\\_trade](http://en.wikipedia.org/wiki/Pairs_trade))
- Cointegration(<http://en.wikipedia.org/wiki/Cointegration>)
- Andrew Neil Burgess, “A Computational Methodology for Modeling the Dynamics of Statistical Arbitrage”
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- Daniel Herlemont, “Pairs trading, convergence trading, cointegration”
- Paul Teetor, “Using R to Test Pairs of Securities for Cointegration”(<http://quanttrader.info/public/testForCoint.html>)
- Ganapathy Vidyamurthy, “Pairs Trading: Quantitative Methods and Analysis ”