

# Study of the correlations between stocks of different markets

Ricardo Coelho

School of Physics  
Trinity College Dublin

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# Outline

## Introduction



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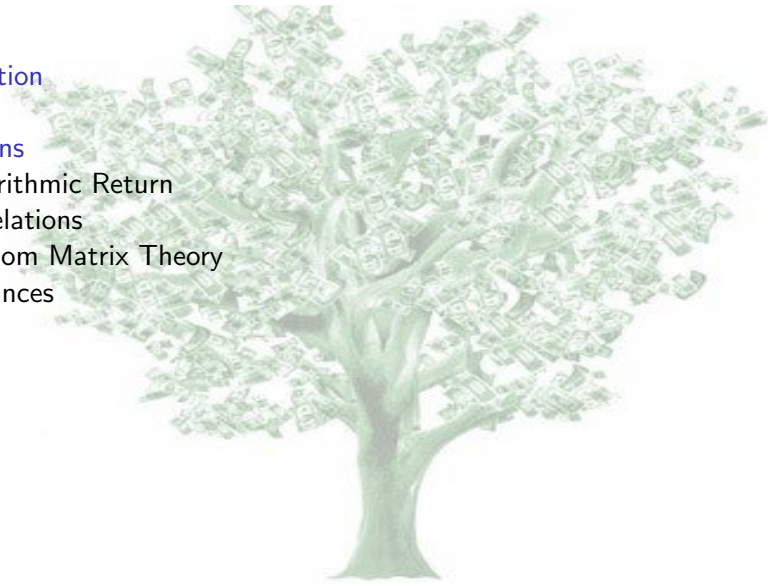
Definitions

Logarithmic Return

Correlations

Random Matrix Theory

Distances



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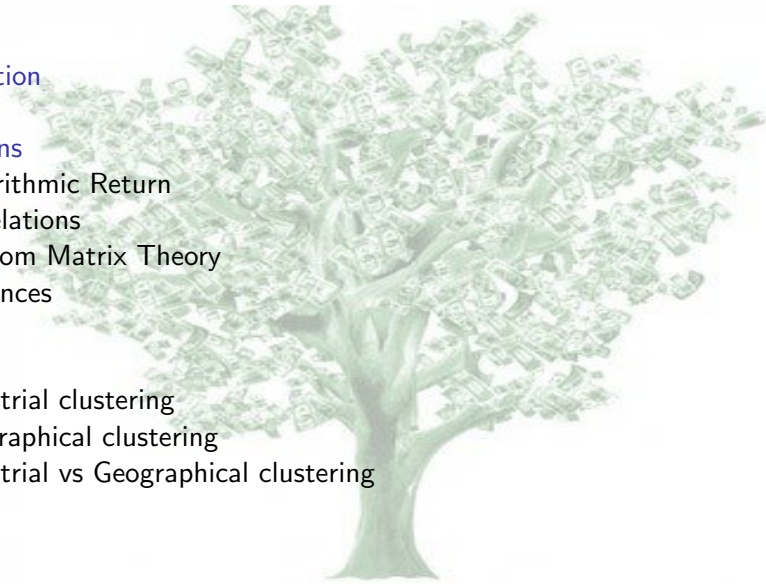
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## Results

Industrial clustering

Geographical clustering

Industrial vs Geographical clustering



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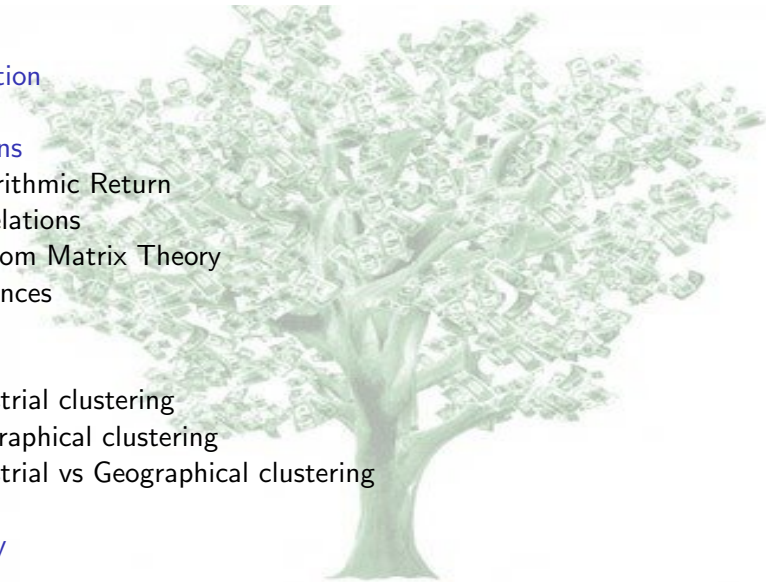
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Industrial clustering

Geographical clustering

Industrial vs Geographical clustering

## Summary



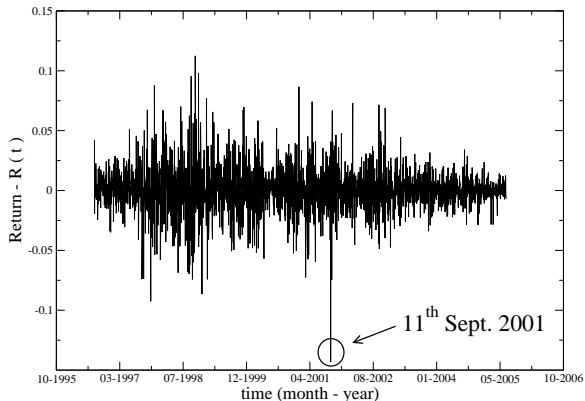
# Introduction

We studied three different sets of data.

- ▶ A portfolio from the London Stock Exchange FTSE100 index:
  - ▶ 67 stocks
  - ▶ Daily closing price
  - ▶ From 2<sup>nd</sup> August 1996 until 27<sup>th</sup> June 2005
- ▶ Different World Indices
  - ▶ 53 countries' equity markets
  - ▶ Wednesday closing price (weekly returns)
  - ▶ From 8<sup>th</sup> January 1997 until 1<sup>st</sup> February 2006
- ▶ More than 6000 stocks from markets around the world
  - ▶ Daily closing price
  - ▶ From 30<sup>th</sup> December 1994 until 1<sup>st</sup> January 2007

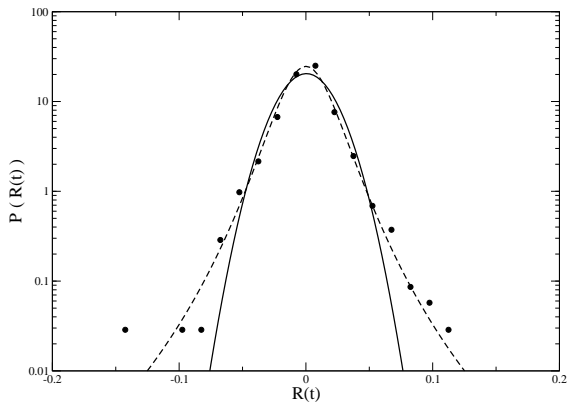
# Log-return of stocks shows extreme events (e.g. HSBC)

$$R_i(t) = \ln P_i(t) - \ln P_i(t - 1) \quad (1)$$



# Distribution of the Log-return is non-Gaussian

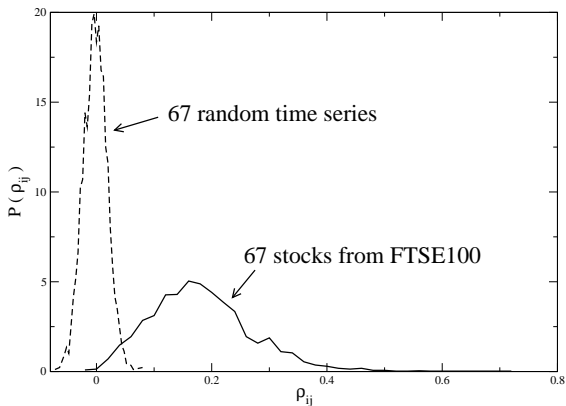
$k \sim 2.90$  and  $q \sim 1.34$



## Correlation between stocks $i$ and $j$

$$\rho_{ij} = \frac{\langle \mathbf{R}_i \mathbf{R}_j \rangle - \langle \mathbf{R}_i \rangle \langle \mathbf{R}_j \rangle}{\sqrt{(\langle \mathbf{R}_i^2 \rangle - \langle \mathbf{R}_i \rangle^2) (\langle \mathbf{R}_j^2 \rangle - \langle \mathbf{R}_j \rangle^2)}} \quad (2)$$

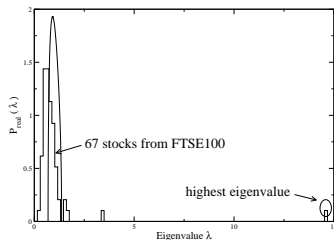
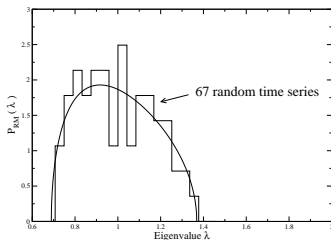
- ▶  $\rho_{ij}$  form a symmetric  $N \times N$  matrix;  $-1 \leq \rho_{ij} \leq 1$ ;  $\rho_{ii} = 1$ .



# Matrix of correlations show non-randomness

Random Matrix Theory for  $N \rightarrow \infty$  and  $T \rightarrow \infty$ , where  $Q = T/N$  is fixed and bigger than 1.

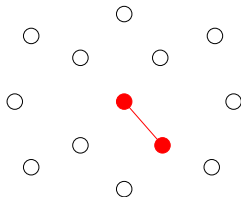
$$P_{RM}(\lambda) = \frac{Q}{2\pi\sigma^2} \frac{\sqrt{(\lambda_{max} - \lambda)(\lambda - \lambda_{min})}}{\lambda} \quad (3)$$



## Distance between stocks $i$ and $j$

$$d_{ij} = \sqrt{2(1 - \rho_{ij})} \quad (4)$$

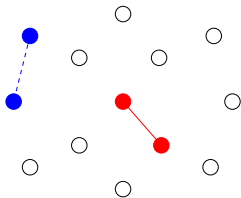
- ▶  $0 \leq d_{ij} \leq 2$ , small values imply strong correlations.
- ▶ From distances we construct the Minimal Spanning Tree (MST).
- ▶ Choose the minimum distance between 2 stocks - one link between these 2.



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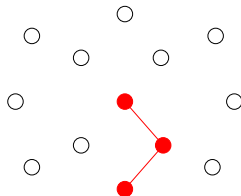
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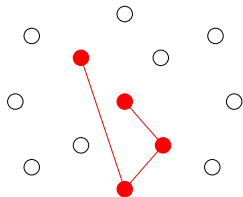
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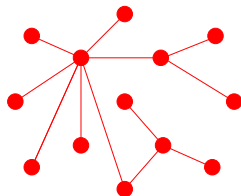
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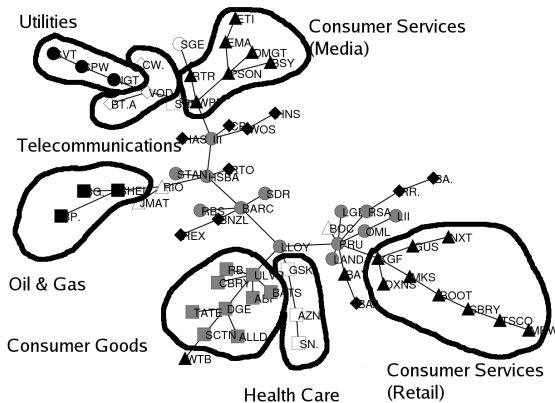
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# Stocks cluster in industrial sectors (ICB classification)

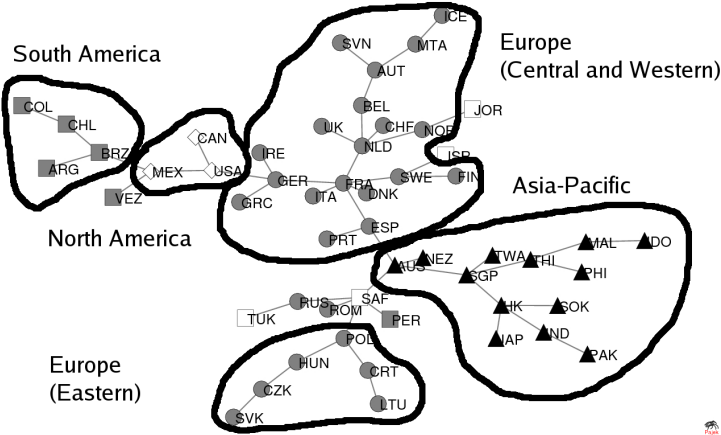
Full time series,  $T = 2322$  days, for the FTSE100 stocks.



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# Markets organised by geographical location

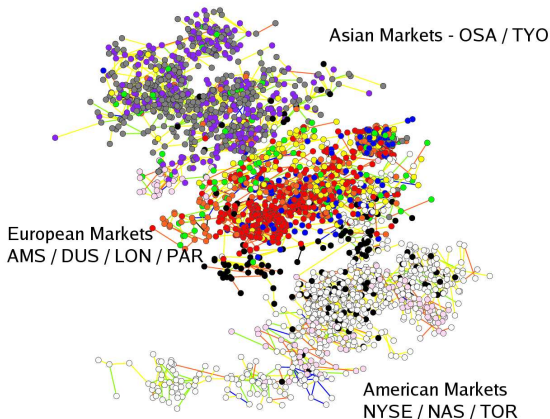
Full time series,  $T = 475$  weeks, for the 53 World Indices.



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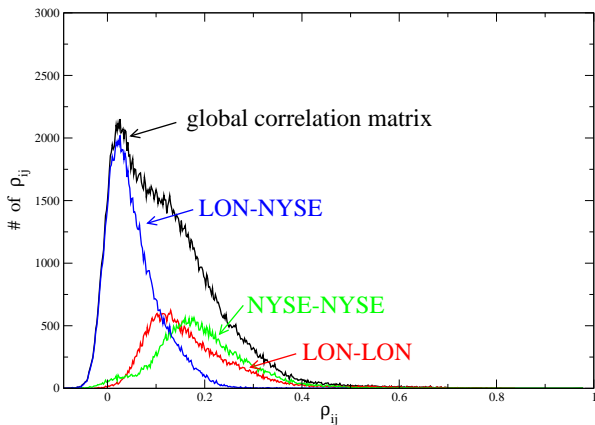
# What about stocks from different countries???

Full time series,  $T = 3127$  days, for 2500 stocks from different markets.



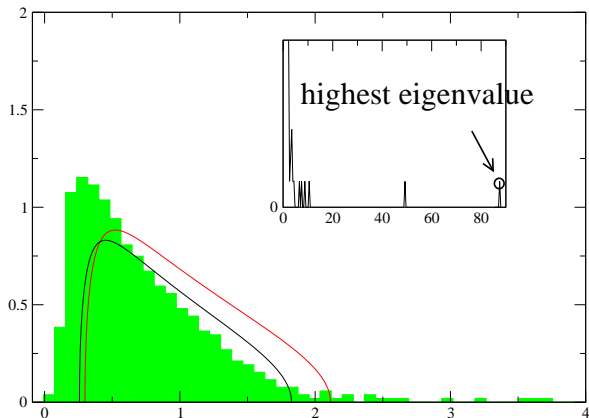
# NYSE vs LON - Correlation between stocks of different markets

322 stocks from each market.

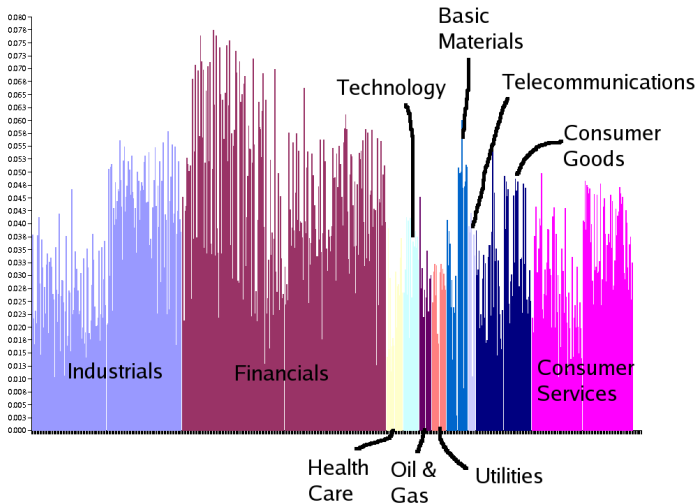


## NYSE vs LON - Eigensystem information

The two largest eigenvalues could represent each market.

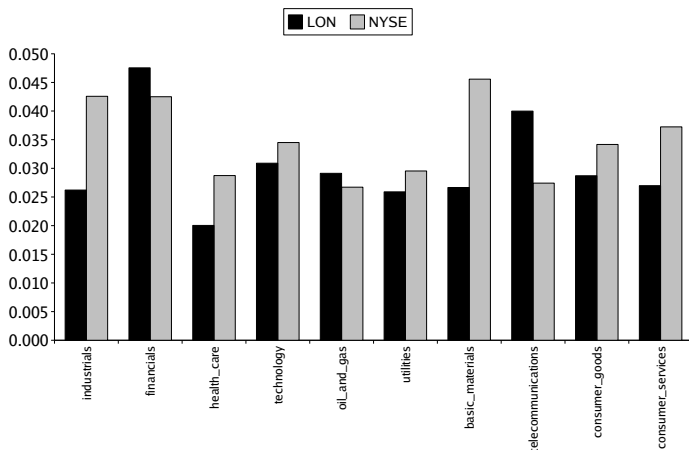


# NYSE vs LON - Highest eigenvector information

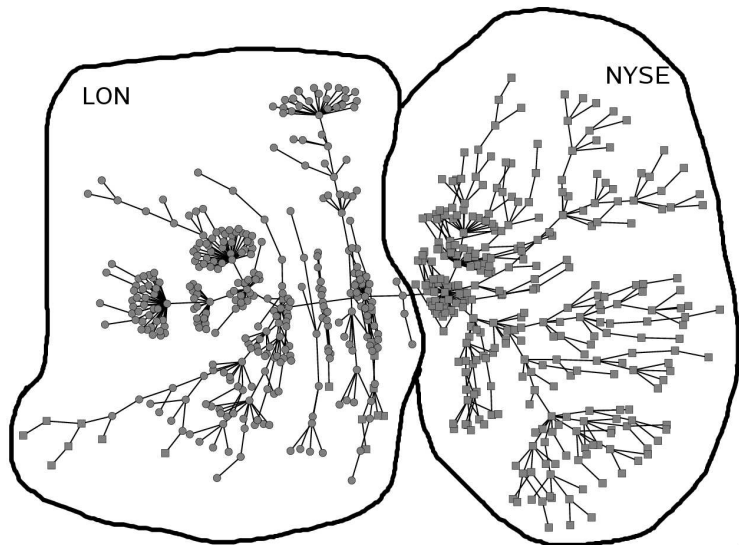


# NYSE vs LON - Highest eigenvector information

Sum of elements from each sector/country -  $\sum_i \lambda_i$



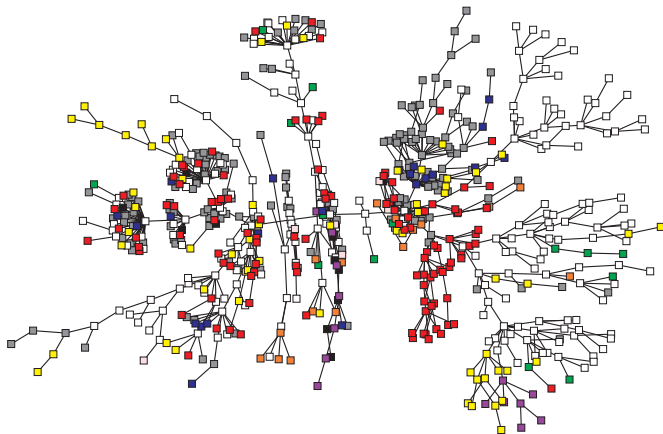
# NYSE vs LON - Clustering of stocks in market



# NYSE vs LON - Clustering in sector for NYSE

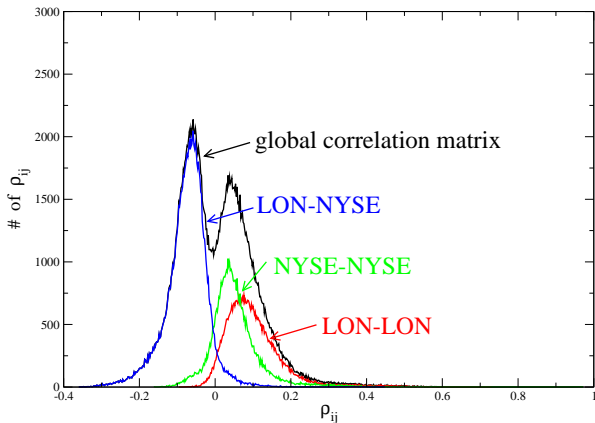
Different choice of stocks gives different clustering for LON.

Oil & Gas - black / Basic Materials - blue / Industrials - gray / Consumer Goods - yellow / Health Care - green  
Consumer Services - red / Telecommunications - pink / Utilities - purple / Financials - white / Technology - orange



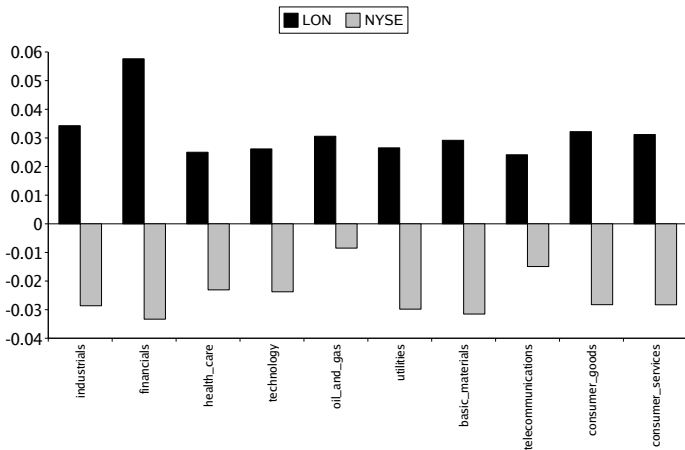
# NYSE vs LON - Correlation (after filtering market mode)

Filtering affects NYSE more than LON.



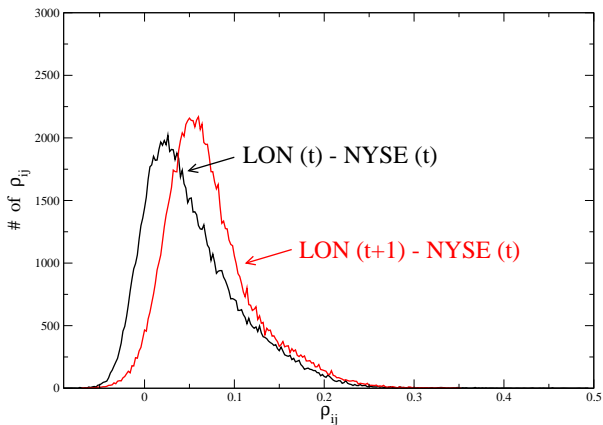
# NYSE vs LON - Highest eigenvector (after filtering)

Sum of elements from each sector/country -  $\sum_i \lambda_i$



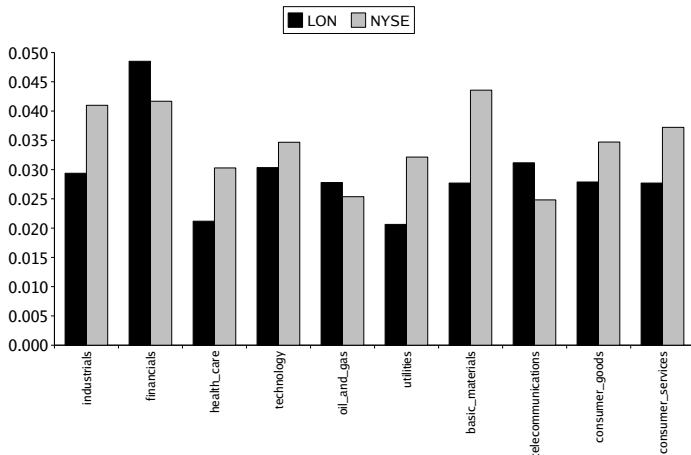
## And if LON is one day ahead?

Correlation between NYSE stocks in time  $t$  and LON stocks in time  $t + 1$ .



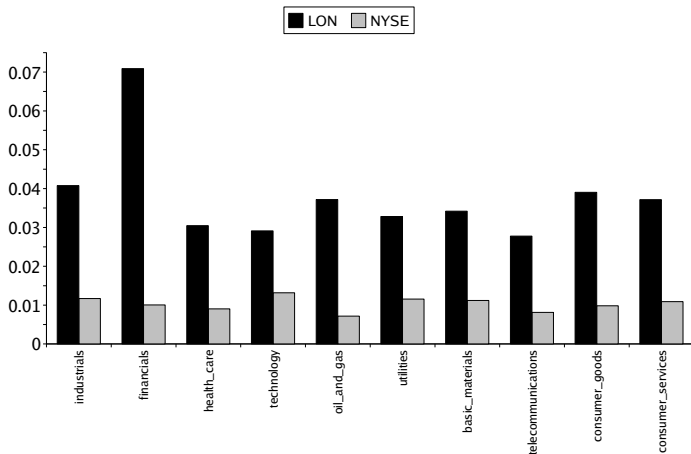
# NYSE (t) vs LON (t+1) - Highest eigenvector

Sum of elements from each sector/country -  $\sum_i \lambda_i$



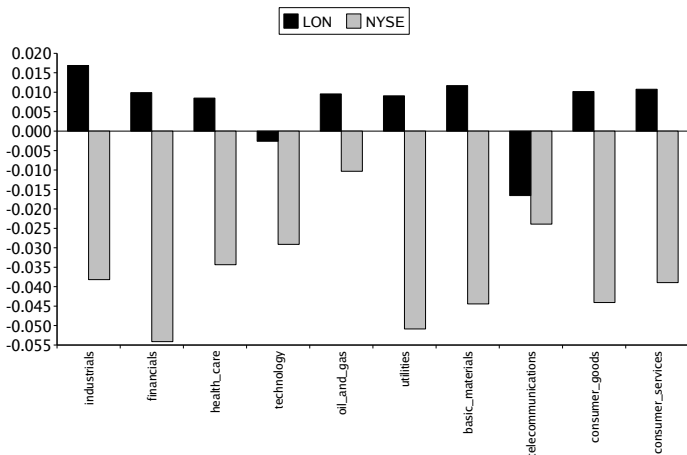
# NYSE (t) vs LON (t+1) - Highest (after filtering)

Sum of elements from each sector/country -  $\sum_i \lambda_i$



# NYSE (t) vs LON (t+1) - 2<sup>th</sup> highest (after filtering)

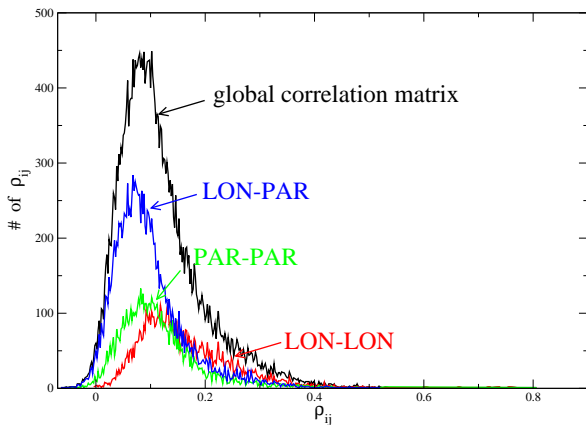
Sum of elements from each sector/country -  $\sum_i \lambda_i$



# What about two markets from the same continent?

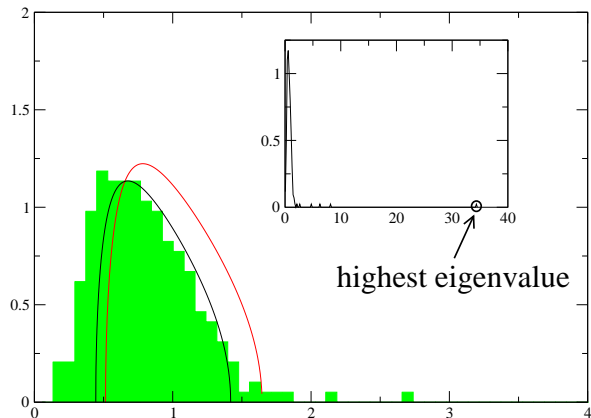
## PAR vs LON - Correlation

125 stocks from each market.



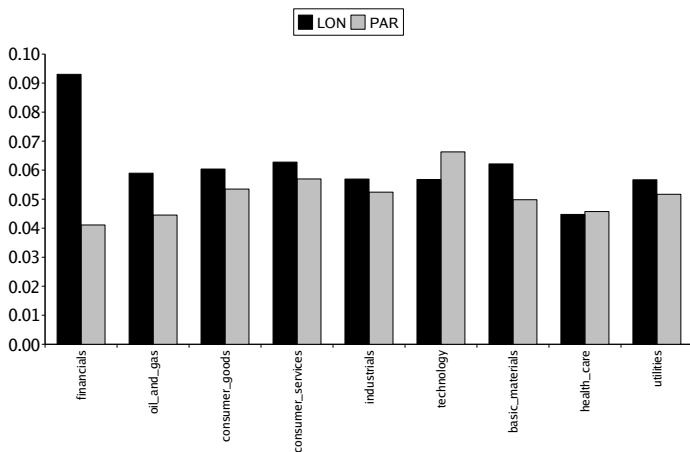
## PAR vs LON - Eigensystem

One major eigenvalue in contrast with the NYSE-LON situation.



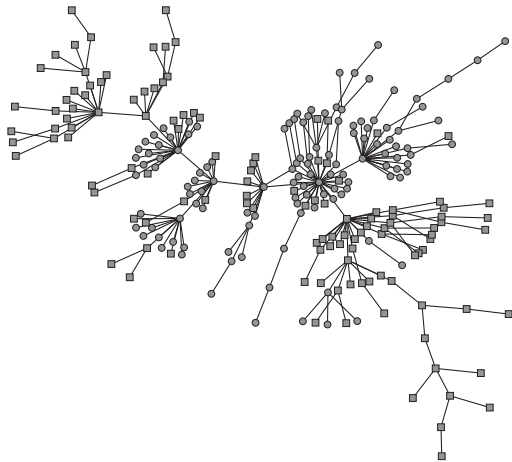
## PAR vs LON - Highest eigenvector

Sum of elements from each sector/country -  $\sum_i \lambda_i$



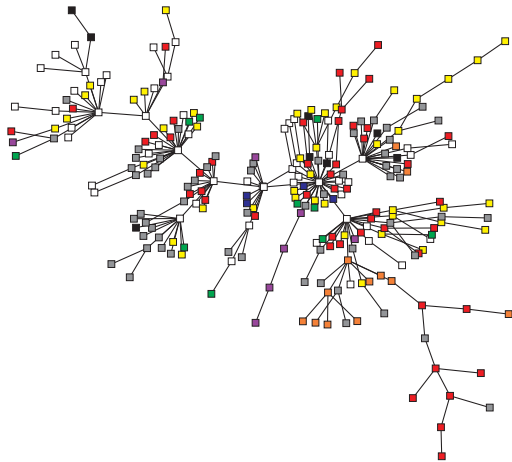
# PAR vs LON - No clustering of stocks in market

Circles for LON and boxes for PAR.



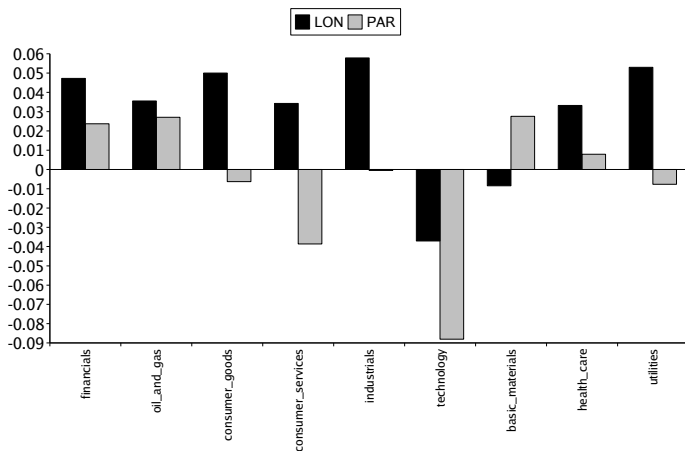
# PAR vs LON - No clustering of stocks in sectors

Oil & Gas - black / Basic Materials - blue / Industrials - gray / Consumer Goods - yellow / Health Care - green  
Consumer Services - red / Telecommunications - pink / Utilities - purple / Financials - white / Technology - orange

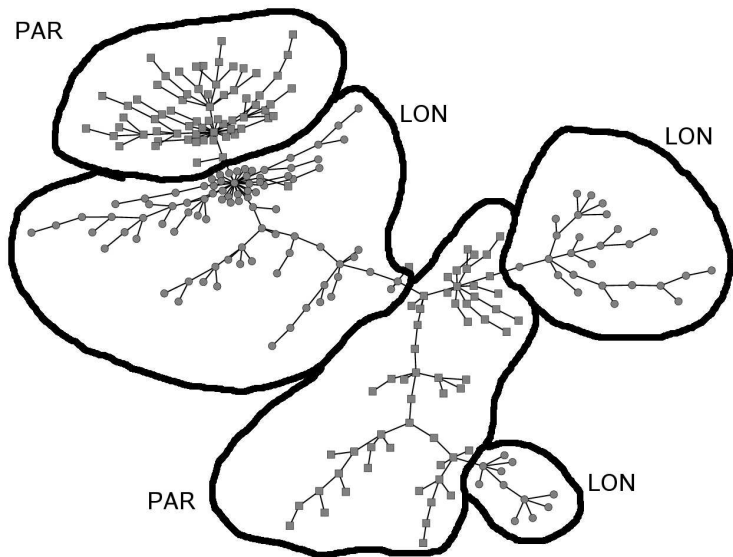


# PAR vs LON - Highest eigenvector (after filtering)

Sum of elements from each sector/country -  $\sum_i \lambda_i$

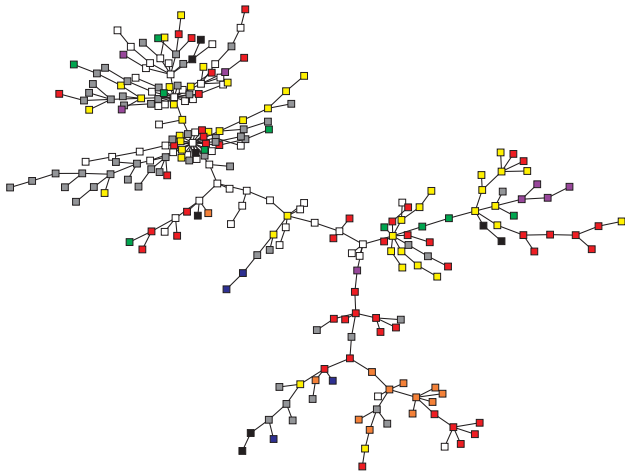


# PAR vs LON - Clustering of stocks in market (a.f.)



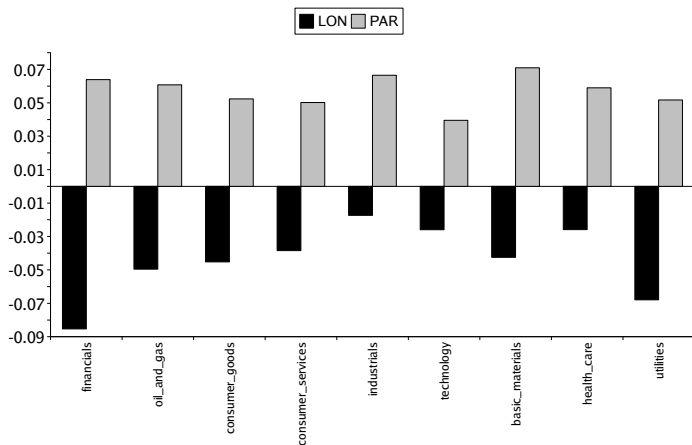
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## PAR vs LON - 2<sup>th</sup> highest eigenvector (after filtering)

Sum of elements from each sector/country -  $\sum_i \lambda_i$



# Conclusions

- ▶ Two different methodologies of analysing large amount of data give same results
- ▶ Similar behaviour for both the FTSE100 stocks and the World Indices:
  - ▶ MST show different clusters (Industrial sectors / Geography)
- ▶ The choice of the stocks can influence the clustering in sectors
- ▶ The stocks cluster in market before clustering in sectors
- ▶ The 3<sup>rd</sup> eigenvalue for the PAR-LON and NYSE( $t$ )-LON( $t + 1$ ) show the segregation of stocks in markets.

## Future work

- ▶ Results for more than 2 markets from the same continent

## Econophysics group of the Trinity College Dublin:

- ▶ Prof. Peter Richmond
- ▶ Dr. Stefan Hutzler
- ▶ Ricardo Coelho
- ▶ Joseph Barry

## Collaborations:

- ▶ Prof. Brian Lucey (Business School of Trinity College Dublin)
- ▶ Prof. Claire Gilmore (McGowan School of Business of King's College, Pennsylvania)

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