# PCA as a Tool for Analyzing the Market

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## Content

- Modeling the Market
- Dimension Reduction and PCA
- An Example: Stock Market
- Another Example: Bond Market
- Conclusions

# Modeling the Market

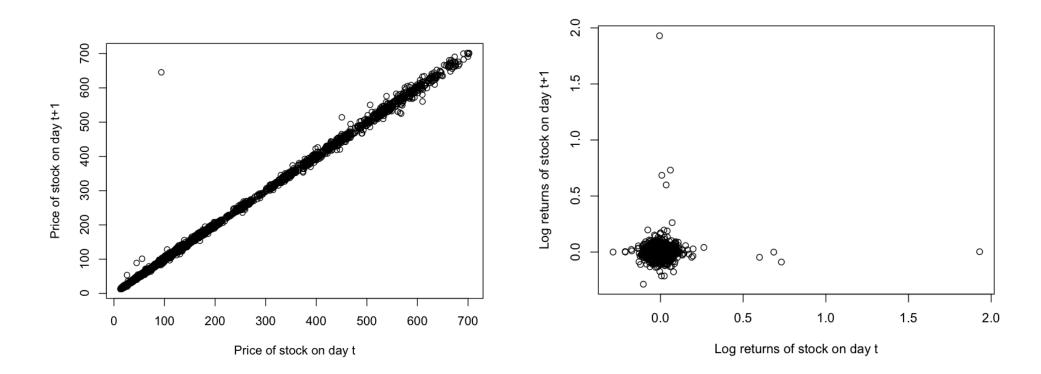
- We have to find a way to choose parameters for our models.
- Our parameters should be invariant in time.
- We should be able to reconstruct prices from invariants.

## Invariants

- Stocks:
  - Price is not an invariant.
  - Logarithmic returns is.
- Bonds:
  - Price is not an invariant.
  - Yield to maturity is.

#### Invariants

• The difference between the invariants and prices:



#### Invariants

• Logarithmic (compounded) returns for a stock:

$$C_{t,\tau} \equiv \ln\left(\frac{P_t}{P_{t-\tau}}\right).$$

• Yield to maturity for bonds:

$$Y_t^{(v)} \equiv -\frac{1}{v} \ln \left( Z_t^{(t+v)} \right).$$

## **Dimension Reduction**

• In general our invariants can be expressed as a single multivariate parameter:

$$X_{T \times K}(Y, C)$$

• Price will be a function of this parameter:

$$P_{T \times K} = f(X_{T \times K})$$

## **Dimension Reduction**

• Usually the dimension of this parameter is larger than the actual degree of randomness in our market.

K >Number of independent dimensions

- Reasons:
  - Derivatives.
  - Hidden dependencies.

## **Dimension Reduction**

- One method of reducing dimensions is Principal Component Analysis (PCA).
- We assume our parameter is a combination of some common factors and small perturbations:

$$\mathbf{X} \equiv \mathbf{q} + \mathbf{BF}\left(\mathbf{X}\right) + \mathbf{U}.$$

#### Principal Component Analysis

• Construct the covariance matrix:

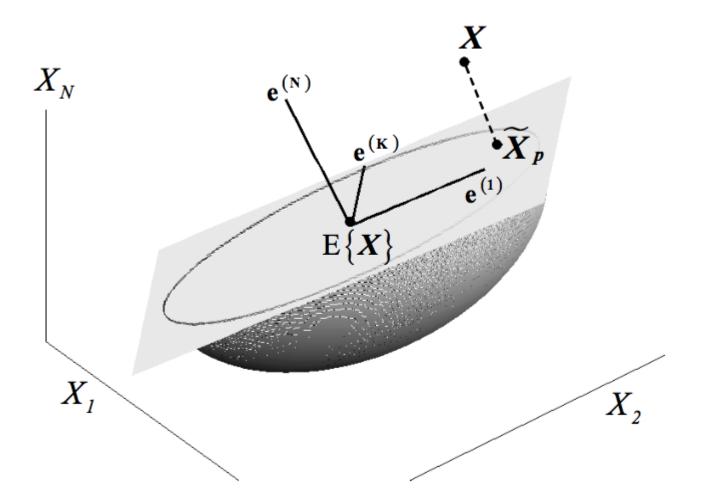
$$C_{K \times K} = \frac{X'X}{T}$$

• Find the eigenvalues and eigenvectors of the covariance matrix.

#### Principal Component Analysis

- The eigenvectors are the principal axes of the location-dispersion ellipsoid.
- They represent the directions of most variance.
- The dimension of the ellipsoid can be reduced depending on the eigenvalues.

#### Principal Component Analysis



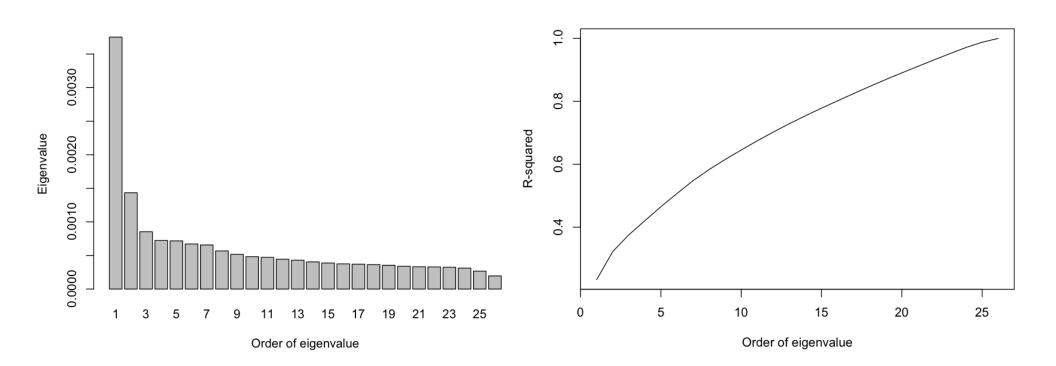
## An Example: Stock Market

- 26 stocks from the Dow-Jones Index.
- Daily close prices from: 1/1/1990 to: 4/20/2015
- Use R-squared for measuring the explanatory power of the first N eigenvalues:

$$R^2 = \frac{\sum_{i=1}^{N} \lambda_i}{\sum_{i=1}^{K} \lambda_i}$$

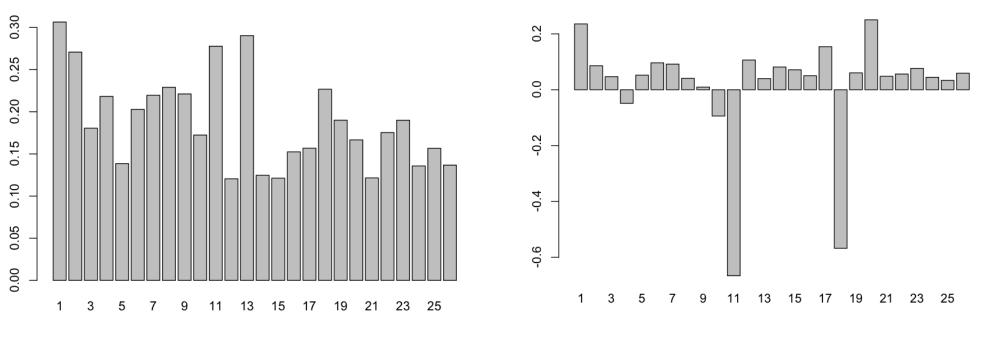
#### An Example: Stock Market

A look at eigenvalues



#### An Example: Stock Market

A look at eigenvectors

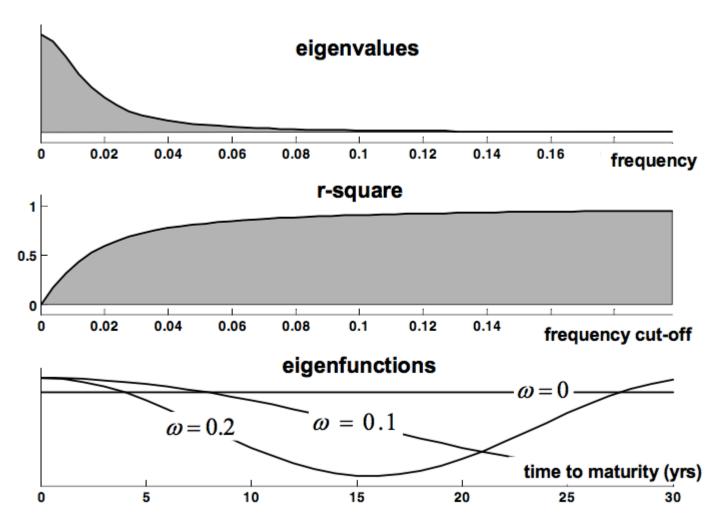


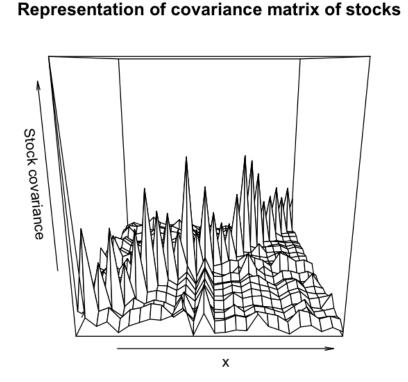
Bar plot of the third eigenvector

Bar plot of the first eigenvector

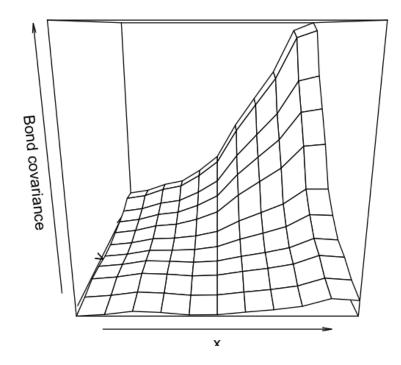
- Daily US Treasury Bond yield rates from: 2/9/2006 to: 4/20/2015.
- Maturities: 1 Mo, 3 Mo, 6 Mo, 1 yr, 2 yr, 3 yr, 5 yr, 7 yr, 10 yr, 20 yr, 30 yr.
- Using the same R-squared as stock market.

- The covariance matrix has some nice properties:
  - Smooth in both of its arguments.
  - Nearly constant diagonal terms.
  - Only depends on one parameter.
- Infinite dimensional case -> Toeplitz Operator.

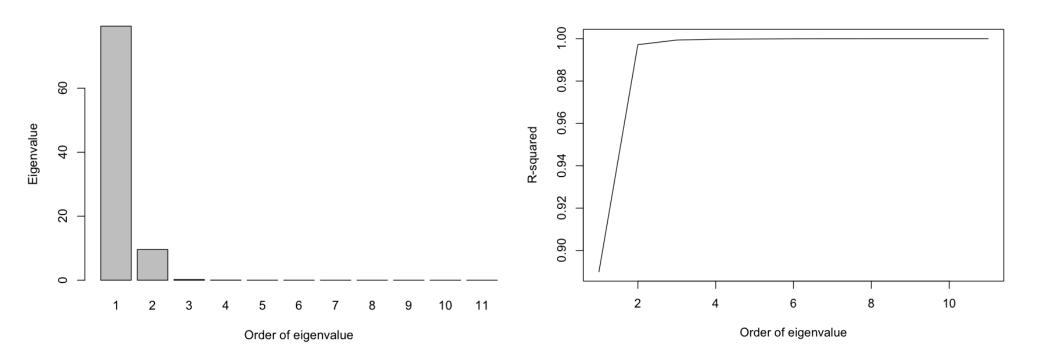




#### Representation of covariance matrix of bonds

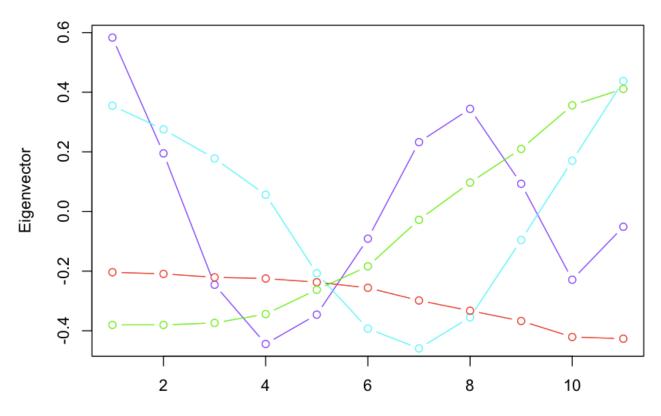


A look at eigenvalues



A look at eigenvectors:

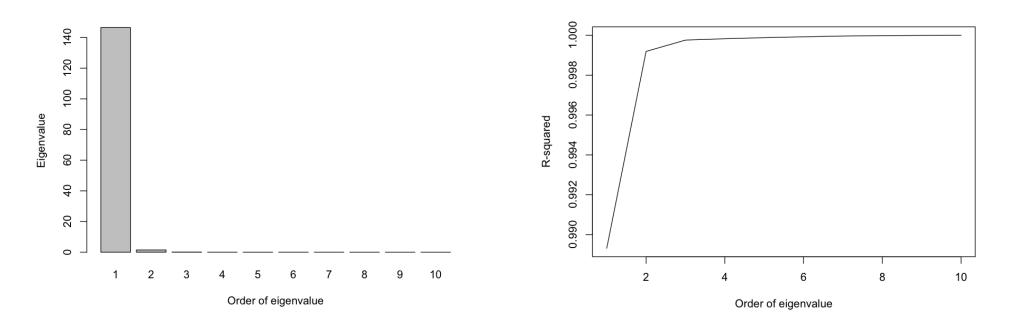
**First 4 eigenvectors** 



Bond maturity rank

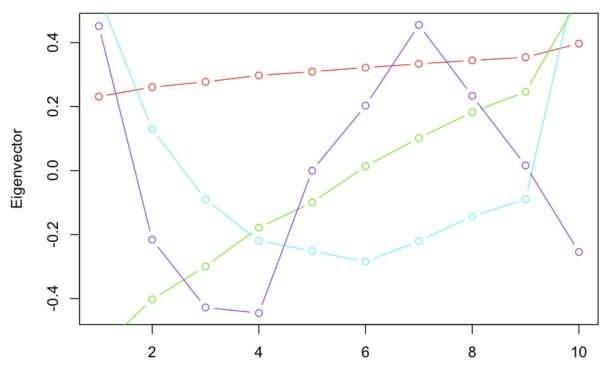
- How about different countries?
- Monthly Spanish Government Bond yields
  - from: 10/1/2004 to: 4/1/2015

A look at eigenvalues:



#### A look at eigenvectors:

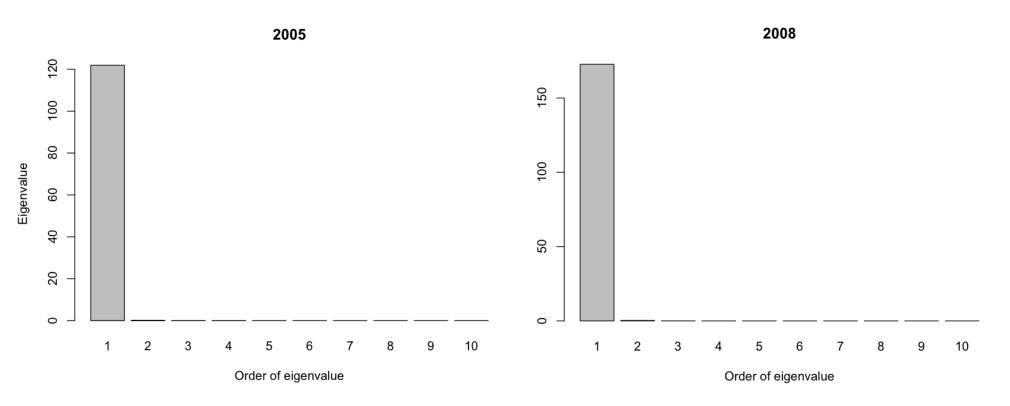
**First 4 eigenvectors** 



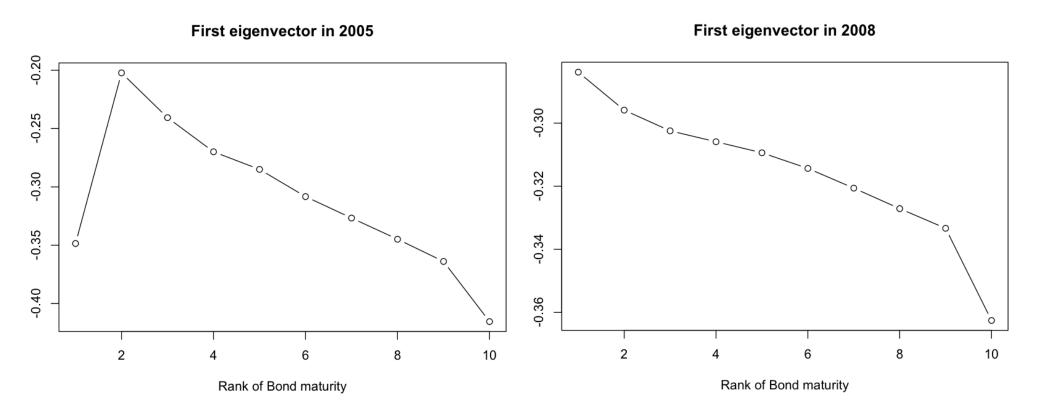
Bond maturity rank

- They look similar.
- Maybe we can look for specific years:
  - Before 2007.
  - After 2007.

Eigenvalues for two different years:



First eigenvectors for two different years:



## Conclusions

- Stocks:
  - Dimension of the stock market is not as easily reducible as the bond market.
  - Gives valuable information about common factors, and correlation between different stocks (sectors?)
  - Might give better results for larger number of stocks.
- Bonds:
  - Number of important dimensions is usually less than 3.
  - Different markets and different years tend to give similar results.
  - Relation to the continuous case can make it easier to analyze.

#### Thank you!