



# Non-linear Patterns in Economic Time Series: High-frequency Data and Non-linear Modeling

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Dissertation Workshop  
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**CERGE-EI** 

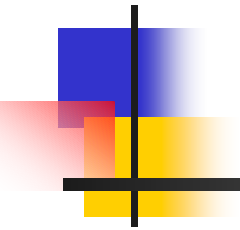


# Organization of the Presentation

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- 1) General overview of dissertation
- 2) Paper1 – Testing of non-linearity
- 3) Paper2 – Effect of CAPM risk/return in CEEC
- 4) Paper3 – Behavior of long-interest rates
- 5) Conclusion

# General Overview of Dissertation





# Overview of Dissertation

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- Paper 1:

- Testing for non-linearity, robustness of the IID-test

- Paper 2:

- Specification of high-frequency data, measure the effect of CAPM risk/return

- Paper 3:

- Behavior of long-interest rates in EMU accession countries



# Status / Proposed Time Plan

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- Paper 1: Status - FINISHED
  - submission to journal after DW
- Paper 2: Status - First draft FINISHED
  - submission as DP after DW, WP – Aug 2006
- Paper 3: Status – First draft in progress
  - first draft – July 2006, WP – Dec 2006

Dissertation submission – expected Dec 2006



# Composition of Committee

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Chair: Evžen Kočenda, CERGE-EI

Members: Jaromír Antoch, MFF, Charles University  
Jan Hanousek, CERGE-EI  
Jan Kmenta, University of Michigan  
Petr Zemčík, CERGE-EI

# Paper1

## Testing for Non-linearity



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How Big is Big Enough?

Justifying Results of the iid Test Based on the  
Correlation Integral in the Non-Normal World



# Motivation

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## Questions:

- How much of the rejections is made by not-normality and how much by non-linearity?
- How does the Bootstrap method work?

## Objectives:

- to explain internal dynamics of the test
- to check the robustness of the test
- to allow testing for broader set of data



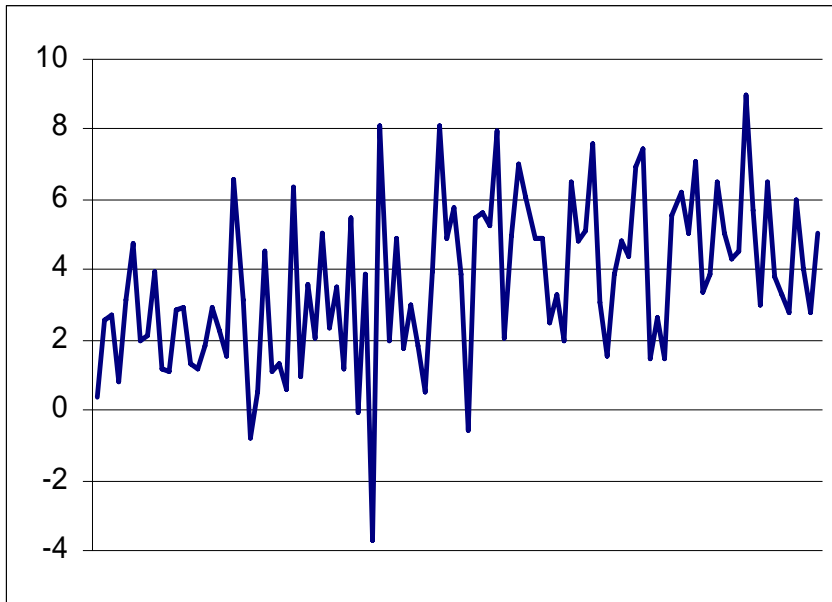
# Economic Implications

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- financial economics
- indices cash stock price volatility
- stock market efficiency
- stock exchange
- behavior of equity indices
- nonlinear dynamics in foreign exchange rates
- interest rates

# Data – Linear vs. Non-linear

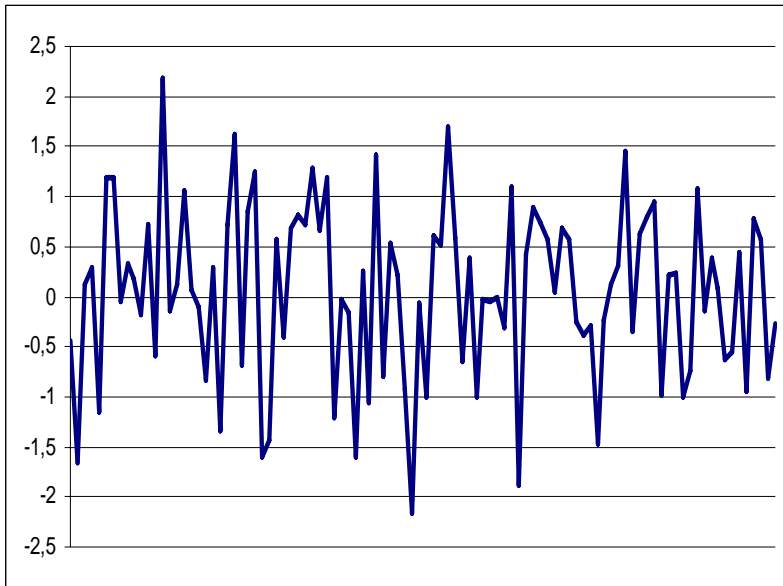
Are there any non-linear dependencies?



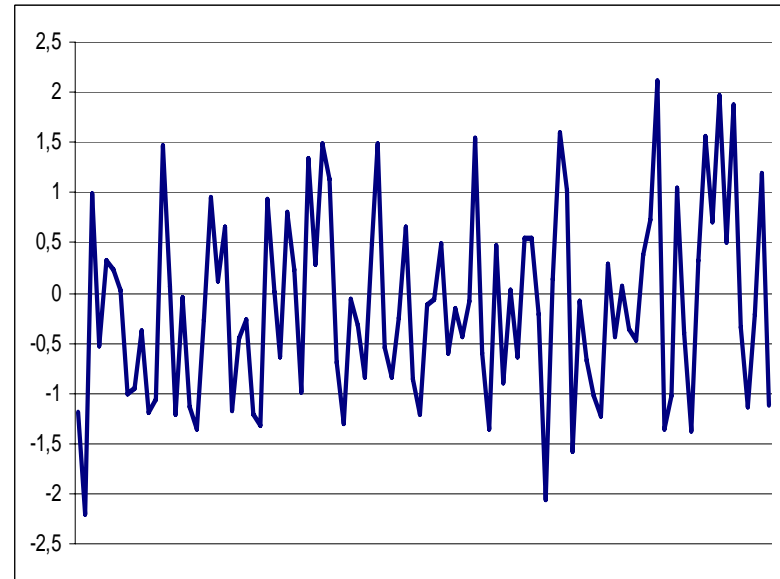
⇒ filter out linearities

# Data – Normal vs. Not-normal

Are patterns in time series independent?



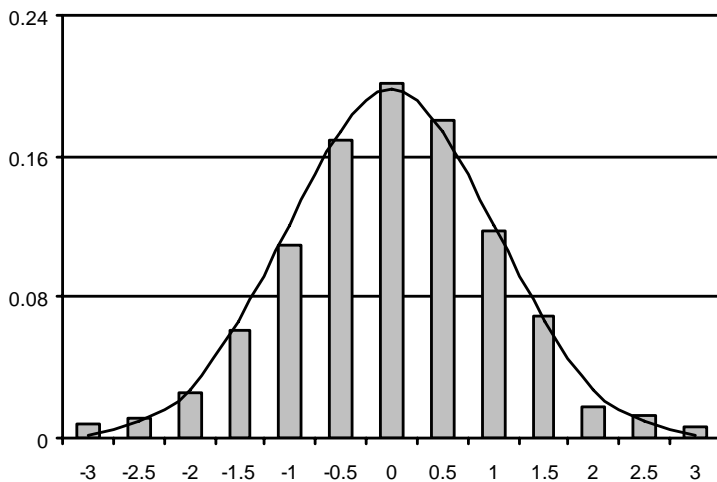
Random time series



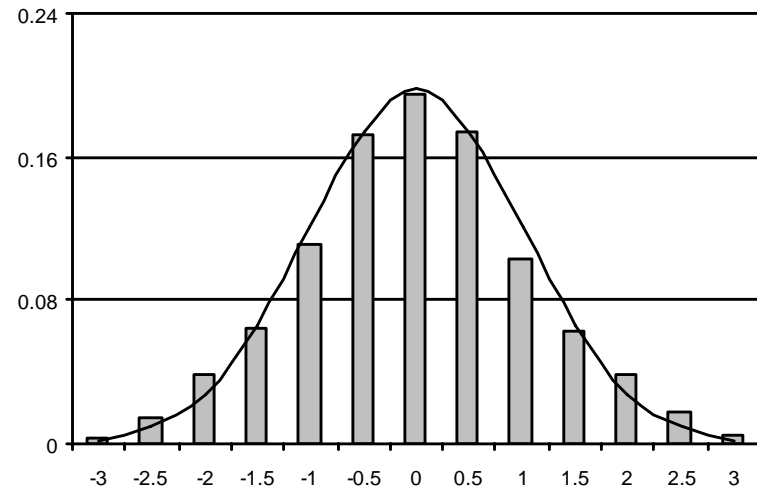
Nonlinear dependency

# Data – IID vs. Non-IID

Are patterns in time series independent?

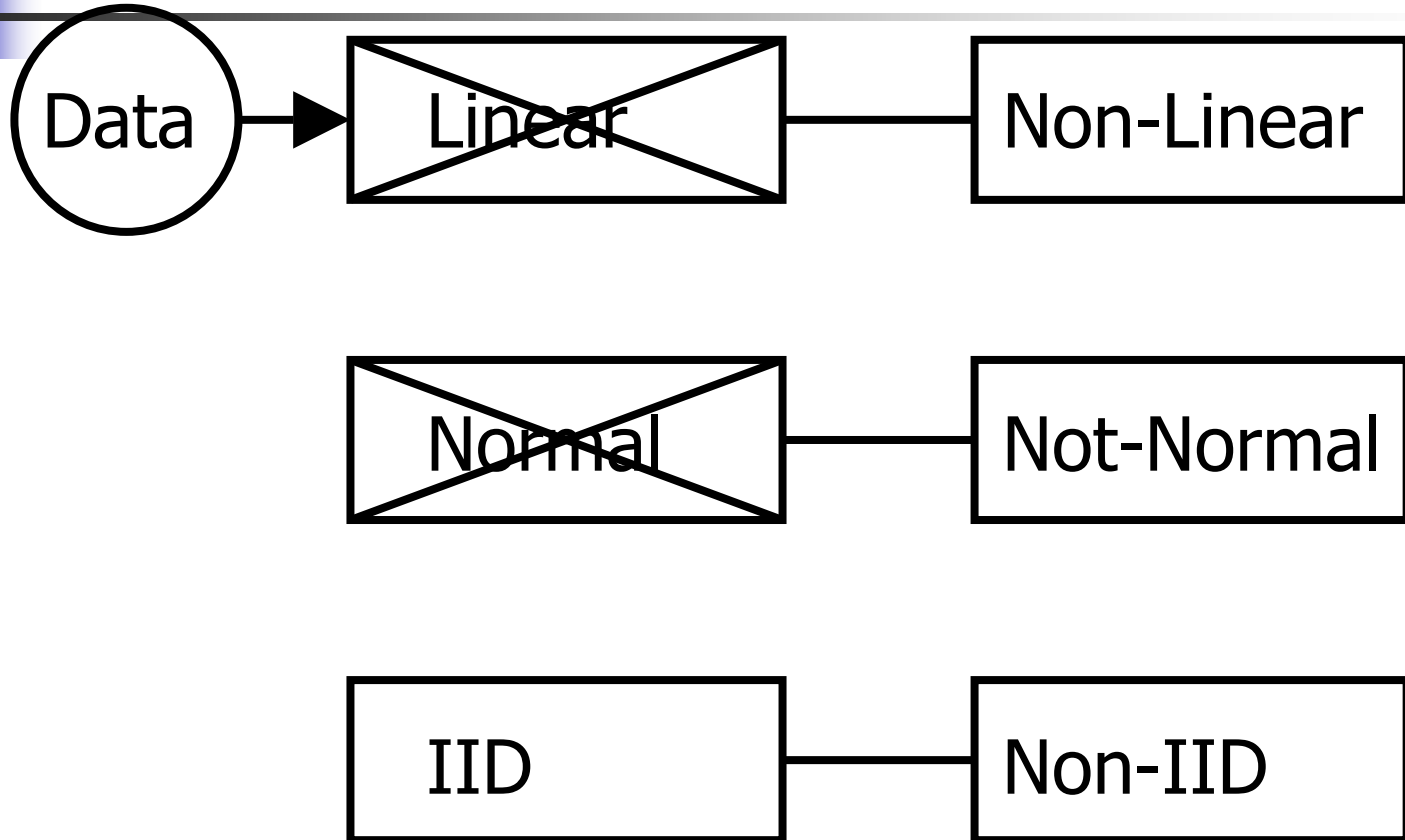


Random time series



Nonlinear dependency

# Data – IID vs. Non-IID





# Nonlinear Tests

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- Bispectral test - Hinich (1982)
- Tsay's test - Tsay (1986)
- White's test - White (1989)
- Lyapunov exponent - Nychka et al. (1993)
- Kaplan's test - Kaplan (1994)
- ⇒ computation is time consuming
- ⇒ ambiguous results



# The BDS-test

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Brock, Dechert, Scheinkman, and LeBaron (1996)

- new method based on the correlation integral

Barnett et al. (Journal of Econometrics, 1997)

- compare the power of the BDS-test with other tests
- found the BDS-test to be one from the most appropriate

# Building stones of the BDS-test

The (sample) correlation integral:

$$C_{m,T}(\varepsilon) = 2 \sum_{t=1}^{T_m-1} \sum_{s=t+1}^{T_m} I_{\varepsilon}(x_t^m, x_s^m) / (T_m(T_m - 1))$$

- it measures the fraction of pairs that lie within the tolerance distance *epsilon* for the particular dimension *m*

- $I_{\varepsilon}(x_t^m, x_s^m)$  is an indicator function of the event  $\|x_t^m - x_s^m\| = \max_{i=0,1,\dots,m-1} |x_{t+i} - x_{s+i}| < \varepsilon$



# The BDS-test

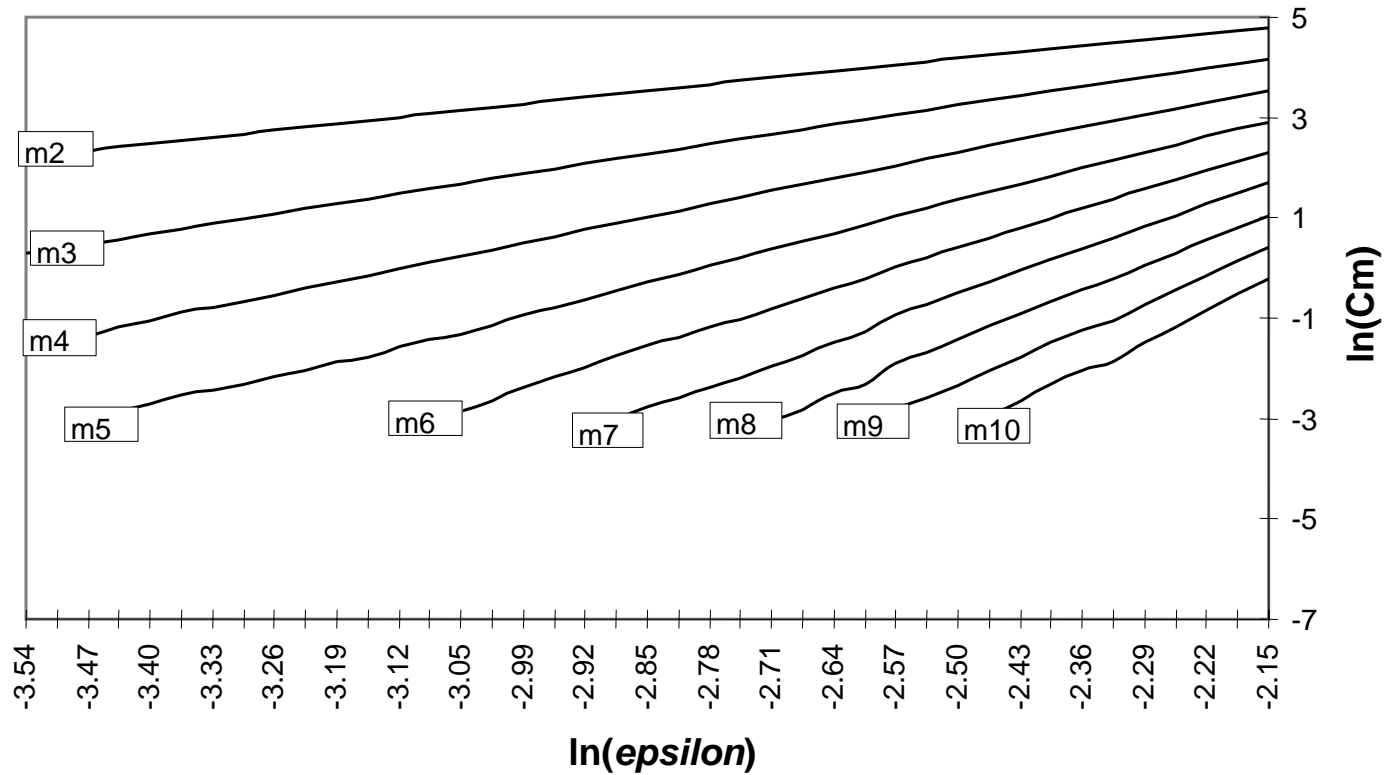
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The test statistic:

$$\text{BDS}_{m,T}(\varepsilon) = T^{\frac{1}{2}} \left[ C_{m,T}(\varepsilon) - C_{1,T}(\varepsilon)^m \right] / \sigma_{m,T}(\varepsilon)$$

- H0: data are *IID*
- it is based on the correlation integral
- it is asymptotically normally distributed

# Relationship between $C_m$ and $\epsilon$



# New Test for Independence

Kočenda (Econometric Reviews, 2001)

$$\beta_m = \frac{\sum_{\varepsilon} \left( \ln(\varepsilon) - \overline{\ln(\varepsilon)} \right) \cdot \left( \ln(C_m(\varepsilon)) - \overline{\ln(C_m(\varepsilon))} \right)}{\sum_{\varepsilon} \left( \ln(\varepsilon) - \overline{\ln(\varepsilon)} \right)^2}$$

- this test does not solve the problem with the correct value of the *epsilon* but circumvents the choice by using range of epsilons



# Properties of the New Test

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Kočenda and Briatka (CERGE-EI WP, 2004)

- sensitivity analysis of the critical values with respect to choice of *epsilon* => to help to choose the optimal range
- new software was developed => easy and user friendly computation



# Properties of the New Test

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Kočenda and Briatka (Econometric Reviews, 2005)

- optimal range for *epsilon* ( $0.60\sigma$ ,  $1.90\sigma$ )
- comparison with Barnett (1997)
- power tests on chaotic and non-linear data  
=> better results than the BDS-test

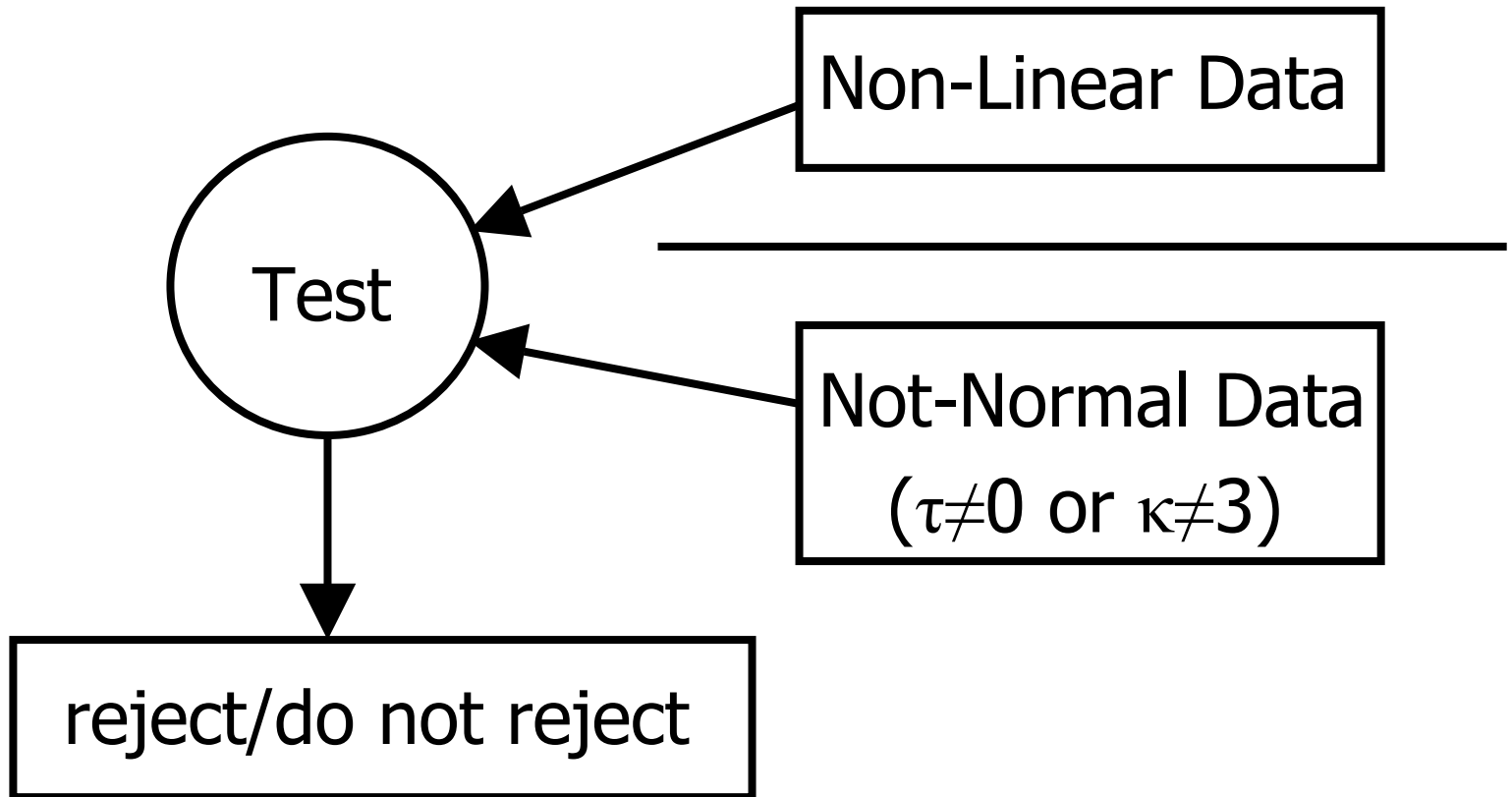


# Research Objectives

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- the method described here is aimed towards situations where data are scarce, the functional form of the mapping is unknown, and the goal is to decide whether there is evidence for a deterministic mechanism
- $\tau$  – coefficient of skewness
- $\kappa$  – coefficient of kurtosis

# Research Objectives





# Methodology I.

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## Method 1:

- Monte Carlo simulation
  - to derive rejection power of the test
  - student, bimodal, mixture, double exp, ...
  - ARMA, NLMA, ARCH, GARCH, ...
  - 1 000 observations
  - optimal range for *epsilon*
  - 10 000 replications



# Methodology II.

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## Method 2:

- Bootstrap method
  - to derive the distribution approximately
  - 1 000 observations
  - optimal range for *epsilon*
  - 200 random shuffles
  - 10 000 replications



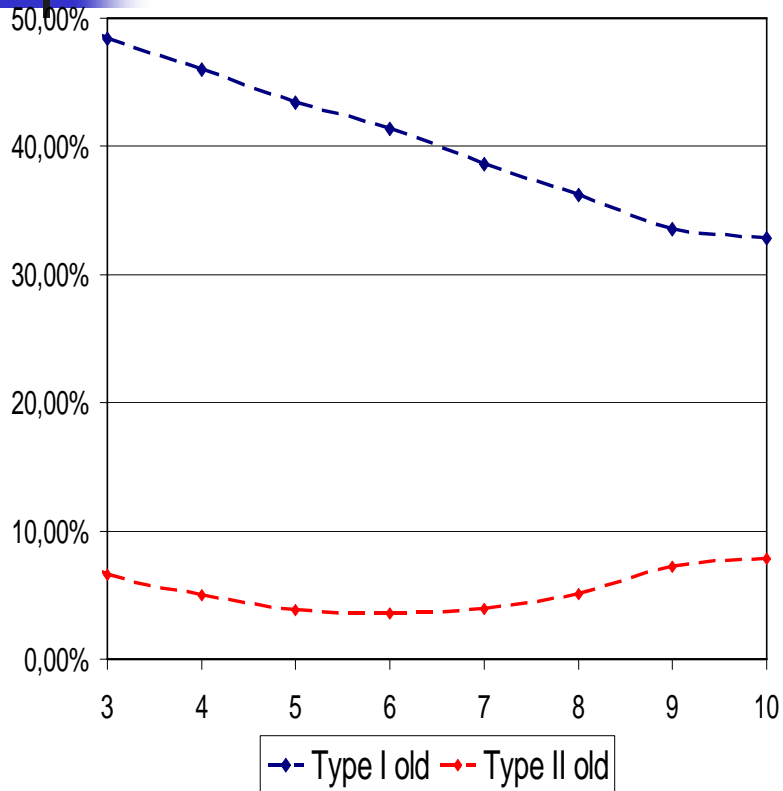
# Results I.

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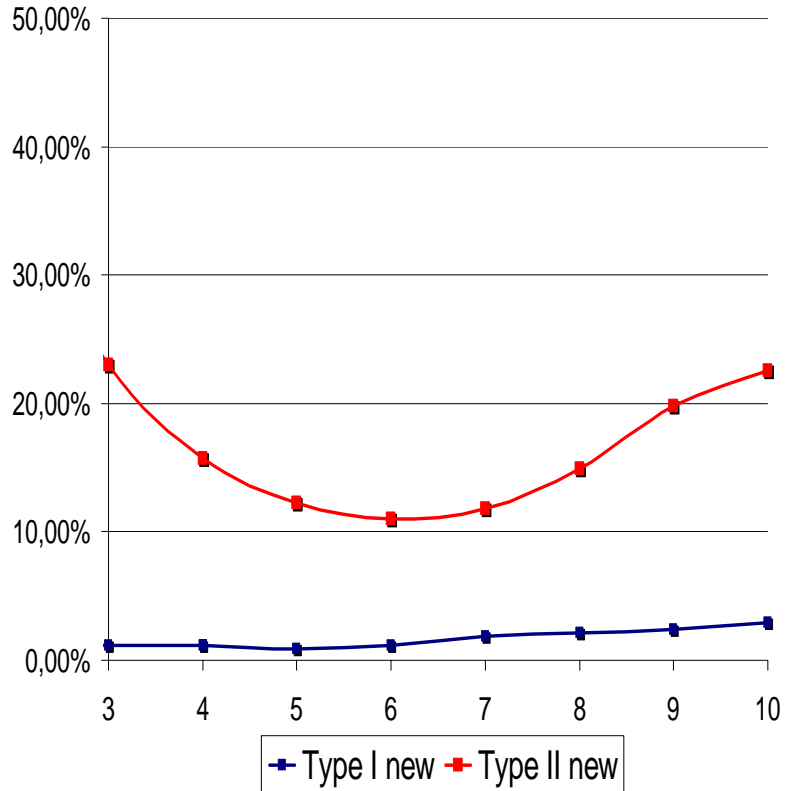
Comparison between type I and type II errors in the graphs and empirical properties computed  
=> practical implication

- type I error
  - a true null hypothesis is incorrectly rejected
- type II error
  - a false null hypothesis fails to be rejected
- standard approach vs. bootstrap method

# Results II.



Standard approach



Bootstrap method

## Results III.



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- new methodology described – allow usage of the test in broader set of data
  - sensitivity analysis implies 2 simple rules:
    - 1) if  $|\tau| > 0.5$  or  $\kappa > 4$   
=> use bootstrap method
    - 2) if  $|\tau| < 0.5$  and  $\kappa < 4$   
=> use standard critical values
- (from Kočenda and Briatka, 2005)

# Paper2

## Modeling of Non-linearity



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Do Non-linearities Matter? Several  
Approaches to High-frequency  
Data Estimation



# Research Objectives

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## Questions:

- Why does non-linear modeling matter?
- How much info. can be taken from data?
- What is specific to high-frequency data?

## Objectives:

- To evaluate outcome of non-linear models
- To find the optimal frequency for modeling



# Economic Implications

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- financial economics
- risk return and risk volatility
- indices cash stock price volatility
- stock market efficiency
- stock exchange
- behavior of equity indices
- nonlinear dynamics in European Stock Markets



# Literature Review I. – Theoretical

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- Linear:
  - Stock and Watson (1998)
- Autoregressive Conditional Heteroskedasticity:
  - Engle (1982), Bollerslev (1986), Brock et al. (1993), Engle and Lee (1999)
- Smooth Transition Autoregressive:
  - D. van Dijk (2002), Teräsvirta et al. (2004)



# Literature Review II. – Theoretical

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- Markov switching models:  
Siliverstovs and D. van Dijk (2003)
- Artificial neural networks:  
Teräsvirta et al. (2004)
- Combined:  
Terui and H. van Dijk (2002)



## Literature Review III. – Empirical

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- Li et al. (Journal of Empirical Finance, 2005)  
risk-return in international stock markets
- Bali and Peng (Journal of Applied Econometrics, 2006)  
risk-return, high-frequency data
- Guo and Nelly (Federal Reserve Bank, 2006)  
risk-return in international stock markets,  
including world markets



# Data Description I.

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## European Stock Markets data

- 1) Western Europe:
  - DAX30 – Germany (Frankfurt)
  - CAC40 – France (Paris)
  - FTSE100 – United Kingdom (London)
- 2) Central and Eastern Europe:
  - BUX – Hungary (Budapest)
  - PX50 – The Czech Republic (Prague)
  - WIG20 – Poland (Warsaw)



## Data Description II.

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- European Stock Markets data – indices
- different sampling frequency – daily, hours, every 5 minutes, every 1 minute
- time span June 2003 – May 2006 (and cont.)
  
- measure the effect of CAPM risk/return



# Methodology

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Comparison of three models:

- Standard GARCH model
- Asymmetric GARCH-in-mean model
- Asymmetric Component GARCH model

CGARCH model permits both a long-run component of conditional variance (that is slowly mean reverting) and also more volatile short-run component



## Results I.

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- in contrast with the previous evidence obtained from weekly and monthly data, daily data show that the relation is positive in almost all markets and often statistically significant
- likelihood ratio tests reject the standard GARCH model in favor of the component GARCH model, which strengthens the evidence for a positive risk-return tradeoff



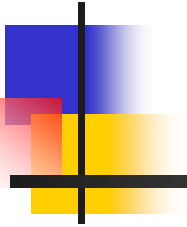
## Results II.

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- consistent with U.S. evidence, the long-run component of volatility is a more important determinant of the conditional equity premium than the short-run component for most European stock markets

# Paper3

## Empirical Paper



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Can Non-linear Econometrics Be Applied  
to the Transition Economies?  
Evidence from EMU Accession Countries



# Motivation

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## Question:

- What is the behavior of bond markets and long-term interest rates in EMU accession countries?

## Objective:

- To explain the behavior of the long-term interest rates using non-linear model



# Economic Implications

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- financial economics
- interest rates behavior
- stock market efficiency
- stock exchange
- behavior of interest rates
- Central Bank policy
- yield curve estimation



# Methodology I.

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## Method:

- use non-linear model (STAR)
- consider 2<sup>nd</sup> Maastricht's criterion:  
“the long-term rate should be no more than 2% above the average of the three countries with the lowest inflation rate”

## Data

- available on ECB webpage
- 10-years bond is not available for each country



# Methodology II.

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## STAR model methodology:

- Lundbergh and Teräsvirta (1998)
- D. Van Dijk (2002)
- Teräsvirta et al. (2004)
  
- smooth transition regime-switching model
- an extension of the STAR model which allows for (possibly asymmetric) autoregressive conditional heteroskedasticity



# Conclusion

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# Conclusion

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- three papers in different stages of progress
- all papers with advanced methodology and broad economic applications
- papers are connected through subjects of non-linearity and high-frequency data

Dissertation submission – expected Dec 2006

Thank you for your attention.

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