Business Cycle Synchronization between the CEE Countries and the Eurozone

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July, 2013

Overview

Economic Foundation

Theoretical background of **Optimal Currency Areas (OCA)**, Mundell (1961):

- The Euro Area can produce more benefits than costs if a high degree of synchronization with the Euro Zone is previously achieved
- Rogoff (1985) and Clarida et al. (1999): the Central Bank will respond more successfully to aggregate shocks and implement its policy with greater efficiency, if the union's members have less volatile and more synchronized business cycles $\Longrightarrow$ lower probability of asymmetric shocks.

Dataset (1)

Period covered: **2000Q1-2012Q4**

11 Countries from the CEE group:

- 8 *First Wave* (2004) - Estonia, Latvia, Lithuania, Poland, Czech Republic, Slovakia, Slovenia and Hungary
- 2 *Second Wave* (2007) - Romania and Bulgaria
- Croatia - expected to join the EU in 2013
- Eurozone Aggregate indicator - EU-15 (over 90% of the EU GDP)

Indicator: Constant Price GDP and ESI, from the Eurostat Database

Part I - Classical Methodology

Univariate filtering techniques

- Quadratic Trend (QT) Filter
- Beveridge-Nelson (BN) Decomposition
- Hodrick-Prescott (HP) Filter
- Band-Pass (BP) Filter
- Unobserved Components (UC) Model

Aggregating the results

Darvas, Vadas (2005) Consensus Measure

$$\mathrm{K}_t^{(m)} = \frac{1}{l_t} \sum_{s=k+1}^{T} \left| \left(q_t - q_{t,s}^{(m)} \right) - \left(q_t - q_{t,s-1}^{(m)} \right) \right| \tag{1}$$

Using the weights:

$$\omega_m = \frac{1/K^{(m)}}{\sum_{i=1}^{p} 1/K^{(i)}} \tag{2}$$

Results obtained from the fitering techniques

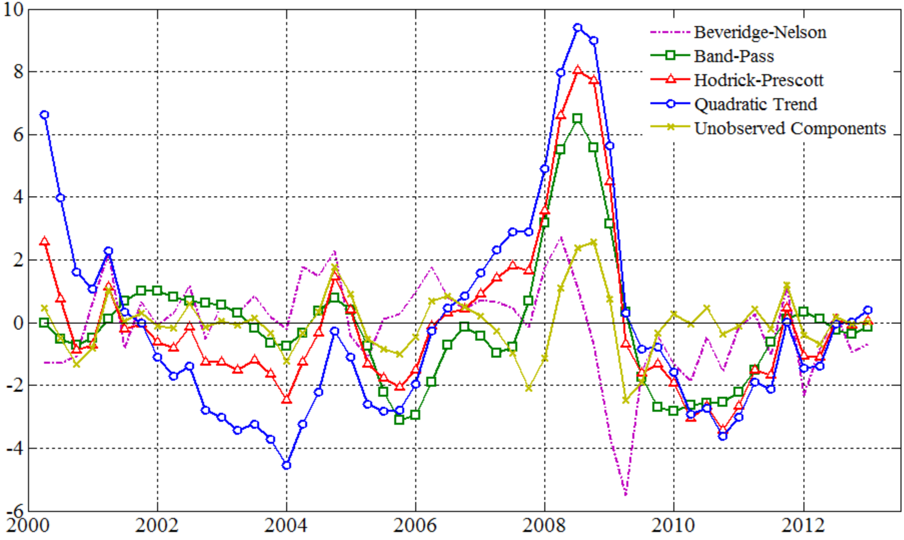
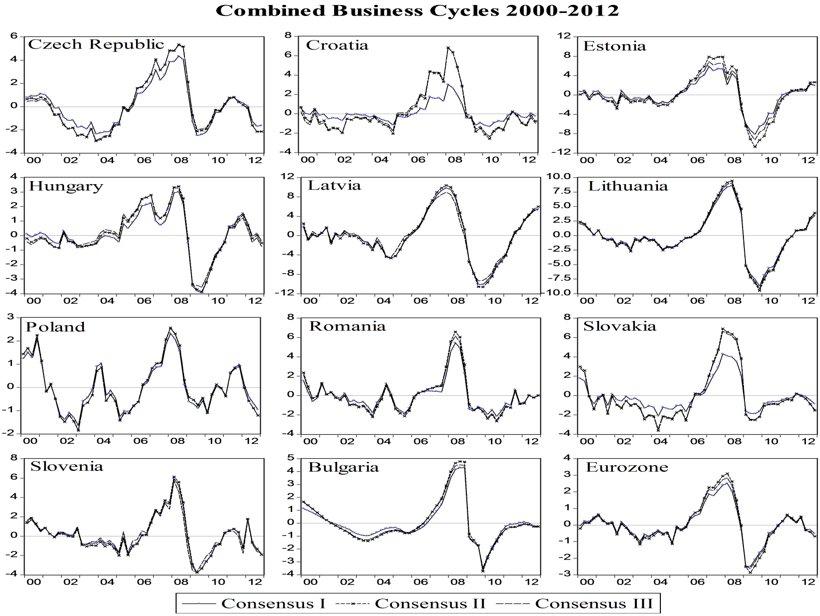


Figure: Estimated Business cycle for Romania 2000-2012

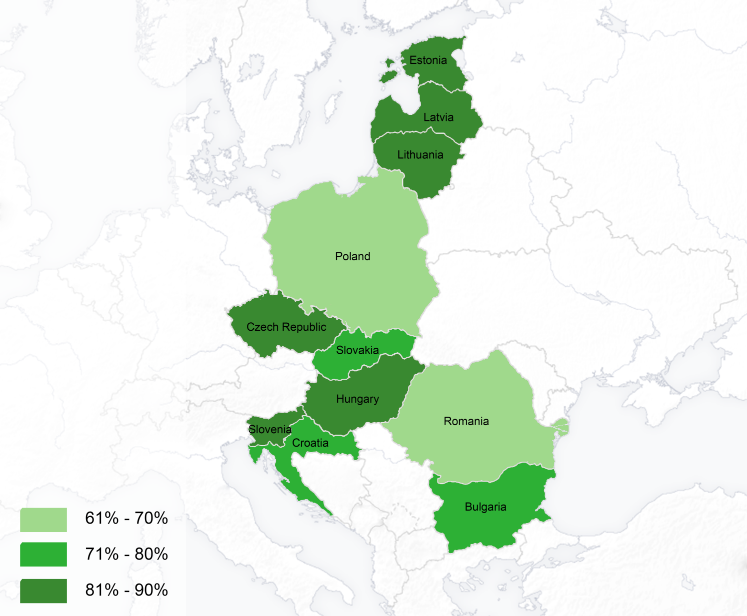

Combined Business Cycles 2000-2012
Czech Republic
Croatia
Estonia
Hungary
Latvia
Lithuania
Poland
Romania
Slovakia
Slovenia
Bulgaria
Eurozone
00 02 04 06 08 10 12
Consensus I
Consensus II
Consensus III

Correlations between CEE countries and the Euro zone 2000-2012

	CRO	CZE	EST	HUN	LIT	POL	ROM	SVK	SLO	BUL	LAT
Cons I	77.1	87.2	87.8	86.1	83.4	63.3	64.1	78.7	91.2	68.9	83.1
Cons II	77.4	84.8	88.8	85.6	84.6	63.5	67.5	79	91	72.7	84.5
Cons III	75.4	**83.9**	**88**	**84.5**	83.6	62.5	67.5	78.1	**89.4**	72.8	82.7

The Highest Correlated Countries are:

Correlations between CEE countries and the Eurozone



Additional Indicators

Concordance Index - Harding, Pagan (2002)

$$\mathrm{IC}_{i,EA} = T^{-1}\left\{\sum_{t=1}^{T}\left(S_{i,t}S_{EA,t}\right) + \left(1 - S_{i,t}\right)\left(1 - S_{i,t}\right)\right\} \tag{3}$$

where S_i is a binary variable, 1 for positive output gap, 0 for negative.

Lead/Lag Correlations

Two economies are synchronized if the maximum correlation occurs *contemporaneously*

Additional Indicators

	CRO	CZE	EST	HUN	LIT	POL	ROM	SVK	SLO	BUL	LAT
CI	0.69	0.83	0.77	0.69	0.75	0.77	0.75	0.75	0.81	0.77	0.77
Lead/Lag	-1	0	0	0	-1	0	-2	-1	0	-2	-1

- According to CI, all countries are *in the same phase* as the Eurozone
- Lead/Lag correlations show that **Romania** and **Bulgaria** are lagging behind the Eurozone, by **two quarters**

Cluster Analysis

- **Hierachical Tree Clustering** - countries are more related to nearby countries than to those farther away.
- Define the distance between two clusters as the **average distance**:

$$d(r,s) = \frac{1}{n_r n_s} \sum_{i=1}^{n_r} \sum_{j=1}^{n_s} dist\left(x_{ri}, x_{sj}\right)$$

- Distance measure - Pearson's correlation

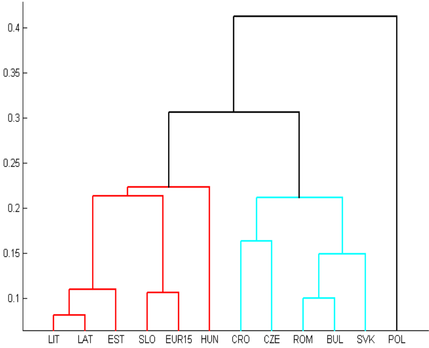


Figure: Dendrogram for the CEE Countries

Multidimensional Scaling Map

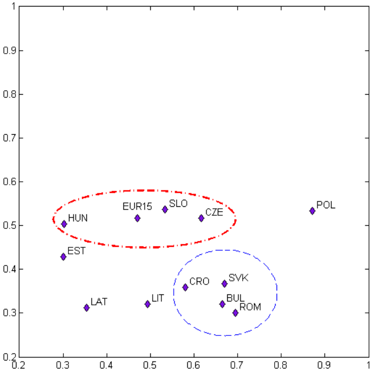


Figure: Distance Map for the CEE countries

Two significant groups:

- **Eurozone**: Hungary, Slovenia and the Baltic States
- **CEE**: Romania and Bulgaria joined by Slovakia and Croatia

The Czech Republic can be included in both clusters

Poland is the most dissimilar country in the dataset

Motivation

- Economic developments are the results of the actions of several agents, who have different term objectives $\Longrightarrow$ Economic time series are an aggregation of components, functioning at *different frequencies*
- **Wavelets** - determine the underlying forces in the time series, over a range of different time horizons, can reveal remarkable insights into cycles, at different time scales.
- are capable to handle non-stationary data or structural breaks that appear in some time series

What are Wavelets?

A wavelet is a wave-like oscillation with an amplitude that increases and then decreases back to zero. Mathematically, it has to fulfill the condition:

$$\int_{-\infty}^{\infty} \psi\left(t\right) dt = 0 \tag{4}$$

Starting with a mother wavelet, we can construct a family of "daughter wavelets" by a simple process of *scaling* and *translating*:

$$\psi_{s,u}\left(t\right) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-u}{s}\right) \tag{5}$$

Discrete Wavelet Transform

The discrete version of the wavelet function is:

$$\psi_{m,n} = a^{-\frac{m}{2}} \psi \left(a^{-m} t - nb \right) \tag{6}$$

Define the Discrete Wavelet Transform of a function *x(t)* as:

$$\mathrm{W}_{m,n} \left(x \right) = a^{-\frac{m}{2}} \int_{-\infty}^{\infty} x \left(t \right) \psi \left(a^{-m} t - nb \right) dt \tag{7}$$

Basic Idea: Convolve the series with a wavelet function and compute the coefficients

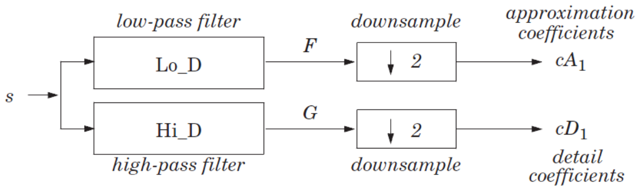
Multiresolution Analysis

The main tool used in wavelet theory - decomposes a signal into its constituent multiresolution components, allowing the separate analysis of these sub-processes (Mallat and Meyer):

$$x(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \qquad (8)$$

where $s_{J,k}$ are the approximation coefficients and $d_{J,k}$, the detail coefficients.

Mallat's Pyramid Algorithm



This approach is equivalent to Subband Filtering Schemes, used in electrical engineering

Daubechies Family of Wavelets

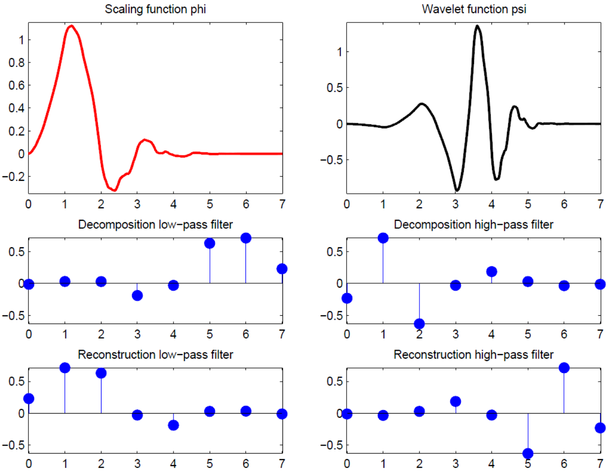


Figure: Scalling and Wavelet Functions (ablove)
The Four Filters associated with the db4 wavelet (below)

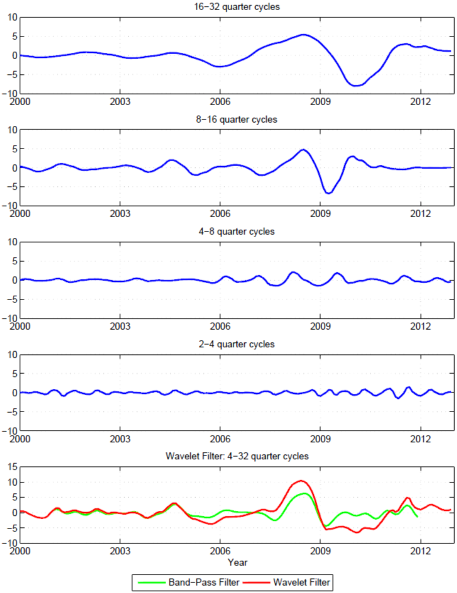


Figure: MRA results for Romania

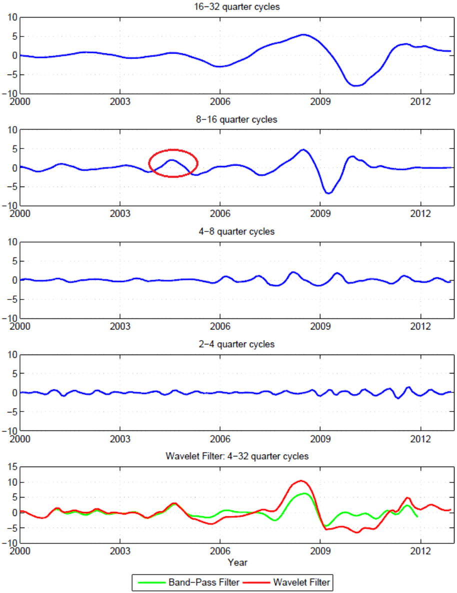


Figure: MRA results for Romania

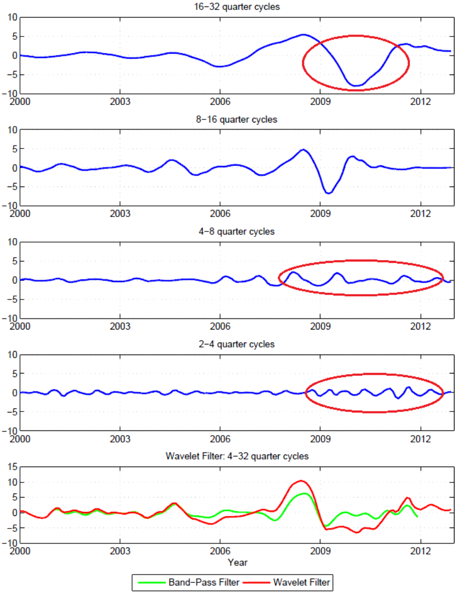


Figure: MRA results for Romania

Results

The correlations between the business cycles, obtained using the Multiresolution Analysis:

	BUL	CZE	EST	LAT	LIT	HUN	POL	ROM	SLO	SVK	CRO
00-12	83.9	**91.9**	91.5	89.4	**92.7**	85	79.9	82.6	**96.3**	**92.2**	85.6
00-06	77.5	85.5	89.8	73.8	87.5	64.9	61.7	58.2	93.1	71.6	81.8
07-12	86.2	93.3	91.7	92.6	94.5	89.2	89.5	87.1	97.1	96.7	86.1

We obtain similar results with the first part of the analysis:

Continous Wavelet Transform

In contrast to the DWT, its continuous counterpart operates on a continuous set of scales:

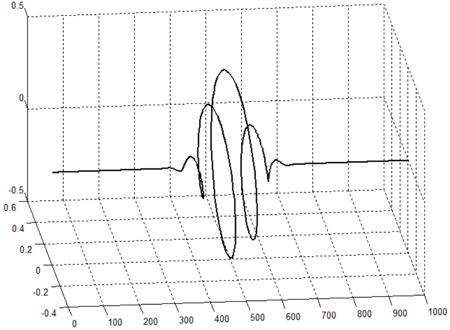
$$\mathrm{W}_x(s,u) = \langle x(t), \psi_{s,u}(t) \rangle = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-u}{s}\right) dt \tag{9}$$

The original function *x(t)* is fully preserved by the wavelet transform, i.e. it can be perfectly reconstructed using:

$$\mathrm{x}(t) = \frac{2}{C_\psi} \int_{0}^{\infty} \left[\int_{-\infty}^{\infty} W_x(s,u) \psi_{s,u}(t)\, du \right] \frac{ds}{s^2} \tag{10}$$

Limiting the integration over a range of scales performs **a band-pass filtering** of the series

Morlet family of Complex Wavelets



Analytic Formula for the Morlet Wavelet Family

$$\psi_{\omega_0}(f) = Ke^{i\omega_0 t}e^{\frac{-t^2}{2}} \tag{11}$$

Wavelet Power Spectrum

The **wavelet power spectrum** or scalogram is defined, in analogy with Fourier Theory, as:

$$\mathrm{WPS}_x(u,s) = |W_x(u,s)|^2 \tag{12}$$

- Measures the *variance distribution* present in the time series, over the time-scale plane
- Has the ability detect *cyclical behavior* present in a time series.

How to interpret the Wavelet Power Spectrum?

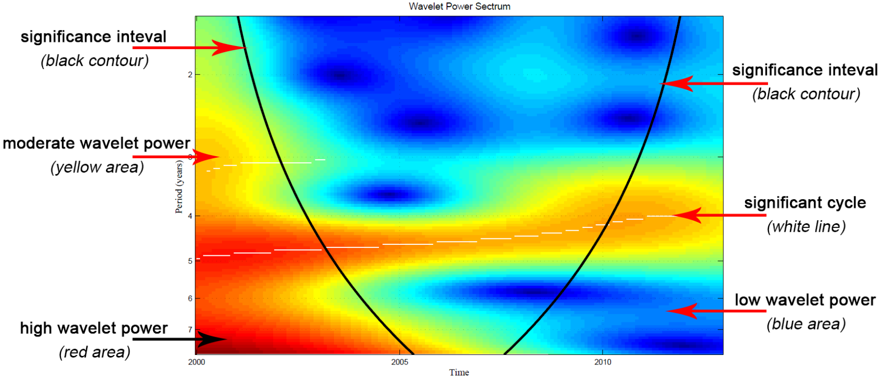


Figure: Wavelet Power Spectrum for Romania

Wavelet Power Spectrum - Results

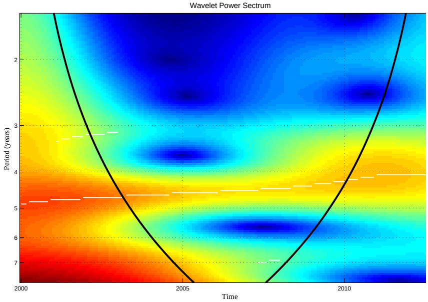


Figure: WPS - Bulgaria

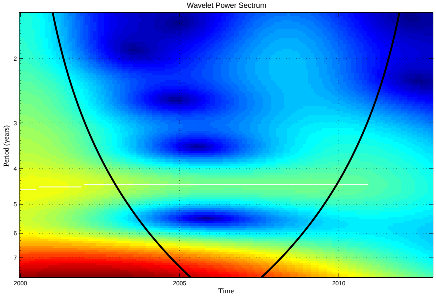


Figure: WPS - Hungary

Wavelet Power Spectrum - Results

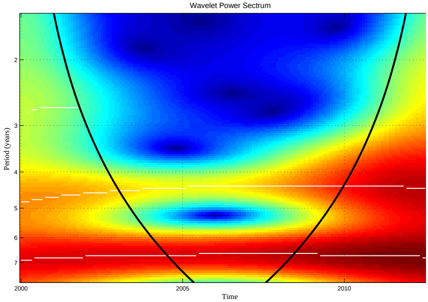


Figure: WPS - Poland

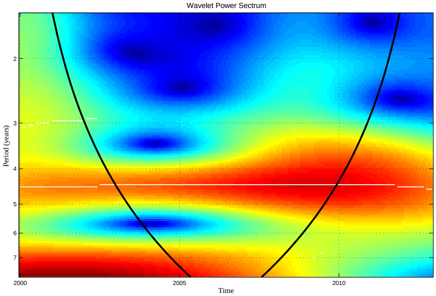


Figure: WPS - Eurozone

Wavelet Coherency and Phase Difference

Wavelet Coherency - a measure of local correlation, in time and frequency, between two series:

$$\mathrm{R}_{xy} = \frac{|S(W_{xy})|}{\left[S\left(|W_x|^2\right)S\left(|W_y|^2\right)\right]^{1/2}} \tag{13}$$

Phase Difference - Measures the delays of the oscillations between two time series:

$$\phi_{xy} = Arctan\left(\frac{\Im(S(w_{yy}))}{\Re(S(w_{xy}))}\right),\ \phi_{xy} \in (-\pi, \pi) \tag{14}$$

Wavelet Coherence - Results

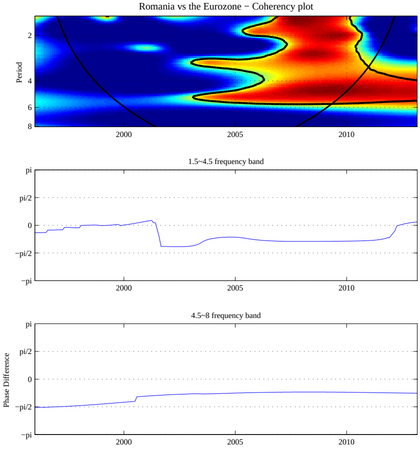


Figure: Coherence Plot - Romania

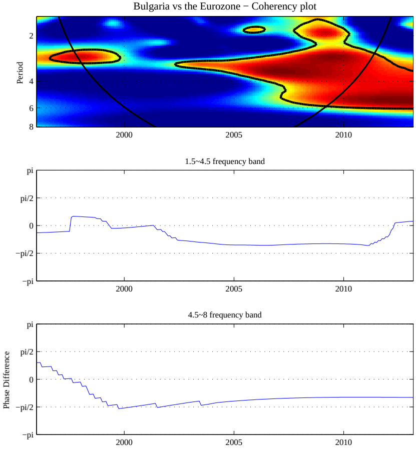


Figure: Coherence Plot - Bulgaria

Wavelet Coherence - Results

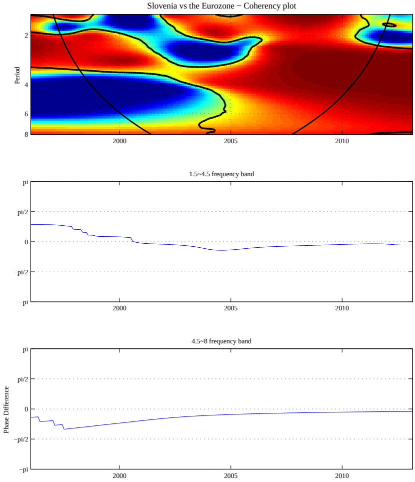


Figure: Coherence Plot - Slovenia

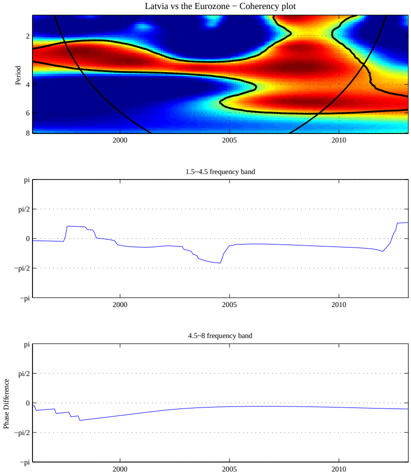


Figure: Coherence Plot - Latvia

Wavelet Coherence - Results

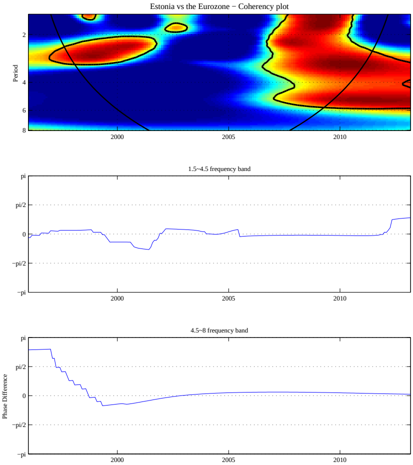


Figure: Coherence Plot - Estonia

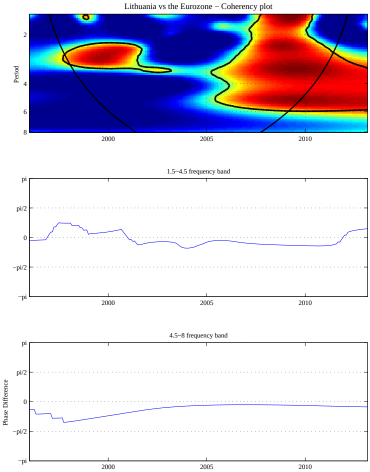


Figure: Coherence Plot - Lithuania

Conclusions (1)

- The most synchronized countries from the CEE group are Slovenia, followed by the Czech Republic, the Baltic States and Slovakia
- The Baltic States form **the most homogeneous** subgroup from the entire CEE region, with a highly correlated business cycle behaviour
- At the bottom of the hierarchy we find Romania, Bulgaria and Poland, results confirmed by both the classical and wavelet approaches
- Concerning lead/lag relationships, all the C.E.E. countries business cycles are in concordance with that of the Euro Area.

Conclusions (2)

- Some countries are in the **same phase** as the Eurozone i.e. Slovenia, Slovakia, Estonia and others, namely Bulgaria and Romania, are **significantly lagging** behind.
- Romania and Bulgaria are not yet prepared to become a part of the single currency area.
- Dating the **business cycle turning points**, using Markov-switching models, could provide further insight into the behavior of business cycles.
- Another direction worth exploring is the use of **structural models**, which rely on certain economic assumptions formulated in the underlying model.

Selective Bibliography

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Thank you for your attention!