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Business cycle synchronization of the Visegrad Four and the European Union

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FINMAP –

**FINANCIAL DISTORTIONS AND MACROECONOMIC
PERFORMANCE: EXPECTATIONS, CONSTRAINTS AND
INTERACTION OF AGENTS**

DATE: 06/11/2015

TITLE

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Keywords: business cycle synchronization, time-frequency, wavelets, co-movement, Visegrad Four, European Union

JEL classification: E32, C40, F15

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Business cycle synchronization of the Visegrad Four and the European Union[†]

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Abstract

In this paper, we map the process of synchronization of the Visegrad Four within the framework of the European Union using the wavelet techniques. In addition, we show that the relationship of output and key macroeconomic indicators is dynamic and varies over time and across frequencies. We study the synchronization applying the wavelet cohesion measure with time-varying weights. This novel approach allows for studying the dynamic relationship among countries from a different perspective than usual time-domain models. Analysing monthly data from 1990 to 2014, the results for the Visegrad region show an increasing co-movement with the European Union after the countries began with preparation for the accession to the European union. The participation in a currency union possibly increases the co-movement. Further, analysing the Visegrad and South European countries' synchronization with the European Union core countries, we find a high degree of synchronization in long-term horizons.

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1 Introduction

One of the most challenging phenomena in economics is the identification, proper understanding, and disentangling of factors and mechanisms influencing dynamics of macroeconomic variables. Number of quantitative econometric techniques was developed to study regularities in fluctuations of macroeconomic indicators and business cycles, e.g., Baxter & King (1999); Harding & Pagan (2002); Hodrick & Prescott (1981). This article investigates the business cycle synchronization at different time horizons. In order to disentangle desired information, we apply the wavelet methodology working in time-frequency space. The analysis considers the case of the Visegrad Four, its inside relationships and those within the framework of the European Union (EU).

It has been more than two decades since the break-up of the Eastern block, when the countries began their independent economic and political journey. The Czech Republic, Hungary, Poland, and Slovakia started discussing the mutual cooperation during their economic transformations. Despite their originally different economic maturities and development, their willingness and regional proximity guided them to establish the Visegrad Four in 1991. One of the aims of the group was to help its member states to organize their institutions for faster convergence and integration with the European Union (Lukášek, 2010).¹ In 2004, these four countries became members of the EU. This obliges them to adopt the Euro currency within the integration process. One of the concerns of a successful integration into the European monetary union (EMU) is the business cycle synchronization, which is motivated by the theory of Optimum Currency Area (OCA) (Mundell, 1961). A country joining the OCA gives up its individual monetary policy and in terms of cost and benefit this requests some level of integration of macroeconomic variable and policies (De Haan et al., 2008). The common currency can be beneficial for both new and former countries in terms of trade transaction costs. Otherwise, at the European level, for instance, the European Central Bank rules policies applicable in all countries, which may be counter-cyclical for countries with low business cycle synchronization (Kolasa, 2013). This may create difficulties for those countries. On the other hand, low synchronized countries may benefit from being members of the OCA because the business cycle synchronization appears as an endogenous criterion. This endogeneity of OCA means that forming a monetary union will make its members more synchronized (Frankel & Rose, 1998).²

The literature concerning the integration has been growing rapidly, even more when focusing on the economic integration of Central and Eastern European (CEE) countries to the EU. In order to study the synchronization of the EU and CEE countries, Fidrmuc & Korhonen (2006) gather 35 studies, on which they conduct a meta-analysis. They find that there exist high synchronization between new member states and the EU. However, concerning the Visegrad countries, only Hungary and Poland reached high degree of

¹The Visegrad countries have also joined the North Atlantic Treaty Organization in 1999 and in 1995-1996 all applied for membership in the European Union.

²Literature focusing on evolution and determinants of business cycle synchronization between the Central and Eastern European countries and the EU is extensive, e.g., Artis et al. (2004); Backus et al. (1992); Darvas & Szapáry (2008).

synchronization. Artis et al. (2004) and Darvas & Szapáry (2008) obtained the same results of correlations between business cycles of the EU and Hungary and Poland. The model of Jagrič (2002) implies that economic movement of Hungary and Poland got very close as well. Analogously, study of Bruzda (2011) shows that Poland's economy synchronization with the EU increases as the synchronization within the EU is stable. In the recent study, Aguiar-Conraria & Soares (2011a) take the industrial production index of Euro-12 countries³ and analyse business cycle synchronizations within the EU framework taking into account distances of regions. They show that closer countries show higher degree of synchronization. Moreover, the transition countries show high similarity to the EU after 2005. Nevertheless, Slovakia, as a member of the Euro area, does not expose any significant pattern of coherence. With respect to Hungary and the Czech Republic, their business cycles co-move with the EU-12 after 2005. Jiménez-Rodríguez et al. (2013) also find high correlations of CEE countries with the European business cycle, except for the Czech Republic. But contrary to this result, they find a lower level of concordance of these countries when using a factor model.

To assess the degree of similarity or synchronization, researchers have searched for appropriate tools to capture the information. One of the most popular tools is the Pearson correlation coefficient, which simply measures the degree of co-movement in time domain. However, market-based economies are dynamic systems structured at different time horizons. For this reason, researchers started surveying the behaviour of such systems at different frequencies corresponding to different time horizons and the interest in frequency domain measures has naturally been growing. Christiano & Fitzgerald (2003) proposed a model known as the Band pass filter allowing for filtering a desired frequencies of time series.⁴ Further, Croux et al. (2001) presented a measure of co-movement, the dynamic correlation, based on the spectral analysis, which equals to basic correlation on band pass filtered time series. Nevertheless, both the time (static) Pearson correlation or the spectral domain dynamic correlation have similar caveats. The first loses the information about frequency horizons and the latter omits the co-movement dependence in time. The wavelet analysis overcomes those limitations due to its operation in both time and frequency domains (Torrence & Compo, 1998). During past two decades, the wavelet applications have been supported by its another advantage, which is the localization of the wavelet basis function in time and its bounded support, and hence the analysis is free from the assumption of covariance-stationarity, from which many filtering methods suffer (Raihan et al., 2005). Literature presents many studies that successfully used the wavelets, which do not necessitate stationary time series, e.g., Aguiar-Conraria et al. (2008) analysing the evolution of monetary policy in the US, Vacha & Barunik (2012) studying energy markets relationships, or Yogo (2008) using the wavelet analysis to determine peaks and troughs of business cycles corresponding to the definition of the National Bureau of Economic Research.

³These countries are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain. We analyse the same group and the Visegrad countries.

⁴Lamo et al. (2013) serve a short presentation filtering methodology applied to the business cycles in the Euro area.

To capture the co-movement of two or more time series, we use several wavelet measures that overcome the above mentioned caveats and obtain desired information about time series relationships. For the bivariate analysis, we employ the wavelet coherence described in Torrence & Compo (1998) and Grinsted et al. (2004). Further, while studying the multiple relationship of several time series, we start with the bivariate measure proposed by Rua (2010). Similarly as Croux et al. (2001) transformed the dynamic correlation to the multivariate measure of cohesion, Rua & Silva Lopes (2012) extend the wavelet quantity of Rua (2010) to the multivariate case of weighted cohesion. The multivariate case relies on the bivariate measure multiplied by fixed weights that represent a share of each pair's value among all time series. However, in order to reflect the dynamics and development of economies, we believe that weights may be changing over time and should not be rigid. Taking that into account, we propose to redefine the weights in the cohesion measure to have the time-varying structure. For example, emerging or developing countries expose higher growth and may get closer to developed countries, hence, the ratio of each pair changes over time with their evolution.

Using the state of art wavelet methods, we find different levels of co-movement between Visegrad countries and EU during the period 1990-2014. The Visegrad countries show strong co-movement at the long-term business cycles. The pairwise synchronization of Visegrad countries with Germany appears to be significant for long-term business cycles from 2000 onward. The measure of multivariate co-movement confirms that the Visegrad countries are well-synchronized at the business cycles periods of 2-4 years. Similarly for the 16 European countries, we observe their higher cohesion for those periods, which becomes stronger after 2000. All countries together promote no considerable relationship for periods up to 1 year, this may reflect some short-term policy heterogeneity.

The contribution of this paper is twofold: we propose the novel measure of cohesion with time-varying weights and we have done the empirical analysis concerning the Visegrad Four. The rest of the paper is structured as follows. Section 2 describes the wavelet methodology and introduces the cohesion measure with time-varying weights. Section 3 provides the data description. In section 4, we carry on the analysis of results. And Section 5 concludes the paper.

2 Methodology

2.1 Wavelet analysis

Our analysis aims to address the behaviour of a dynamics among time series at different time horizons. Economic time series might be locally stationary or non-stationary. The Fourier analysis is convenient for observing relations at different frequencies, however it requires time series to be stationary, this comes at the cost of losing some information of time series when differencing, for instance. In other words, using the Fourier transform (FT) makes the analysis time-invariant and hence not suitable to provide any information about dynamics of a process. For this reason, Gabor (1946) developed the short-time Fourier transform (or windowed FT), which is based on applying the Fourier transform

on a shorter part of the process. Still, this approach leads to shortcomings, which arise with fixed time and frequency resolution; it is not possible to change the resolution at different frequencies. A series of lower or higher frequencies needs lower or higher time resolution, respectively (Gallegati, 2008). As the window width is constant, the resolution, especially for low frequencies, is limited.

In order to find a better balance between time and frequency resolutions the wavelet transform has been developed. The wavelet functions used for the decomposition are narrow or wide when we analyse high or low frequencies, respectively (Daubechies, 1992). Thus, the wavelet analysis is suitable to research different types of processes using optimal time-frequency resolution in great detail (Cazelles et al., 2008).⁵ The wavelet analysis is also able to work properly with locally stationary time series.

The wavelet transform decomposes a time series using functions called mother wavelets $\psi(t)$ that are functions of translation (time) and dilation (scale) parameters, τ and s , respectively. In many applications, it is sufficient that the mother wavelet has zero mean, $\int_{-\infty}^{\infty} \psi(t)dt = 0$, and the function has a sufficient decay. These two properties cause the function to behave like a wave. Further, the elementary functions called daughter wavelets resulting from a mother wavelet $\psi(\tau)$ are defined as

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-\tau}{s}\right), \quad s, \tau \in \mathbf{R}, s \neq 0. \quad (1)$$

The continuous wavelet transform (CWT) of a process, $x(t)$, with respect to the wavelet ψ ,⁶ is defined as a convolution of the given process and the family $\psi_{\tau,s}$,

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^*\left(\frac{t-\tau}{s}\right) dt, \quad (2)$$

where $*$ denotes the complex conjugate. As several wavelet functions are available for CWT, in our analysis we use the Morlet wavelet as the mother wavelet. Its use is common in the literature due to its well-localized properties in time and frequency (Aguiar-Conraria & Soares, 2011b; Cazelles et al., 2008). It is a complex wavelet, with a real and an imaginary part, that allows us to perform the phase difference analysis. The simple definition of the Morlet wavelet is

$$\psi(t) = \pi^{-\frac{1}{4}} e^{-i\omega_0 t} e^{-\frac{t^2}{4}}. \quad (3)$$

As a complex function with a Gaussian envelope, the Morlet wavelet's parameter ω_0 (wavenumber) is set equal to 6. Having this parameter, we obtain that a relation between

⁵There exists a possibility to use methods of evolutionary spectra of non-stationary time series developed by Priestley (1965). However, to run a spectrum over time at different frequencies, it would be necessary to have larger data to obtain similarly good time resolution as using wavelet techniques. And while we study the short-term fluctuations such as 2-4 months, we would not obtain such localized information because of number of needed observations to start with.

⁶More details about conditions that a mother wavelet must to fulfil consult, e.g., Mallat (1999) or Daubechies (1992).

wavelet scales and frequencies is inverse, $f \approx \frac{1}{s}$. This makes easier further interpretation of results (Grinsted et al., 2004; Torrence & Compo, 1998).

A convenient property of the wavelet transform is that one can reconstruct the original time series back from the wavelet transform,

$$x(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} \psi_{\tau,s}(t) W_x(\tau, s) d\tau \right] \frac{ds}{s^2}, \quad (4)$$

where C_ψ comes from the admissibility condition that allows the reconstruction, $C_\psi = \int_0^\infty \frac{|\Psi(f)|^2}{f} df < \infty$, where $\Psi(\cdot)$ is the Fourier transform of $\psi(\cdot)$.

Defining the single wavelet power spectrum, $|W_x(\tau, s)|^2$, given the wavelet transform, we get the measure of energy of the time series. For given two time series, $x_i(t)$ and $x_j(t)$, the cross-wavelet transform is defined as the product of their transforms $W_{x_i x_j}(\tau, s) = W_{x_i}(\tau, s) W_{x_j}(\tau, s)^*$, where $*$ denotes the complex conjugate.

In our application, we use the wavelet coherence to quantify the pairwise relationship of two time series. This coherence in the Fourier analysis is defined as a measure of the correlation between the spectra of two time series (Cazelles et al., 2008). The coherence comes from the definition of the coherency as its power of two. Having two time series x_i and x_j , the wavelet coherency that measures their relationship is defined as (Liu, 1994):

$$\Gamma(\tau, s) = \frac{W_{x_i x_j}(\tau, s)}{\sqrt{W_{x_i}(\tau, s) W_{x_j}(\tau, s)}}. \quad (5)$$

Given that the coherency is a complex measure as the wavelet powers are, we preferably use the squared wavelet coherence to measure co-movement between two time series, which is given by:

$$R^2(\tau, s) = \frac{|S(s^{-1} W_{x_i x_j}(\tau, s))|^2}{S(s^{-1} |W_{x_i}(\tau, s)|^2) \cdot S(s^{-1} |W_{x_j}(\tau, s)|^2)}, \quad R^2 \in [0, 1], \quad (6)$$

where S is a smoothing function as $S(W) = S_{scale}(S_{time}(W_n(s)))$ (Grinsted et al., 2004).⁷ We smooth the coherence through convolution in both time and frequency domains.

Since the wavelet coherence does not have a theoretical distribution, the testing procedure uses Monte Carlo methods to obtain its significance. We follow Torrence & Compo (1998) to assess the statistical significance, which is depicted in figures as a black contour and the level of significance is 5%.

As we work with finite-length time series and Fourier transform assumes cyclical data, we would obtain wavelet power spectrum containing errors at the beginning and end of analysed periods. One of the solution of these edge effects is to pad both ends of time series with a sufficient number of zeros. This area effected by zero-padding is called the cone of influence (COI). We indicate the COI in figures as a shaded area having

⁷We use the package developed by Grinsted et al. (2004) to compute the coherence. For further details, please consult Grinsted et al. (2004).

e -folding shape.⁸ For more details consult Cazelles et al. (2008); Torrence & Compo (1998).

Further, from the cross wavelet transform of two time series, the phase difference provides the information about a relative position of the two series. The phase difference defined on $[-\pi, \pi]$ has the form:

$$\phi_{x_i, x_j} = \tan^{-1} \left(\frac{\Im\{W_{x_i x_j}(\tau, s)\}}{\Re\{W_{x_i x_j}(\tau, s)\}} \right), \quad (7)$$

where $\Im\{W_{x_i x_j}(\tau, s)\}$ and $\Re\{W_{x_i x_j}(\tau, s)\}$ are imaginary and real part of cross wavelet transform, respectively. The two time series are positively correlated if $\phi_{x_i, x_j} \in [-\pi/2, \pi/2]$, otherwise the correlation is negative. Moreover, the first variable, x_i , leads the second, x_j , if the phase is in $[0, \pi/2]$ and $[-\pi, -\pi/2]$, when in $[-\pi/2, 0]$ and $[\pi/2, \pi]$, the second variable is leading.

The assessment of statistical significance is always a crucial task. According to Cazelles et al. (2008), bootstrap methods are used to provide the significance of the power spectrum and the cross-spectrum. Those methods are also used for wavelet coherence. However, testing the significance of the phase difference is difficult because there is no “preferred” value as the phase may be distributed on the interval of $[-\pi, \pi]$. Aguiar-Conraria & Soares (2014) discuss that there are no good statistical tests for the phase difference. They conclude with support of Ge (2008) that the significance of phase should be connected with the significance of the power spectrum or coherence. To obtain the confidence intervals, we use classical bootstrap techniques.⁹ We show the coherence and phase difference of two artificial time series:

$$x_t = \sin(t) + \varepsilon, \quad t \in [1, 1000] \quad (8)$$

$$y_t = \begin{cases} \frac{1}{100} \sin(t) + \varepsilon, & t \in [1, 100] \\ \sin(t) + \varepsilon, & t \in [101, 350] \\ \frac{1}{1000} \sin(t - 0.01) + \varepsilon, & t \in [351, 605] \\ \sin(t + \frac{\pi}{2}) + \varepsilon, & t \in [606, 900] \\ \frac{1}{100} \sin(t) + \varepsilon, & t \in [901, 1000] \end{cases}. \quad (9)$$

We observe that when the coherence is high and significant the confidence interval of phase difference is narrow, see Figure 1. In contrast, for the observations 351-600, we have the sine function with high amplitude and very noisy time series, which in this scale does not resemble the sine. The phase difference of these two is very unstable and the confidence interval at some point covers the interval $[-\pi/2, \pi/2]$. This does not provide relevant information about the phase of the two time series.

⁸We use the Morlet wavelet thus the COI is e^{-2} -folding.

⁹We add a 5% noise to each series, run 1000 Monte Carlo simulations, and determine the 95% confidence interval.

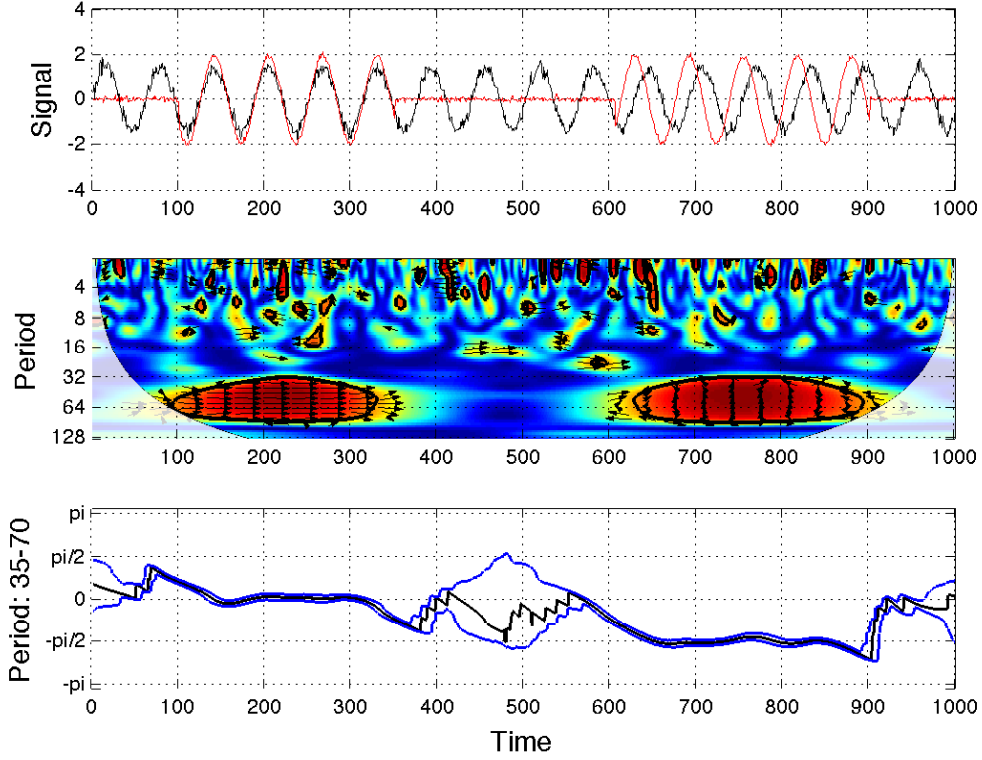


Figure 1: Artificial time series (top), their wavelet coherence (middle), and the phase difference of the time series (bottom) with 95% confidence interval. The shaded area is the cone of influence.

2.2 Cohesion measure

Many co-movement measures from the time or frequency domain rely on the bivariate correlation. Croux et al. (2001) propose a powerful tool for studying the relationship of multiple time series. This measure uses the dynamic pair-wise correlation and composes the new measure of cohesion over the frequencies. Let $x_t = (x_{1t} \cdots x_{nt})$ be a multiple time series for $n \geq 2$, then the cohesion measure in frequency domain is

$$coh_x(\lambda) = \frac{\sum_{i \neq j} w_i w_j \rho_{x_i x_j}(\lambda)}{\sum_{i \neq j} w_i w_j}, \quad (10)$$

where λ is the frequency, $-\pi \leq \lambda \leq \pi$, w_i is the weight associated with time series x_{it} , and $coh(\lambda) \in [1, 1]$. Since the dynamic correlation provides the information over frequencies and disregards the time information, Rua (2010) proposes a wavelet-based measure of co-movement of two time series that is in fact similar to the coherency and the dynamic correlation but in the time-frequency domain. Using this measure, Rua & Silva Lopes (2012) developed wavelet-based the measure of cohesion in the time-frequency. Firstly,

the time-frequency measure of degree of synchronization, $\rho_{x_i x_j}(\tau, s)$, is

$$\rho_{x_i x_j}(\tau, s) = \frac{\Re(W_{x_i x_j}(\tau, s))}{\sqrt{|W_{x_i}(\tau, s)|^2 |W_{x_j}(\tau, s)|^2}}, \quad (11)$$

where $\Re(W_{x_i x_j}(\tau, s))$ is the real parts of the cross-wavelet spectrum of two time series and in the denominator it has squared root of two power spectra of given time series.

Secondly, in the same manner as Croux et al. (2001) in the frequency domain, Rua & Silva Lopes (2012) take the advantage of this wavelet-based quantity and define the multivariate weighted measure of cohesion in the time-frequency space. The cohesion is a weighted average, where the weights, $\bar{\omega}_{ij}$, are attached to the pair of series (i, j) , e.g., for two series we have two weights inversely related. The cohesion exists on the interval of $[-1, 1]$ and we have

$$coh(\tau, s) = \frac{\sum_{i \neq j} \bar{\omega}_{ij} \rho_{x_i x_j}(\tau, s)}{\sum_{i \neq j} \bar{\omega}_{ij}}. \quad (12)$$

Measuring co-movement of multiple time series, the cohesion uncovers important information about common dynamics. However, the fixed weights, e.g., population at some time τ , do not take into account that data used for weights may also vary over time. Since the developing or emerging countries may have different speed of development then the importance for allowing time-variation of weights appears relevant.

We redefine the cohesion of Rua & Silva Lopes (2012) to our new proposed measure with time-varying weights as:

$$coh(\tau, s) = \frac{\sum_{i \neq j} \omega_{ij}(\tau) \rho_{x_i x_j}(\tau, s)}{\sum_{i \neq j} \omega_{ij}(\tau)}, \quad (13)$$

where $\omega_{ij}(\tau)$ is the weight attached to the pair of time series (i, j) at given time τ . Cohesion allows using different types of weights. For example, using weights as unemployment levels, then a country with higher or lower unemployment is less or more productive than other, it makes a greater emphasis on its production and in the cohesion this may lead to a greater dissimilarity of co-movement within the group.

2.2.1 Real wavelet-based measure examples

We demonstrate how the real wavelet-based measure captures the dynamics in time-frequency of two artificial time series in two particular cases. We show the cohesion with constant weights of a white noise, $u_t \sim N(0, 1)$ and its lagged values u_{t-1} , u_{t-4} , and u_{t-8} . For the first 200 observations in Figure 2, we see the negative correlation equal to minus one in the shortest period changing to positive correlation equal to one in the long term. If we averaged this part of Figure 2 over time, we would obtain the same dynamic correlation result as Croux et al. (2001).¹⁰ In the second part of Figure 2, the series have more lags, u_{t-4} and u_{t-8} , whose relationship is negative with the original u_t

¹⁰The correlation follows a curve from 1 at zero frequency to -1 at frequency equals π .

at longer horizons. This demonstrates the possibility of the well-localized information in the time-frequency plane. In Figure 3, we plot the dynamic correlation of the white noise u_t with its cumulative sum. Contrary to Figure 2 of lagged noises, these two series are positively correlated in the short-term period and not-correlated at in the long-term period.

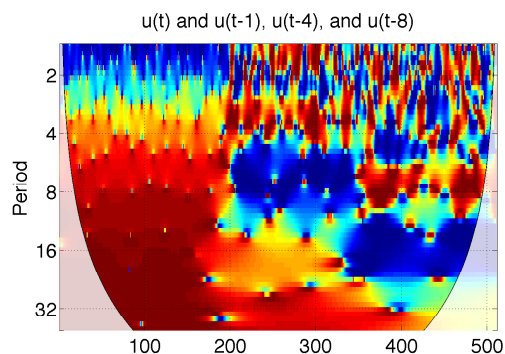


Figure 2: Real wavelet-based measure of two series: u_t and u_{t-1} , u_{t-4} , and u_{t-8} .

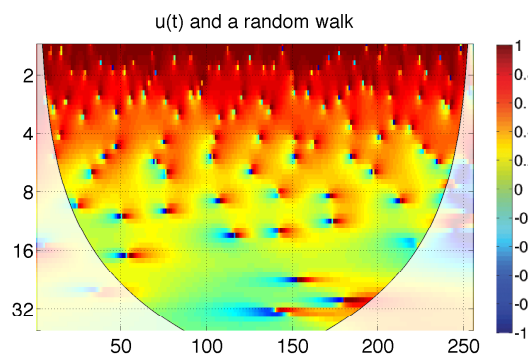


Figure 3: Real wavelet-based measure of two series: u_t and $u_t = u_{t-1} + \varepsilon_t$.

3 Data

In order to study business cycle synchronization, we use the data of the Index of Industrial Production (IIP) from the database of Main macroeconomic indicators (OECD, 2015).¹¹ Fidrmuc & Korhonen (2006) cite many studies where the IIP is broadly used while studying business cycle synchronization. The dataset period is spanning from January 1990 to December 2014 and the time series are seasonally adjusted. The dataset includes monthly data of 16 EU countries, from which 13 are EMU members (Austria, Belgium, Germany, Greece, Finland, France, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovakia, Spain) and 3 countries are not (Czech Republic, Hungary, Poland). In order to cover longer period, we use the IIP data to represent the economic activity on monthly basis. In the multivariate analysis, we divide the countries into three groups: EU core, Visegrad Four (V4), and PIIGS. Into the PIIGS group, we comprise 5 countries: 4 from Southern Europe (Portugal, Italy, Greece, and Spain) and Ireland. As the EU core we take Belgium, Germany, Finland, France, Luxembourg, and Netherlands. For these countries, we also use the data of Total Harmonized Unemployment: All persons. The time series are at level (number of persons) including all unemployed persons of all ages of a particular country. We use the unemployment level to weight the industrial production in the multivariate analysis. The maximum span of this data is from January 1993 to December 2014.

¹¹Obtained via Federal Reserve Economic Data, <https://research.stlouisfed.org/fred2/>

4 Results

4.1 Bivariate synchronization of the Visegrad countries and the EU

At first, we compare the business cycles of the Visegrad countries between each other in order to disclose similarities in their pairwise co-movements and development of particular relationships within the group. The Visegrad group's cooperation started at early 90s, the countries share higher coherence at the beginning of transition for 1-2 year period during 3-4 years, see Figure 4. Another common feature among V4 countries is a weak relationship of all pairs at short-term periods, from 2 months to 1 year during whole 25 years. Only Hungary and Poland co-move significantly around 2010 at periods shorter than 1 year. The important result is that all pairs show a high degree of synchronization at 2-4 year period starting around 1998 for Hungary with Slovakia, 1999 for the Czech Republic with both Poland and Hungary, 2000 for Poland with Slovakia. Also, the Czech Republic and Slovakia have been synchronized at 2-year period through the whole sample period with a small decrease around 2000. For Hungary and Poland, we observe a high degree of synchronization at all business cycle frequencies, 2-5 years. Their co-movement covers the largest part of the spectrum at the beginning of the transition period and during the last 5 years.

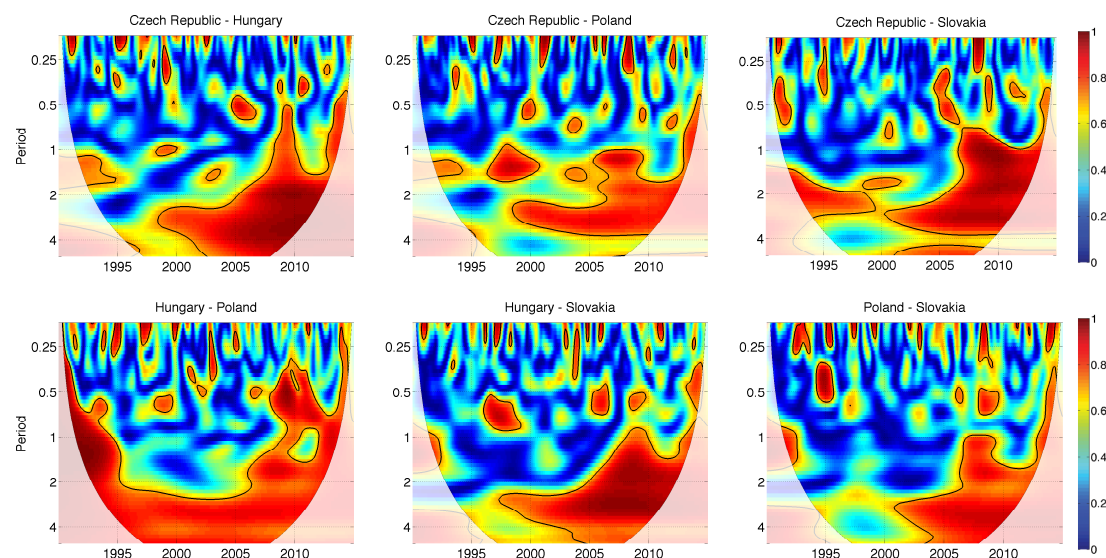


Figure 4: Wavelet Coherence within the Visegrad Four. The significance level of 5% against the red noise is contoured by the solid black line. The shaded area is the cone of influence.

The fact that at the beginning of transition countries shared high common volatility of business cycles across CEE countries (Jagrič, 2002) is not reflected in our results of co-movement. We find a short time of higher pair synchronization of the first 3-5 year at 1-2 year period. However, we see that all countries have almost zero co-movement around 1995, except Hungary and Poland. This low degree of similarity may be caused

by Slovakia's cold-shoulder participation in the political discussions during 1993-1997 that translated into the business cycles with a delay (Lukášek, 2010). We may find another explanation relevant for all countries that after a few years of formally intensive cooperation the monetary and fiscal policies started diverging. For example, during late 1990s the Czech Republic went through difficult stabilization years (Antal et al., 2008). These diverging economic situations could cause some asynchrony in business cycles behaviour in both short and long-terms. This long-term low synchronization may also come from the low level of convergence of macroeconomic other variables (Kutan & Yigit, 2004).

Further, we are interested in the co-movement of each country of the Visegrad Four within the framework of the European Union. In the pairwise analysis, we take Germany as a representative of the EU. It is usually used as a reference country (Fidrmuc & Korhonen, 2006) of the EU, a great portion of exports of V4 goes through Germany, and as well as the proximity to the Visegrad region plays a role. We plot the relationships between the Visegrad countries and Germany in Figure 5.

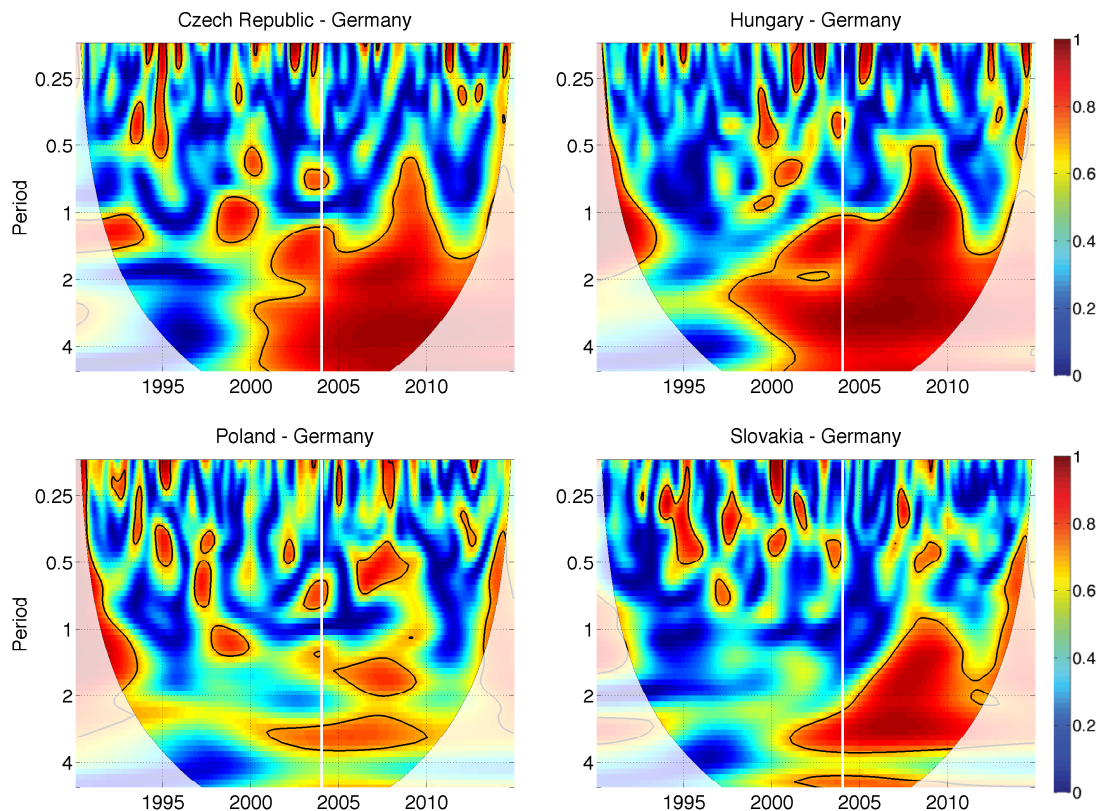


Figure 5: Wavelet Coherences of the Visegrad Four and Germany. The vertical solid white line indicates 2004 - the enlargement of the EU. The significance level of 5% against the red noise is contoured by the solid black line. The shaded area is the cone of influence.

We observe the strongest co-movement of Germany and two countries: the Czech

Republic and Hungary. The large area of high coherence for both begins around 2000, at 1-5 year period. Hungary-Germany high coherence starts slightly sooner than in 2000 at 2 year period but from 2000 it continues at 1-5 year period onward. These findings are in line with the results of Aguiar-Conraria & Soares (2011a). The synchronization of Slovakia with Germany shows an interesting pattern. The coherence increases gradually from 2000 and spreads from 2-4 year to 1-4 year period around 2008. This is important because that time Slovakia adopted the Euro, precisely on January 1, 2009. Slovakia may be also considered as an example where the degree of synchronization increases after the accession to the EU and EMU, which is in concordance with the theory of endogeneity of optimum currency areas. This high coherence may be caused also as a reaction to the global financial crises, however, it may support higher synchronization with the EU as the shock would spill over the Euro area to countries as those of Visegrad group. For all the Visegrad countries, we see an increase of coherence after they started their preparation for the accession to the EU, which was shortly before 2000. The high degree of synchronization of Hungary supports the previous results of Fidrmuc & Korhonen (2006), for example. However, this is not true for Poland because we observe the weakest relationship between Poland and Germany. Although, we may find a few isolated island of higher coherence but in comparison to other countries they appear unimportant.

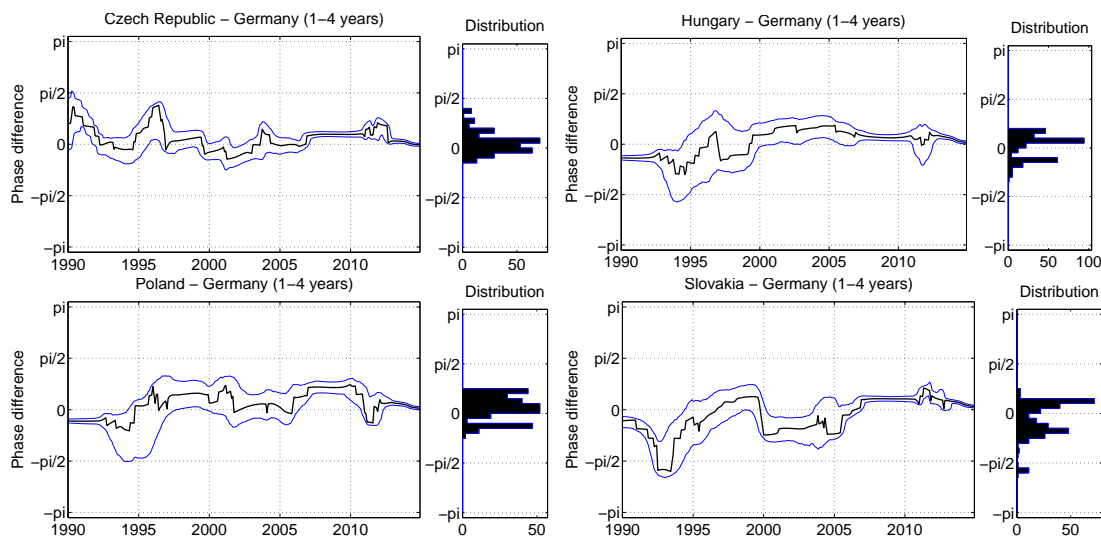


Figure 6: Phase differences. The black solid line is the true phase difference of two time series. The blue solid line is the 95% bootstrapped confidence interval. For each phase difference its distribution is provided.

Additionally, we provide the analysis of phase differences between each of the Visegrad countries and Germany. We observe that the phase difference for 1-4 year period most of the time fluctuates around zero, which correspond to changing leading position between two countries that have a positive relationship – in phase. We present confidence intervals of these phase differences. In the most cases, as the phases fluctuate

the confidence intervals overlap zero and thus, we cannot surely determine, which of the countries is in the leading position. Further, the first and last five years of data are affected by edge effects of zero-padding, thus, we do not have complete information here. As said in Aguiar-Conraria & Soares (2014), we rely on the significance of coherence to know whether the phase difference is also significant. We find that for all countries between 2000 and 2010 the coherence is high and mostly significant. This we see in Figure 6 where the phase difference in 2006-2010 period does not overlap zero and is in the interval $[0, \pi]$. This shows that during 2006-2010 the Visegrad countries' business cycles lead the cycles of Germany in long-term period. Possible explanation is the recession and its faster promotion to productions of V4 than to one of Germany. For example, in case of Slovakia, we have the significant leading position of Germany during 2000-2004. Showing the bootstrapped confidence intervals, we demonstrate that this technique is relevant for conclusion about phase differences between time series. Even if the phase difference clearly belongs to some interval, we need some level of confidence to make a conclusion.

4.2 Multivariate co-movement

Until now, we have used the bivariate analysis and the assessment of synchronization of more than two time series was left out. In this part, we investigate the multivariate relationship of countries in the European Union. The proposed measure of cohesion with time-varying weights allows us to assess the co-movement within the groups of countries. This measure captures the information in the time-frequency plane; we provide the results in form of heat-map as in the previous section. In contrast to the coherence, the cohesion may be negative that means it can capture a counter-cyclical co-movement among the time series. As the weights we use time series of Total Harmonized Unemployment (number of persons), which is available at monthly basis. The choice of unemployment levels as weights is particular for our case and has reasoning that we want to distinguish size of economies of countries.¹²

4.2.1 Example of different weights in the multivariate case

On this example we show the concept of time-varying weights for the multivariate measure of co-movement. We use the Visegrad Four and Germany to demonstrate that the nature of weighting in such measure matters. As the measure puts a weight to each pair in the multivariate analysis, the pair of Germany and Poland possibly represents the biggest share as the unemployment is in levels and they are most populated. We show three cases of weighting: equal weights for each pair, fixed weight corresponding to one moment of the time span (Eq. 12), and then time-varying weights (Eq. 13). The dynamic multivariate relationship of the Visegrad Four and Germany looks very similar for all three types of weights, see Figure 7.

¹²In the multivariate analysis, we analyse only parts of the time span 1990-2014 due to the lack of unemployment data for some countries.

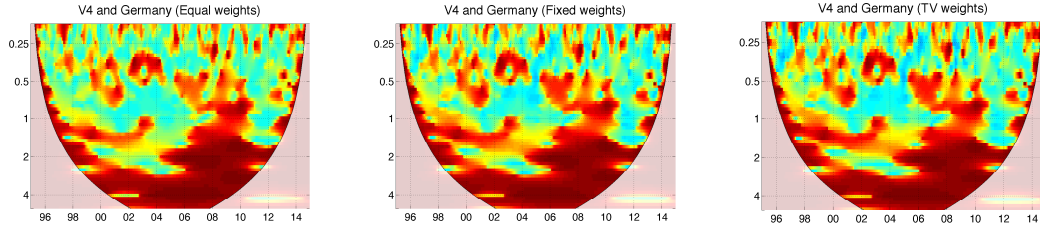


Figure 7: Wavelet Cohesion of the Visegrad Four and Germany using different type of weights: equal (left), fixed (centre), and time-varying (right). As weights we use Total Harmonized Unemployment.

In order to distinguish whether these three results are the same or not, we depict their differences. Using the differences, we show that employing equal, fixed, and time-varying weights gives very different results.

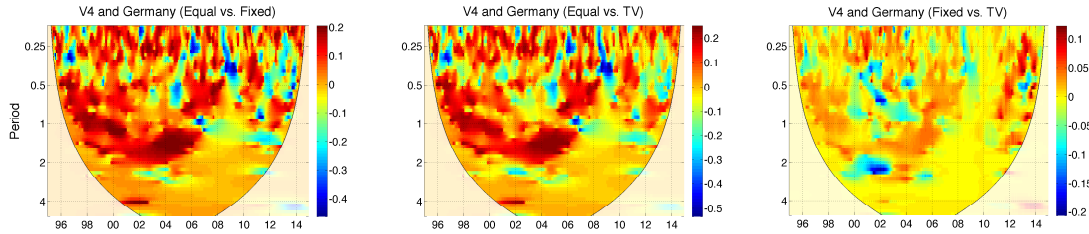


Figure 8: Differences between cohesions from Figure 7: equal vs. fixed (left), equal vs. time-varying (centre), and fixed vs. time-varying (right).

Moreover, we demonstrate that it is favourable to take into account dynamic weights changing over time. In our particular case, the absolute maximum in the difference between fixed and time-varying weights results is around 0.2, which makes 10% of the scale $[-1, 1]$, see Figure 8 (right). And as the time varying weights correspond to precise moment of time, the information should be better localized than the one obtained using the fixed weights. Here for instance, the unemployment level emphasizes actual situation of an economy and thus, time accurate weights may have shown an information in greater accordance with reality.

4.2.2 Cohesion of the Visegrad Four and the EU

We compute the multivariate relationship quantities for three groups of countries: the Visegrad Four, EU core, and PIIGS countries. We analyse those groups individually as well as their combinations.¹³ We concentrate on the Visegrad Four itself and within the framework of the EU. Looking at the synchronization of PIIGS countries with the EU core, we supply a direct comparison of already integrated countries with those in the process.

¹³The combination does not mean an analyse of co-movement of 2 groups but this provides the information about co-movement of all countries of both groups with respect to their weights.

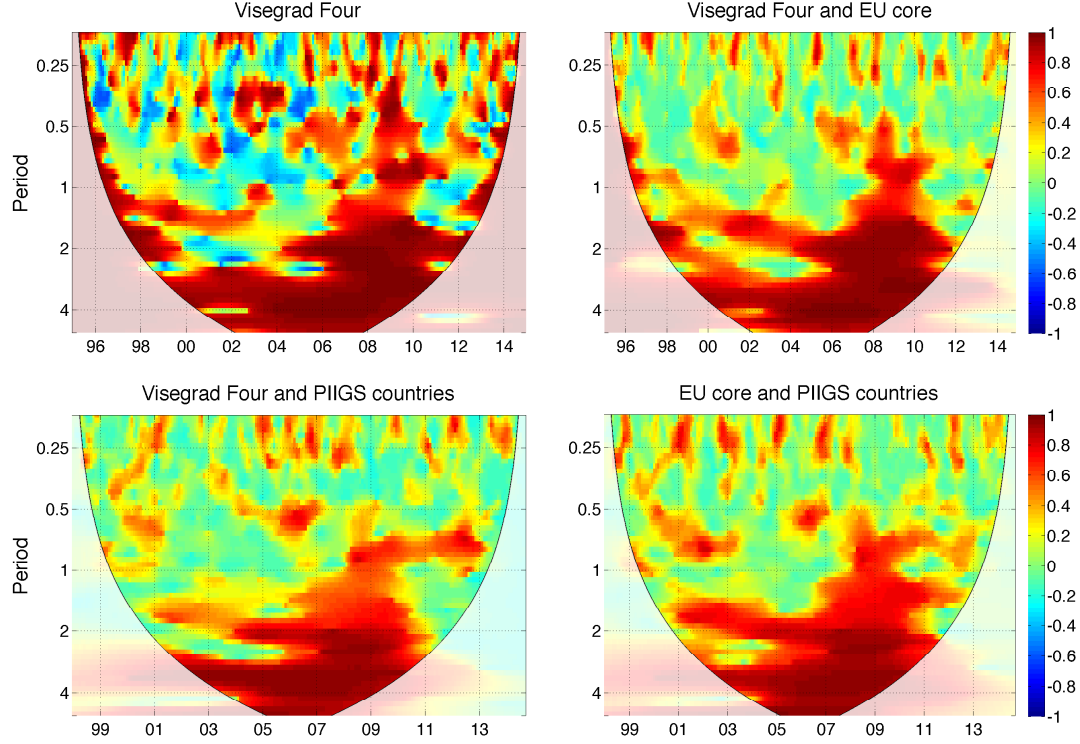


Figure 9: Wavelet Cohesion of the Visegrad Four and parts of the EU. We use Total Harmonized Unemployment: All Persons as weights for this analysis. The shaded area is the cone of influence.

With regard to the Visegrad countries, in Figure 9, we present that the degree of synchronization within this region is high at long-term period. Their strong co-movement at 2-4 year period lasts from 1997 to 2014; further from 2008, it spreads over half a year to 5 year period. The short-term synchronization, up to 1 year, provides some insights that countries often co-move at that frequency but only for short periods of time. This short-term fluctuation co-movement appears as well as for groups of EU core and PIIGS countries in Figure 10. These may reflect common reactions to some events in the markets.

Comparing the multiple relationships of V4 and EU core, EU core and PIIGS, and V4 and PIIGS countries in Figure 9, we observe similar patterns of co-movement in the long-term. This result of is in line with the findings of Rua & Silva Lopes (2012), who find a large cohesion of the long-term dynamics. Regarding to the Visegrad countries within the EU, in period after 2000 the strongest relationship is among countries of the group of Visegrad Four and EU core compared to other groups.

Further, we investigate the relationship of all 16 selected countries and the sub-samples of the EU core and PIIGS countries. Surprisingly, the analysis reveals low cohesion in the short-term, half a year to 1 year, while it is quite high in the long-term. Regarding the EU core, there is more common in short dynamics. Further for all groups,

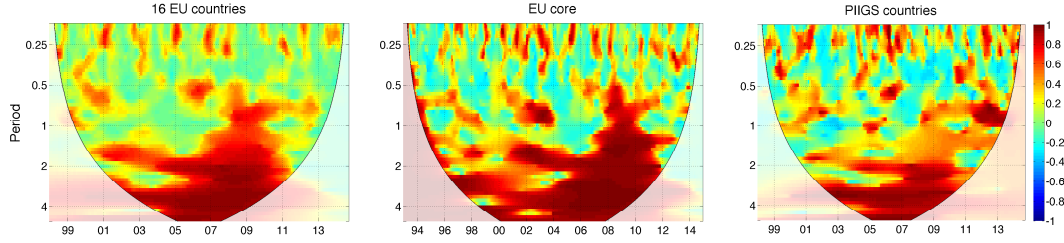


Figure 10: Wavelet Cohesion of 16 European countries (left), EU core (centre), and PIIGS countries (right). We use Total Harmonized Unemployment: All Persons as weights for this analysis. The shaded area is the cone of influence.

we observe that the cohesion is high at long-term business cycles. In the second half of the sample, the relationship has increased for the shorter periods. Looking at the case of PIIGS countries their cohesion appears to be in similar fashion but these countries do not exhibit any co-movement at 1-2 year period. Interestingly, we have seen that the cohesion of the Visegrad Four with the EU core is stronger than one of 16 European countries. Providing the example of Slovakia, the gradual increase of co-movement with Germany after both the accession and the Euro adoption. In terms of synchronization, the Visegrad countries could benefit from joining the European Monetary Union, but we do not know the specific sources of the higher co-movement.

5 Concluding remarks

Business cycle synchronization is one of the central questions of the economic integration and as such it has been during last years rigorously examined. We have overcome the problems of traditional measures, such as operation in time or frequency domain only or necessity of stationary time series, by using the wavelet methodology. In this paper, we have proposed the multivariate measure of co-movement with time-varying weights called the wavelet cohesion. This wavelet-based measure allows for precise localization of information in time and frequency.

We have investigated the impact of Visegrad countries cooperation, which began with the aim to help each other to converge faster to the European Union. We have found out short but high co-movement for the first years of their cooperation until the economic turbulences in the late 90s. During the period between 1995 and 1999, their business cycles of 2-5 year period show very low level of synchronization.

Further, we have studied the business cycle synchronization of the Visegrad Four with Germany. The results have confirmed some already known but interesting patterns. The Slovakia's synchronization with the EU was poor before its accession to the EU but after 2005 it gets stronger, which supports the theory of endogeneity of the OCA. We have revealed that the highest coherence is between Germany and both the Czech Republic and Hungary starting in the year 2000. In contrast, the degree of synchronization of business cycles of Poland and Germany is the lowest among Visegrad countries.

Employing the multivariate measure, we have uncovered relationships at both time and frequency domains for multiple time series. Regarding the Visegrad Four, the EU core countries, or the PIIGS countries, we show that among those countries there is very weak synchronization of short-term dynamics this means at periods less than 1 year. Contrary, we have found that the cohesion within the EU is high after 2000 at 2-5 year period. Furthermore, we have found high co-movement of the long-term business cycles of the Visegrad Four as well as of the EU core countries over the whole sample. This supports that countries tend to have similar approach to their long-term dynamics or policies.

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