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CONVERGENCE OF BUSINESS CYCLES AS A CONFIRMATION OF OCA THEORY

Konvergenca poslovnih ciklov kot potrditev teorije optimalnega valutnega področja

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Abstract

This paper examines business cycles in EU members and compares them with the business cycles of the economic and monetary union in Europe (EMU) members assumed to satisfy the optimal currency area (OCA). Accordingly, a multi-resolution decomposition of GDP growth signals is used, and correlation coefficients are computed for decomposed signals to assess the numerical values of synchronicities of business cycles. Our results reveal indications that areas adopting the euro in many ways confirm OCA theory and that the business cycles of most of the new EU members are not synchronized with the EMU; as such, these members might experience some difficulties if joining the euro too early.

Keywords: convergence, business cycles synchronization, wavelets, multi-resolution analysis

Izvleček

V članku so obravnavani konjunkturni cikli in še posebej njihova konvergenca v evrskem območju, kakor to predpostavlja teorija optimalnega valutnega področja (OCA). Uporabljena je bila multiresolucijska dekompozija časovnih vrst BDP, za pridobitev numeričnih vrednosti sinhronizacije konjukturnih ciklov pa so bili izračunani korelacijski koeficienti dekomponiranih časovnih vrst. Rezultati kažejo, da območje evra v marsičem potrjuje teorijo OCA, hkrati pa tudi opozarjajo, da utegnejo imeti nove članice EU težave, če se odločijo prezgodaj pridružiti evrskem območju.

Ključne besede: konvergenca, konjunkturni cikli, valčki, multiresolucijska analiza

1 Introduction

The topic of business cycles, especially convergence, has received a great deal of attention in recent years, mainly motivated by the economic and monetary union in Europe (EMU). In the context of a single currency and common monetary policies in the euro-adoption area, the similarity of the business cycles of the participant countries is a major concern. Nowadays, the enlargement process of the European Union has resulted in pressing questions about the preparedness of the candidate countries for integration. The literature on business cycle synchronization is related to that on optimal currency areas and, more broadly, on economic unions. If several countries delegate to some supranational institution the power to perform a common monetary (or fiscal) policy, then they lose this policy stabilization instrument. With the recent enlargement of the European Union, the interest on this topic is guaranteed for a while. The optimal currency area (OCA) theory states that countries are more suited to belonging to a monetary union when they meet certain criteria related to the real convergence of an economy—namely, a high degree of external openness, mobility of factors of production,

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and diversification of production structures. According to this theory, if there is a clear convergence between business cycles of countries willing to join the monetary union and the business cycle within the currency area, then this tends to prove that these countries are ready to enter the currency area. A revival of the empirical testing of the OCA theory preceded the introduction of the monetary union in Europe. Usually, empirical studies tend to assess the correlation between the German (or another large EU economy) business cycle and business cycles in other potential member countries (De Bandt, Herrmann, & Parigi 2006).

A relatively unexplored tool for forecasting is wavelets. Wavelet multi-resolution analysis allows one to decompose a time series into a low-frequency base scale and higher-frequency scales. Those frequency components can be analysed individually or compared across variables (Rua, 2010). As business cycles can be statistically decomposed into components with different frequencies (trend, season, noise), it is natural to use multi-resolution analysis to compare gross domestic product (GDP) with the components of well-defined frequencies that allow such comparison. The aim of this paper is to treat business cycles in the EU members and compare them with the business cycles of EMU members that are assumed to satisfy the optimal currency area. Accordingly, a multi-resolution decomposition of GDP growth signals is used, and correlation coefficients are computed for decomposed signals to assess the numerical values of the synchronicities of business cycles.

This paper is organized as follows. After a brief literature review, the methodological framework is addressed, the multi-resolution decomposition is presented, and a brief description of the database and calculations is provided. The results of the convergence of business cycles are then discussed. Finally, the results are summarized in the conclusion.

2 Literature Review

The term *economic convergence* refers to a diminishing of the differences in living standards (in the opposite case, we use the term *divergence*), economic levels, and the manufacturing performance of particular countries or their regions (Nachtigal et al., 2002). A widely used device for measuring the symmetry or asymmetry of shocks is a measure of the synchronicity of business cycles (Artis, Marcellino, & Proietti, 2004). Various authors have attempted to assess and explain business cycle convergence and synchronization. Artis and Zhang (1997) addressed the question of whether the exchange rate mechanism (ERM) has implied an increasing conformity among the business cycles of the participant countries. Angeloni and Dedola (1999) compared business cycle fluctuations of output, industrial production, stock indices, and prices across countries in various sub-samples. Wynne and Koo (2000) documented differences and similarities between business cycles in the European Union and business cycles in the Federal Reserve districts in the United States.

The literature on business cycle synchronization is related to the literature on optimal currency areas and, more broadly, economic unions. The topic of business cycles—especially their convergence—has received a great deal of attention in recent years, mainly motivated by the economic and monetary union in Europe. The optimal currency area theory (OCA) is one theory that helps make decisions on whether or not certain countries enter the monetary union. According to OCA theory, developed roughly five decades ago, two countries or regions will benefit from a monetary union if they share similar business cycles, trade intensively, and rely on efficient adjustment mechanisms to smooth out asymmetric shocks. OCA theory was developed in the Bretton Woods system by Mundell (1961), McKinnon (1963) and Kenen (1969). After the breakdown of the Bretton Woods system, the OCA theory was regularly used to assess the desirability of having a fixed exchange rate in different countries.

Although papers on this topic apply various methods (see Table 1) to reach different results, most find that the business cycles in several new member states are about as synchronized with the euro area as several of the peripheral members of the euro area. Many approaches have been used by various authors to assess the numerical values of the European economic activity convergence. Some papers examine the correlations of a detrended indicator of aggregated output. Business cycle coordination is analyzed mainly from the perspective of the international transmission of business cycles. Several authors apply various filters (e.g., Hodrick-Prescott [HP] or Band-Pass filters) or use time-series models. In addition, value at risk models (VaR), particularly structural VaR, are used to recover underlying shocks with properties derived from the economic theory.

Economic time series contain important information about economic activity, from long-run movements in productivity to business cycle fluctuations. They also contain high frequency noise, whose sources range from transitory shocks to measurement error. Linear filtering is a useful tool for extracting the component of interest (e.g., the business cycles component of real gross national product [GNP]) from the economic time series. Prominent examples in the economics literature include the Hodrick and Prescott (1980) filter and the approximate Band Pass filter (Baxter & King, 1999). Multi-resolution wavelet analysis is an alternative linear filter-based method; it is a natural way to decompose an economic time series into the long-run trend, the business cycle component, and high frequency noise (Yogo, 2008).

3 Methodological Framework

Fourier analysis is a mathematical tool for studying the cyclical nature of a time series in the frequency domain. However, under the Fourier transformation, the time information of a time series is completely lost. Meanwhile, the wavelet transformation breaks down a time series into shifted and scaled versions of a mother wavelet function that has a limited spectral band and limited time duration.

Table 1: *Various Methods Used for Correlation of Business Cycles*

Author(s)	Methodology and Economies	Results
Boone and Maurel (1998)	Assessed whether it would be optimal for the Central and Eastern European Countries to form a monetary union with either Germany or the EU using the Hodrick Prescott filter method.	The percentage of the Central and Eastern European Countries business cycle fluctuations explained by a German shock is very high; furthermore, the impulse responses are positively correlated.
Fidrmuc and Korhonen (2001, 2003)	Assessed the correlation of supply and demand shocks between the countries of the euro area and the accession countries in the 1990s.	Some accession countries have a quite high correlation of the underlying shocks with the euro area. Many EU countries seem to have a much higher correlation with the core euro area countries than in the previous decades. Continuing integration within the EU also seems to have aligned the business cycles of these countries.
Fidrmuc (2001, 2004)	Computed the potential correlation of the business cycle in Germany and in the Central and Eastern European Countries using Frankel and Rose's (1998) relation between the degree of trade integration and the convergence of the business cycles of trading partners.	The discussion focused on five associated countries (Czech Republic, Hungary, Poland, Slovenia, and Slovakia) and confirmed previous findings, such as that the Central and Eastern European Countries have rapidly converged to the EU countries in terms of business cycles and trade integration. In particular, business cycles in several Central and Eastern European Countries (Hungary, Slovenia and, to a lesser extent, Poland) have been strongly correlated with the business cycle in Germany since 1993.
Korhonen (2001, 2003)	Examined the correlation of short-term business cycles in the euro area and the EU accession countries with the help of vector autoresression models.	Clear differences emerged in the degree of correlation among accession countries. Generally, for smaller countries, the relative influence of the euro area business cycle is larger. Also, the most advanced accession countries are at least as integrated with the euro area business cycle as are some small current member countries of the Economic and Monetary Union.
Artis et al. (2004)	Analyzed the evolution of the business cycle in the accession countries after a careful examination of the seasonal properties of the available series and the required modification of the cycle-dating procedures. The analysis was based on the industrial production index (total industry) series using the Hodrick Prescott filter method.	The degree of concordance within the group of accession countries is not, in general, as large as that between the existing EU countries (the Baltic countries constitute an exception). Between them and the euro area, the indications of synchronization are generally rather low, with the exception of Poland and Hungary, and lower relative to the position obtained for countries taking part in previous enlargements (again with the exceptions of Poland, Hungary, and this time Slovenia).

4 Wavelet Multi-resolution Decomposition

As a coherent mathematical body, wavelet theory was developed in the mid-1980s (Goupillaud & Morlet, 1984; Grossmann & Morlet, 1984). The literature rapidly expanded, and wavelet analysis is now extensively used in physics, statistics, econometrics, and applied economics. In this respect wavelet tools have also been generalized to accommodate the analysis of time-frequency dependencies between two time series, e.g. the cross-wavelet power spectrum, the cross-wavelet coherency, and the phase-difference (Aguiar-Conraria & Soares, 2009)

Computational tools known as wavelets, particularly multi-resolution (MR) analysis, allow for the decomposing of a signal (e.g., a time series of gross domestic product [GDP], industrial production, inflation, stock returns) into high and low frequency components (Chui, 1992; Percival & Walden, 2000). High frequency (irregular) components describe the short-run dynamics whereas low-frequency components represent the long-term behaviour of a signal. Identification of the business cycle involves retaining the intermediate frequency components of a time series—namely, we disregard very high- and low-frequency components. For instance, it is customary to associate a business cycle with cyclical components between 6 and 32 quarters (Burda & Wyplosz, 2005).

Wavelets were specifically designed for isolating short-lived phenomena from long-term trends in a signal (Baqaee, 2009). Wavelet methods have been popular due to their computational efficiency, flexibility, and overall superiority to established techniques of analyzing and transforming data. One of the greatest strengths of wavelets over conventional frequency-domain techniques is their ability to deal with non-stationary data (Crowley, 2007). Wavelet analysis performs the estimation of the spectral characteristics of a time series as a function of time, revealing how the different periodic components of the time series change over time. Although the Fourier transformation breaks down a time series into constituent sinusoids of different frequencies and infinite duration in time, the wavelet transform expands the time series into shifted and scaled versions of a function that has limited spectral band and limited duration in time. Wavelets can be a particularly useful tool when the signal shows a different behaviour in different time periods or when the signal is localized in time as well as frequency. As it enables a more flexible approach in time-series analysis, wavelet analysis is seen as a refinement of Fourier analysis (Rua, 2010).

We can also describe this in a more formal manner (Wolfram Research, 1996). Let us mark the resolution level with an integer j (i.e., $j \in N_0$), and let the scale associated with the level $j=0$ have a value of one while at the level j have a value of $1/2^j$. Let $f(t)$ be a function, where $f(t)\in L^2(R)$, where $L^2(R)$ is the space of measurable functions f, defined on the real line R, that satisfy

$$\int_{-\infty}^{\infty} |f(t)|^2 \, dt < \infty.$$

Mark with $f_j(t)$ the approximation function $f(t)$ on resolution level j. On the next level of resolution, $j+1$, we add fluctuation or details and mark them with $d_j(t)$; the approximation function $f(t)$ on the new resolution level is then $f_{j+1}(t)= f_j(t)+ d_j(t)$. We obtain the original function $f(t)$ when we let the resolution go to infinity:

$$f(t) = f_j(t) + \sum_{k=j}^{\infty} d_k(t).$$

The concept of multi-resolution marks the simultaneous presence of different resolutions. However, the previous equation presents only one possibility of the development or decomposition function $f(t)$ to its smooth part and details. We can suppose analogously that $L^2(R)$ is the space of square-integrable functions as composed of a sequence of subspaces $\{W_k\}$ and V_j. With V_j we denote the subspace of functions that contain signal information down to scale 2^{-j}. The multi-resolution analysis involves a decomposition of the function space into a sequence of subspaces V_j, such that subspace V_j is contained in all the higher subspaces. If we denote the approximation to $f(t)$ at level j by $f_j(t)$, then $f_j(t)\in V_j$. Since information at resolution level j is necessarily included in the information at a higher resolution, V_j must be contained in V_{j+1} for all j. The difference between $f_{j+1}(t)$ and $f_j(t)$ is the additional information about details at scale $2^{-(j+1)}$, which is denoted by $d_j(t)= f_{j+1}(t) - f_j(t)$. Thus, we get

$$f_{j+1}(t) = f_j(t) + d_j(t)$$

and can further decompose our subspaces accordingly, writing

$$V_{j+1} = V_j \oplus W_j,$$

where W_j is called the detail space at resolution level j and is orthogonal to V_j. We can continue the decomposition of the space V and obtain

$$V_{j+1} = W_j \oplus V_j = W_j \oplus W_{j-1} \oplus V_{j-1} = \mu = W_j \oplus W_{j-1} \oplus W_{j-2} \oplus \mu \oplus W_{j-J} \oplus V_{j-J}.$$

Thus, we can conclude that the approximation space at resolution j (i.e., Vj) can be written as a sum of subspaces. Similarly, the approximation of the function $f(t)$ at resolution j (i.e., $f_j(t)$) is contained in subspaces V_j, and details $d_k(t)$ in W_k. The function that we are using for this purpose is called a "wavelet".

We can introduce wavelets in many possible ways (Chui, 1992; Valens, 1999), including considering the space $L^2(R)$. The local average value of every function in $L^2(R)$ must "decay" to zero at $\pm\infty$. It follows that the base function must be oscillatory (wavelike). Therefore, we look for "waves" generating $L^2(R)$ that, for all practical purposes, decay sufficiently fast. We can say we look for small waves or "wavelets" to generate the space $L^2(R)$ and we prefer to have a single function, say ψ, to generate all of $L^2(R)$. Because the wavelet ψ has very fast decay, an obvious way to cover the entire real line R is to shift the wavelet function ψ along the real line. Shifting a wavelet simply means considering all the integral shifts of ψ—namely,

$$\psi(t-k),\ k\in Z,$$

where Z denotes the set of integers. Next, to properly represent $f(t)$, we must also consider waves with different frequencies—in particular, waves with frequencies partitioned into consecutive "octaves" or frequency bands or scales. For computational efficiency the integral powers of 2 are used for frequency partitioning. So we can now consider wavelets of the form

$$\psi(2^j t-k),\ j,k\in Z.$$

The family $\psi(2^j t-k)$ is thus obtained from a single wavelet function $\psi(t)$ or mother wavelet by a binary dilation (by 2^j) and a dyadic translation (or shift of $k/2^j$). The definition of wavelets along with $\psi(t)$ also requires a scaling function $\varphi(t)$. The wavelet function is in effect a band-pass filter; scaling it for each level halves its bandwidth. As a result, in order to cover the entire spectrum, an infinite number of levels is required. The scaling function filters the lowest level of the transformation and ensures that the entire spectrum is covered (Valens, 1999).

For example, the simplest possible wavelet is the Haar wavelet, defined as

$$\psi(t) = \begin{cases} 1, & 0 \le t < 1/2 \\ -1, & 1/2 \le t < 1 \\ 0, & otherwise \end{cases}$$

Its scaling function φ can be described as

$$\varphi(t) = \begin{cases} 1, & 0 \le t < 1 \\ 0, & otherwise \end{cases}$$

We can note that any continuous real function can be approximated by linear combinations of the constant function $\psi(t),\psi(2t),\psi(4t),\ldots,\psi(2^j t),\ldots$ and their shifted functions. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable, yet this property can be an advantage for the analysis of time series with sudden jumps.

Wavelets have many characteristics. Here we mention just a few important ones. According to Sheng (1996), functions $\psi(t)\in L^2(R)$ satisfying the admissibility condition expressed as

$$\int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega = 0,$$

where $\Psi(\omega)$ stands for the Fourier transformation of $\psi(t)$, can be used to first analyze and then reconstruct a time series without the loss of information. Moreover, the admissibility condition implies that the Fourier transformation of $\psi(t)$ vanishes at the zero frequency:

$$|\Psi(\omega)|^2\Big|_{\omega=0} = 0.$$

A zero at the zero frequency also means that the average value of the wavelet in the time domain must be zero:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0.$$

This implies, as previously mentioned, that the wavelet function $\psi(t)$ must be oscillatory—in other words, a wave. Finally, we can state some sort of admissibility condition for the scaling function $\varphi(t)$ as well

$$\int_{-\infty}^{\infty} \varphi(t)dt = 1,$$

which implies that the zero moment of the scaling function cannot vanish.

As previously mentioned, the shift and scaling of the wavelet function ψ can be written as

$$\psi_{b,a}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right),$$

where a is the scale factor, b is the translation factor, and $a^{-1/2}$ stands for energy normalization across the different scales. To express the time series $f(t)$ based on function ψ, we define wavelet transformation as

$$(W_\psi f)(b,a) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)dt,$$

where $a = 2^{-j}$, $b = k/2^j$, $(j,k)\in Z^2$. The time series $f(t)$ can now be written as

$$f(t) = \sum_{j,k=-\infty}^{\infty} c_{j,k}\psi_{j,k}(t),$$

where the coefficient $c_{j,k}$ is expressed as

$$c_{j,k} = (W_\psi f)\left(\frac{k}{2^j}, \frac{1}{2^j}\right)$$

and we call them the wavelet transformation coefficients.

Let us now return to the multi-resolution analysis. As previously stated, the multi-resolution analysis of a time series breaks it into pieces or "decomponents" it into a hierarchical set of its approximations and detail levels. On every level j, we build approximation A_j of this level and deviation from this level, which we call details j of level D_j. In the original time series, it can look like an approximation of level 0, A_0. Of course, it is valid as this:

$$A_j = A_{j+1} + D_{j+1}$$

At a given j, the detail level D_j of MR analysis of time series can now be written as function

$$D_j(t) = \sum_{k\in Z} c_{j,k}\psi_{j,k}(t),$$

and finally, we make the entire time series as

$$f(t) = \sum_{j\in Z} D_j.$$

If we define approximation level J, A_J, as

$$A_J = \sum_{j>J} D_j,$$

we can express time of series f as sum of approximation A_J and details of level D_j

$$f = A_J + \sum_{j\le J} Dj.$$

Concerning the choice of the wavelet function for the multi-resolution decomposition, we chose the Meyer family wavelets for those members that are infinitely continuous differentiable; this allowed for smooth functions at every level of details. The Meyer wavelet ψ and its scaling function φ are in the frequency domains defined as follows (Misiti, Oppenheim, & Poggi, 2005)

$$\psi(\omega) = \begin{cases} (2\pi)^{-1/2} e^{i\omega/2} \sin\left(\frac{\pi}{2}\nu\left(\frac{3}{2\pi}|\omega|-1\right)\right), & \frac{2\pi}{3} \le |\omega| \le \frac{4\pi}{3} \\ (2\pi)^{-1/2} e^{i\omega/2} \cos\left(\frac{\pi}{2}\nu\left(\frac{3}{4\pi}|\omega|-1\right)\right), & \frac{4\pi}{3} \le |\omega| \le \frac{8\pi}{3} \\ 0, & |\omega| \notin \left[\frac{2\pi}{3}, \frac{8\pi}{3}\right] \end{cases}$$

and

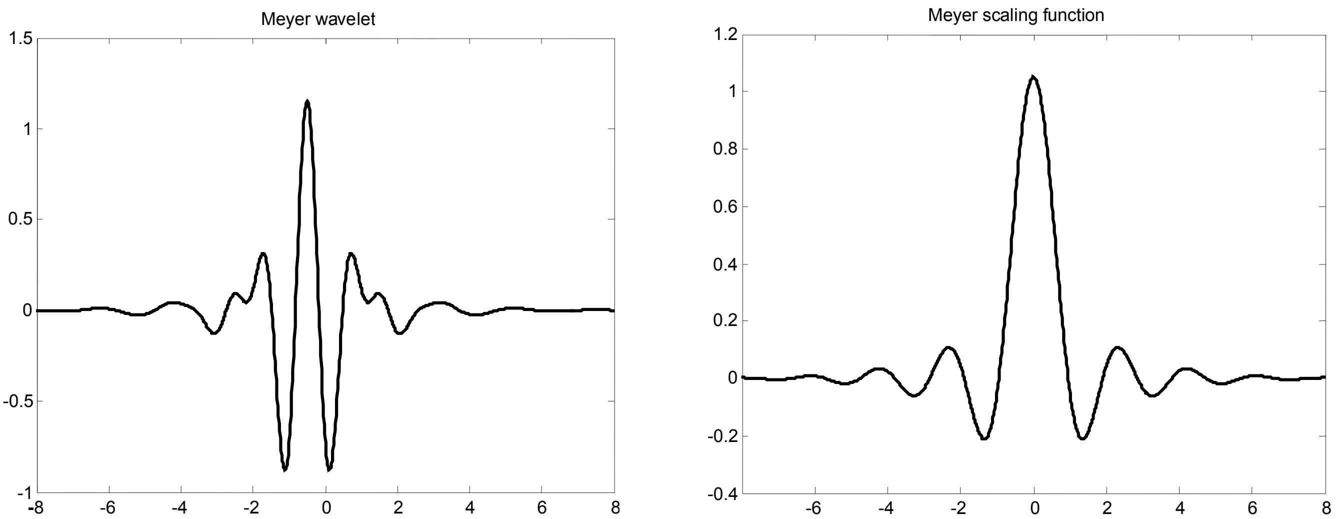
$$\phi(\omega) = \begin{cases} (2\pi)^{-1/2}, & |\omega| < \frac{2\pi}{3} \\ (2\pi)^{-1/2} \cos\left(\frac{\pi}{2}\nu\left(\frac{3}{4\pi}|\omega|-1\right)\right), & \frac{2\pi}{3} \le |\omega| \le \frac{4\pi}{3} \\ 0, & |\omega| > \frac{4\pi}{3} \end{cases}$$

where $v(a) = a^4(35 - 84a + 70a^2 - 20a^3)$, $a \in [0,1]$. Both functions are shown in Figure 1.

5 Database and Calculations

In this paper, quarterly data are analyzed. The multi-resolution scales are such that scale (or detail) 1 (D1) is associated with 1- to 2-quarter dynamics, scale 2 (D2) with 2- to 4-quarter dynamics, scale 3 (D3) with 4- to 8-quarter or 1-

Figure 1: *Meyer wavelet family (author's calculations).*



to 2-year dynamics, scale 4 (D4) with 8- to 16-quarter or 2- to 4-year dynamics, and scale 5 (D5) with 16- to 32-quarter or 4- to 8-year dynamics. Quarterly data for the GDP of EU countries, Austria (at), Belgium (be), Bulgaria (bg), Czech Republic (cz), Germany (de), Denmark (dk), Estonia (ee), Spain (es), EU 15 (eu15), EU 25 (eu25), Euro Area 12 (ez12), Finland (fi), France (fr), Hungary (hu), Ireland (ie), Italy (it), Latvia (lt), Lithuania (lv), the Netherlands (nl), Poland (pl), Romania (ro), Sweden (se), Slovenia (si), Slovakia (sk), and the United Kingdom (uk), measured in millions of euros at constant 1995 prices and exchange rates, were obtained from Eurostat. Most data range from 1996Q1 to 2008Q2, except for Romania (2000Q1–2008Q2) and Ireland (1998Q1–2008Q2). From these, due to potential seasonality in the data, the business cycle time series for a country *i* was computed as $GDP_{i,t}/GDP_{i,t-4}$. Descriptive statistics for the obtained real GDP growth series are presented in the Appendix (Table A1).

The GDP growth time series was then fed into the MATLAB software with the wavelets toolbox, through which every GDP growth series was decomposed into smooth level and five detail levels (D1-D5) using, due to their indefinitely differentiability, the Meyer family of wavelet functions. To ensure better convergence illustration or synchronization of cycles at the different scales of detail, for selected analyses we show countries together with components at all scales (D1-D5) as well as the original signals in the Appendix (Figure A1). At first glance, one can assess the different synchronizations of business cycles on individual scales of details, which also confirms the numerical calculation of correlation coefficients in the Appendix (Table A2).

6 Results

Numerically, different levels of synchronicity of the GDP growth time series can be represented by correlation coefficients. All correlation coefficients for different EU member countries are computed with respect to the euro area and the results are shown in the Appendix (Table A2). For each country, the overall correlation coefficient was computed between that country's GDP growth series and the euro area's GDP growth series (second column), together with correlation coefficients among the five MR components of the country's GDP growth series and the five MR components of the euro area's GDP growth series. The diagonal cells with the same frequency are shaded grey; for convenience, the correlation coefficients with the absolute value above 0.5 are printed in bold.

From the overall correlation coefficients, four main different levels of synchronicity of business cycles can be seen. Large, old EU members have a high synchronicity to the euro area and correlation coefficients values above 0.8 (e.g., Germany 0.91, Italy 0.90, France 0.89) The same high level of synchronicity can also be seen at almost all different same-frequency levels of GDP MR components. The second group includes the smaller euro area economies, with correlation coefficients above 0.5 (e.g., the Netherlands 0.78, Belgium 0.75, Finland 0.65). Also in this group are the old EU members not in the euro area, with Sweden being the most synchronous with the euro area (correlation coefficient=0.71). The third group is composed primarily of new members of the EU (in 2004), with $0.1<\rho<0.5$. Among these, Slovenia, which joined the euro area in 2007, has only a weak correlation with euro area (0.43). The last group is composed of new EU members that have negative, although weak, overall correlation with the euro area (e.g., Czech Republic, Slovakia). The same results also hold for different MR components of GDP growth series.

Once detail correlations have been obtained, co-correlations can be calculated so as to study the individual country phase relationship versus the euro area. These co-correlations only measure how the correlations change by lagging the country series against the equivalent euro area series, thereby allowing for a study of phasing of the cycles rather than the magnitude of the correlations themselves. Somewhat surprisingly, the results of co-correlation analysis show that, in terms of synchronicity of cycles, the EU member countries roughly fall into the following groupings:

(a) member states that are relatively well synchronized against the euro area (France, the Netherlands, and Bulgaria);

(b) member states that are synchronized at high frequency cycles, but not at low frequency cycles with a slight lead in long-term cycles (Austria, Belgium, Germany, Denmark, Italy, Spain, and Sweden);

(c) member states that are synchronized at high frequency cycles, but not at low frequency cycles with the slight lag in long-term cycles (Slovenia, Hungary, Estonia, Latvia, Lithuania, and the UK); and

(d) member states that are not synchronized at either low or high frequency cycles (Finland, Czech Republic, Slovakia).

Thus, it can be concluded that the euro area in many ways confirms OCA theory and that most of the new EU members might experience some difficulties if they join the euro area too early.

7 Conclusion

This paper considered business cycles, especially their convergence in the euro area, which was assumed to satisfy the optimal currency area requests. A major advantage of wavelet techniques is their ability to decompose a time series locally, both in frequency and time domain. In our research, the multi-resolution decomposition of the GDP growth signal was used, and correlation coefficients were computed for decomposed signals to assess the numerical values of the synchronicities of business cycles. Although the performance of the approach based on the wavelets remains overall comparable with those of the two filters (i.e., Hodrick Prescott and Baxter King), filtering by wavelets allows us to perform the temporal and frequency analyses of the cyclical component simultaneously. Using an example based on the American GDP, Ahamada and Jolivaldt (2010) showed that filtering based on wavelets is more powerful. The conclusion is that the euro area in many ways confirms OCA theory and that most of the new EU members might experience some difficulties if they join the euro area too early.

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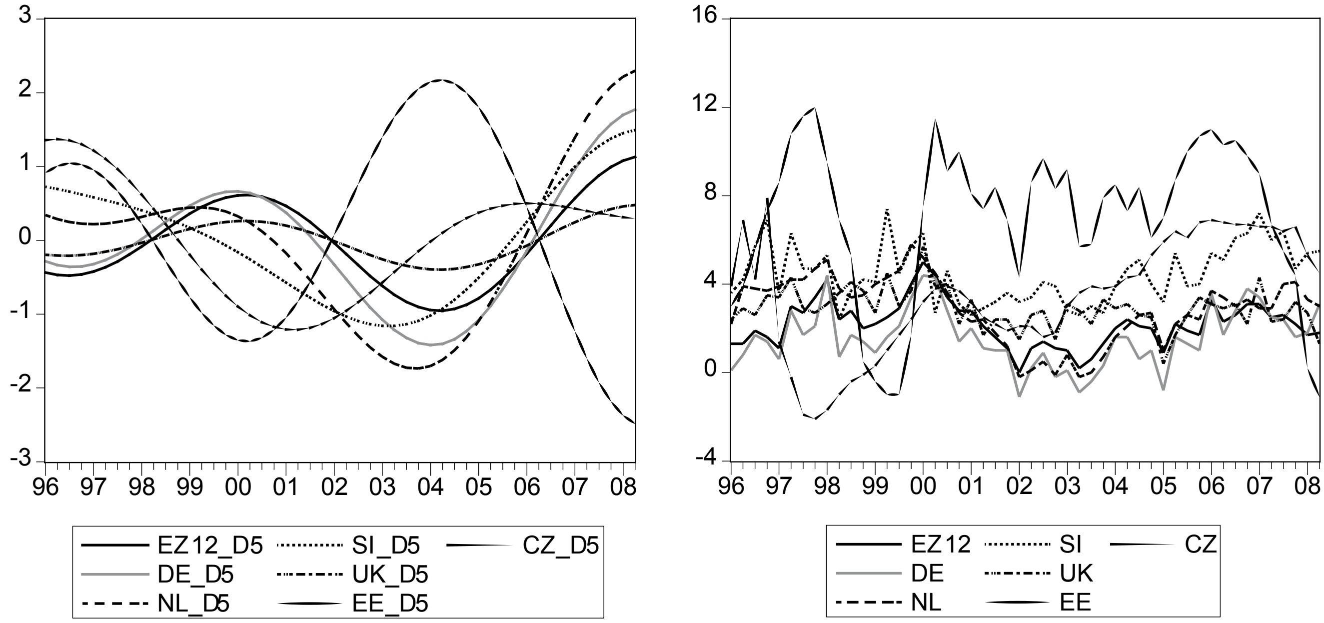
APPENDIX

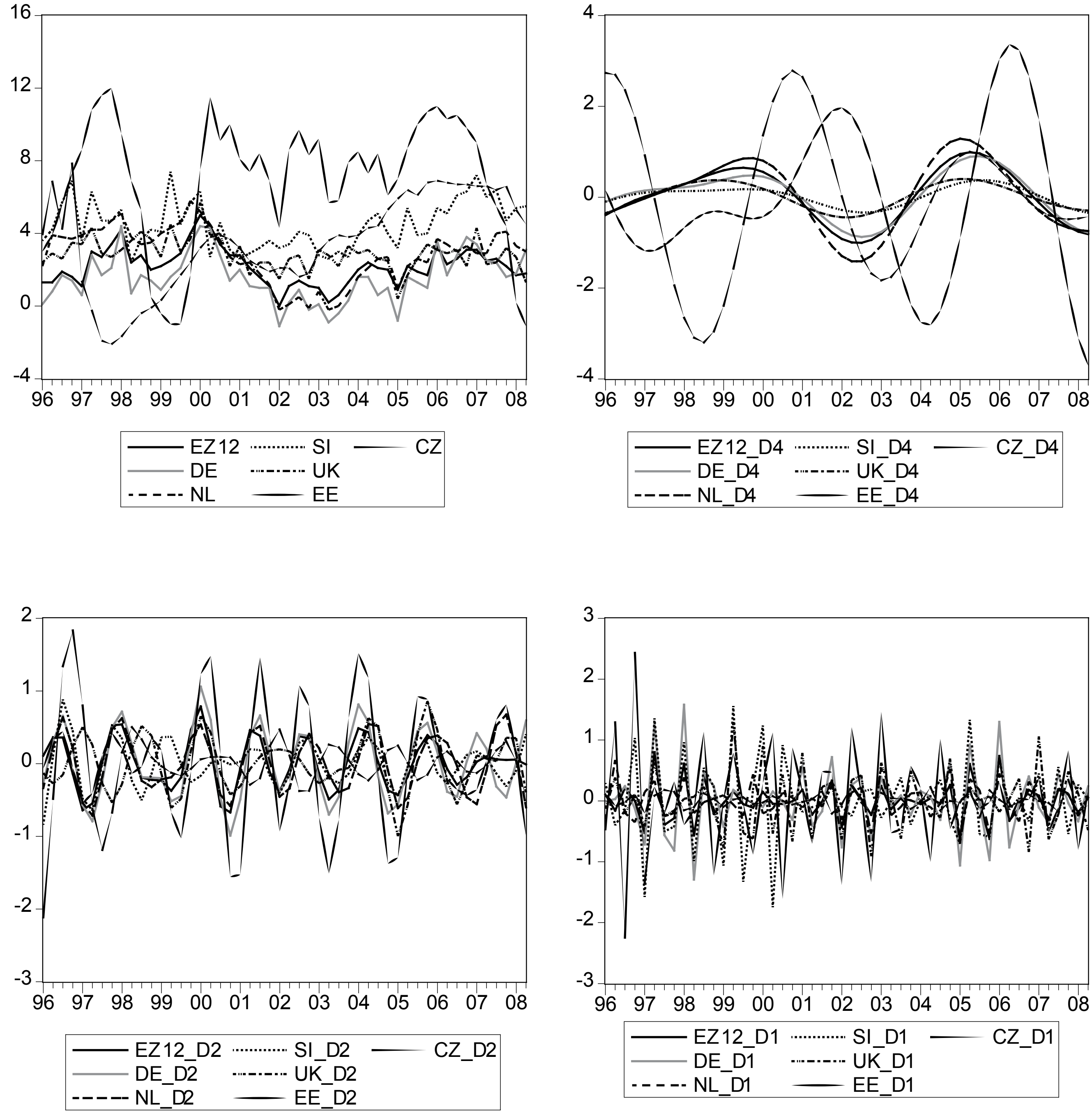
Table 1: *Descriptive statistics for the real GDP growth series*

	Average	Standard deviation	Maximum	Minimum	Asymmetry	Skewness
Austria	2.4	1.3	5.0	-0.5	-0.27	-0.59
Belgium	2.3	1.2	5.2	-0.6	0.13	-0.27
Bulgaria	3.3	6.6	18.3	-21.5	-2.27	6.96
Czech Republic	3.5	2.7	7.9	-2.1	-0.37	-0.68
Denmark	2.1	1.6	4.5	-1.3	-0.43	-1.04
Estonia	6.9	3.6	12.0	-1.1	-0.92	0.09
EU 15	2.3	1.0	5.1	0.3	0.40	0.42
EU 25	2.4	1.0	5.1	0.4	0.34	0.33
Euro area 12	2.2	1.0	5.0	0.0	0.38	0.37
Finland	3.8	1.6	7.1	-1.3	-0.35	0.68
France	2.2	1.1	5.2	0.4	0.44	0.15
Irland	6.5	3.2	14.4	-1.3	0.02	0.64
Italy	1.4	1.2	4.2	-0.6	0.50	-0.49
Latvia	7.3	3.2	12.9	0.1	-0.31	-0.52
Lithuania	6.6	3.3	11.6	-4.3	-1.36	2.56
Hungary	3.8	1.5	6.6	0.6	-0.84	0.12
Germany	1.6	1.3	4.4	-1.1	0.27	-0.16
Netherland	2.8	1.5	5.8	-0.2	-0.47	-0.48
Poland	4.7	2.4	11.8	-0.3	0.27	0.38
Romania	5.5	3.3	9.8	-5.7	-2.06	5.85
Slovakia	5.2	3.2	14.3	-2.7	-0.21	0.84
Slovenia	4.5	1.3	7.4	2.4	0.37	-0.78
Spain	3.6	1.0	7.3	1.6	0.84	2.42
Sweden	3.0	1.6	6.2	-1.5	-0.50	0.10
United Kingdom	2.9	0.9	5.7	0.4	0.19	1.58

Source: Eurostat, own calculations.

Figure 1: *MR components of GDP growth at different scales of details*





Source: Eurostat, own calculations.

Table 2: *Correlation coefficients of GDP growth between EA and EU members countries*

Euro area 12							
Country	*Correlation*	*L*	d1	D2	d3	d4	d5
EU25	0.9770	d1	0.953752	0.004493	-0.003975	-0.003641	-0.003703
		d2	-0.006145	0.934317	0.009582	-0.016525	-0.013868
		d3	-0.007213	0.018677	0.990372	0.037329	0.042178
		d4	-0.004723	-0.027715	0.042398	0.998219	0.135373
		d5	-0.005428	-0.003962	0.046966	0.240061	0.992227

Euro area 12							
Country	*Correlation*	*L*	d1	D2	d3	d4	d5
EU15	0.9814	d1	0.959111	0.004415	-0.003289	-0.003347	-0.003403
		d2	-0.003350	0.945447	0.014130	-0.017631	-0.015363
		d3	-0.006978	0.022870	0.992213	0.039622	0.042446
		d4	-0.004628	-0.027397	0.044016	0.997837	0.130394
		d5	-0.005373	-0.005861	0.047946	0.165739	0.999982
Austria	0.7267	d1	0.221615	-0.013512	0.004412	0.008193	0.005469
		d2	0.008791	0.551204	0.035231	-0.028576	-0.012460
		d3	-0.007923	-0.130513	0.745668	-0.003088	0.038970
		d4	6.98E-05	0.031206	-0.006458	0.602028	0.592158
		d5	-0.003051	-0.032062	0.023135	0.771726	-0.288128
Belgium	0.7511	d1	0.244746	-0.026349	0.003470	0.018998	0.004229
		d2	0.002427	0.463686	-0.001840	0.007603	-0.017793
		d3	-0.011423	0.022295	0.855342	0.068431	0.047890
		d4	0.004843	0.065799	-0.028445	0.237741	0.457648
		d5	-0.002934	-0.030143	0.024163	0.766913	-0.255445
Germany	0.9143	d1	0.916335	-0.008807	0.002924	0.007536	0.001821
		d2	-0.011282	0.845426	0.005632	-0.006739	-0.006604
		d3	-0.011483	-0.017649	0.960187	0.077957	0.065914
		d4	-0.003143	-0.004493	-0.000544	0.822916	0.522826
		d5	-0.001068	-0.005782	0.024373	0.610699	0.433593
Spain	0.7389	d1	0.232214	-0.023824	0.009215	0.015346	0.007185
		d2	-0.022159	0.195177	-0.000497	0.028376	0.019600
		d3	-0.011107	0.083164	0.485736	0.076802	0.056102
		d4	0.006014	0.068939	-0.040926	0.121846	0.486614
		d5	-0.002816	-0.041915	0.042982	0.702226	0.147526
Finland	0.6582	d1	0.404893	-0.007645	0.003548	0.007027	-0.000159
		d2	-0.004789	0.183430	0.020013	0.025999	0.010029
		d3	-0.009720	-0.071808	0.867501	0.007402	-0.036164
		d4	-0.003807	0.046464	-0.082226	0.162488	0.733442
		d5	0.003885	-0.000589	-0.011487	0.468575	-0.210425
France	0.8865	d1	0.788831	0.009152	-0.006027	-0.006696	-0.005213
		d2	0.003949	0.931527	0.012191	-0.028121	-0.020396
		d3	-0.012532	-0.011675	0.806189	0.090417	0.050699
		d4	0.003856	0.045745	-0.051823	0.570423	-0.004155
		d5	-0.004820	-0.034371	0.054166	0.620719	0.672344
Ireland	0.6219	d1	0.034247	-0.003750	-0.005454	-0.002731	-0.000559
		d2	0.011503	0.466659	0.024766	-0.000583	0.000205
		d3	0.006187	0.029541	0.638025	0.003253	0.016160
		d4	-0.044933	0.015634	0.188287	-0.006750	0.516102
		d5	0.043476	-0.002117	-0.091410	0.839392	0.347320
Italy	0.9045	d1	0.797997	-0.001365	-0.001164	0.001281	-0.002544
		d2	0.008453	0.839144	0.027627	-0.035797	-0.014922
		d3	-0.008898	0.065115	0.907917	0.081863	0.057536
		d4	0.001522	0.044549	-0.048528	0.296512	0.720939
		d5	-0.002909	-0.042378	0.045228	0.689488	0.189953
Netherland	0.7762	d1	0.610808	-0.016453	-0.006174	0.009572	-6.17E-05
		d2	-0.003976	0.717838	-0.033273	-0.015649	-0.027906
		d3	-0.008811	-0.023475	0.736669	0.032510	-0.002305
		d4	-0.000787	0.026985	0.017112	0.370969	0.718304
		d5	-0.001327	-0.013659	0.000779	0.793836	-0.128897
Slovenia	0.4383	d1	0.463952	0.040292	-0.023124	-0.031356	-0.017091
		d2	-0.036525	0.273216	-0.038937	0.017112	0.002676
		d3	-0.015467	-0.187438	0.339077	-0.008406	-0.002994
		d4	0.000994	0.044913	0.041432	0.264106	0.666294
		d5	0.000545	-0.007411	-0.006576	0.640032	-0.379520

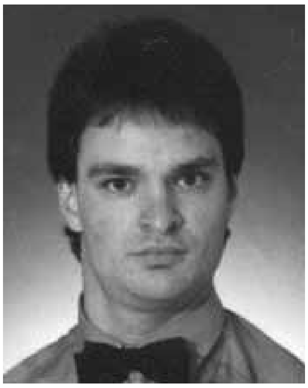
Euro area 12							
Country	*Correlation*	*L*	d1	d2	d3	d4	d5
United Kingdom	0.5582	d1	0.440933	-0.013967	0.004817	0.009926	0.005741
		d2	0.012807	0.246886	-0.008436	-0.007249	-0.004945
		d3	-0.010388	-0.171022	0.764814	-0.040809	-0.013740
		d4	-0.004015	0.037436	-0.065790	0.087530	0.656455
		d5	0.004993	0.006707	-0.025100	0.418329	-0.356038
Sweden	0.7119	d1	0.750696	-0.016912	0.007216	0.012551	0.005373
		d2	0.000834	0.426320	-0.014615	-0.016828	-0.033004
		d3	-0.007498	0.056066	0.652777	0.066009	0.063388
		d4	0.000829	0.044120	0.005872	0.485278	0.397688
		d5	0.002194	-0.003840	-0.010581	0.603667	-0.250228
Denmark	0.5516	d1	0.744414	-0.015639	0.003707	0.011546	0.003823
		d2	-0.016402	0.306012	-0.021566	-0.005414	-0.018197
		d3	-0.014390	-0.273655	0.328073	0.081528	-0.051045
		d4	-0.002282	0.006732	0.052323	0.535333	0.668383
		d5	0.003865	0.018804	-0.043349	0.410551	-0.554542
Czech Republic	-0.2224	d1	-0.183917	-0.003059	-0.000600	0.003314	0.000539
		d2	-0.032550	-0.450248	-0.129607	0.031627	-0.011535
		d3	0.008479	0.041839	-0.356920	-0.005123	0.098226
		d4	0.007126	0.016343	0.027367	-0.043548	0.174019
		d5	0.001969	0.012885	-0.031348	0.318478	-0.686259
Poland	0.4673	d1	0.018754	-0.006183	0.000475	0.004349	0.000865
		d2	0.012605	0.838604	0.058924	-0.040491	-0.009589
		d3	-0.001679	0.099140	0.811693	0.012552	0.086035
		d4	-0.001478	-0.038569	0.041335	0.867092	-0.083008
		d5	0.002920	0.017318	-0.031815	0.429657	-0.499836
Hungary	0.4016	d1	0.086229	0.006322	0.011257	0.000373	0.004616
		d2	-0.003471	0.503662	-0.010206	-0.012392	-0.021968
		d3	-0.007421	-0.028442	0.597110	0.062781	-0.068015
		d4	-0.006103	-0.022644	0.040922	0.584100	-0.202258
		d5	-0.003996	-0.017526	0.041996	-0.274862	0.727780
Slovakia	-0.2317	d1	0.282341	0.000638	0.011722	0.006080	0.006834
		d2	-0.023639	0.048875	-0.009270	0.019093	-0.010061
		d3	-0.009638	0.041192	0.413700	0.071956	0.099270
		d4	-0.006244	-0.011548	0.047270	-0.260726	0.820830
		d5	0.008413	0.031452	-0.059975	0.094142	-0.659212
Estonia	0.2371	d1	0.336771	0.006878	-0.001689	-0.004143	-0.001565
		d2	0.008066	0.838602	0.054474	-0.027623	-0.009407
		d3	-0.005963	-0.002362	0.651685	0.061304	-0.054919
		d4	0.001835	0.041663	-0.036439	-0.466674	0.501049
		d5	0.002269	0.015875	-0.033917	0.352139	-0.629330
Latvia	0.1174	d1	0.515277	0.004087	0.004177	-0.001845	0.000862
		d2	0.001597	0.731896	0.044161	-0.017963	0.000237
		d3	-0.007105	-0.032310	0.472825	0.060387	-0.074309
		d4	-0.005583	0.028042	-0.035941	-0.003753	0.687280
		d5	0.001031	0.013536	-0.024616	0.432807	-0.511381
Lithuania	-0.2773	d1	0.591051	0.004955	-0.003121	-0.005275	-0.002548
		d2	-0.000269	0.150302	-0.000887	0.001715	0.016680
		d3	-0.001932	-0.008769	0.300380	0.022602	-0.078080
		d4	-0.001439	0.015498	-0.057654	-0.777292	-0.131135
		d5	0.004703	0.013651	-0.045760	0.178073	-0.844302
Bulgaria	0.3525	d1	0.322482	-0.016906	0.005630	0.011514	0.005716
		d2	0.013024	0.651294	0.032749	-0.058798	-0.014800
		d3	-0.004951	0.116993	0.280922	0.075319	0.055107
		d4	0.004641	0.057039	-0.019272	0.481563	0.152503
		d5	-0.008909	-0.041416	0.077538	0.297245	0.896321

Euro area 12							
Country	*Correlation*	*L*	d1	d2	d3	d4	d5
Romania	0.0186	d1	0.310376	-0.011776	0.003404	-0.009169	-0.010616
		d2	0.050558	0.533389	-0.154589	0.029973	-0.010387
		d3	0.011205	0.117284	0.545343	-0.054872	-0.009940
		d4	-0.010032	-0.030445	-0.214020	-0.935397	-0.313396
		d5	-0.017401	-0.026685	-0.138098	0.475455	-0.713575

Source: Eurostat, own calculations.

In 2011, **Vesna Dizdarević** graduated from the University of Maribor, Faculty of Economics and Business, with a doctorate in international economics. Her research focuses on macroeconomics, economic analysis, and politics. She is currently employed at the Promo + d.o.o. Ljubljana.

Vesna Dizdarević je leta 2011 doktorirala na Ekonomsko-poslovni fakulteti Univerze v Mariboru z doktorsko disertacijo s področja mednarodne ekonomije. Osredotoča se na raziskovanje na področjih makroekonomije, ekonomske analize in politike. Zaposlena je v podjetju Promo + d.o.o. v Ljubljani kot direktorica projektov.



In 2000, **Robert Volčjak** earned his Ph.D. in information administration sciences at the University of Ljubljana, Faculty of Economics. He was associated with the Economic Institute EIPF, the leading Slovenian institution in econometric research, in 1996 as a junior researcher; since 2003, he has worked as research associate. His research focuses on macroeconomic modelling, operations research, and mathematical economics, and he has developed more 60 scientific and professional papers in these areas that have been published in prominent national and international journals and presented at conferences in Slovenia and abroad.

Robert Volčjak je leta 2000 doktoriral na Ekonomski fakulteti Univerze v Ljubljani. Kot znanstveni sodelavec je zaposlen na Ekonomskem inštitutu EIPF v Ljubljani. Glavna področja njegovega raziskovalnega dela so makroekonomija, ekonomske analize in politika, ekonomsko modeliranje, statistična in ekonometrična analiza, matematična ekonomija ter operacijske raziskave in upravljavske znanosti. Z omenjenih raziskovalnih področij je do danes nastalo več kot 60 znanstvenih in strokovnih del, ki so bila objavljena v priznanih domačih in tujih revijah ter predstavljena na konferencah v Sloveniji in v tujini.