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MEASURING BUSINESS CYCLES – A DYNAMIC PERSPECTIVE[1]

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Abstract

In this paper we study cyclical patterns by applying multivariate wavelet analysis. The wavelet covariance and wavelet correlation are defined and applied to the analysis of business cycles as an alternative to the traditional cross-spectrum analysis. The main findings for Slovenia are that there is a significant business cycle component in aggregate economic activity. Business cycles are asymmetric and highly synchronized with the EU cycle. Additionally we find that there are three distinctive periods of business cycle synchronization, which have an important impact on the properties of a business cycle.

Key words: business cycle, multivariate wavelet analysis, synchronization

Povzetek

V članku analiziramo ciklične vzorce z uporabo multivariatne wavelet analize. Definirani sta wavelet kovarianca in korelacija, ki ju uporabimo v analizi poslovnih ciklov kot nadomestilo za tradicionalno križno spektralno analizo. Ključna ugotovitev prispevka je, da v agregatni ekonomski aktivnosti v Sloveniji obstaja signifikantna ciklična komponenta. Poslovni cikli so asimetrični in močno sinhronizirani s poslovnim ciklom v EU. Ugotavljamo, da obstajajo tri ločljiva obdobja sinhronizacije, ki pomembno vplivajo na lastnosti poslovnega cikla.

Ključne besede: poslovni cikli, multivariatna wavelet analiza, sinhronizacija

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Computer program for wavelet cross-covariance and cross-correlation is available upon request from the author.

1. INTRODUCTION

Business cycles are persistent features of market-oriented economies. Burns (1947) wrote: "For well over a century, business cycles have run an unceasing round. They have persisted through vast economic and social changes; they have withstood countless experiments in industry, agriculture, banking, industrial relations, and public policy; they have confounded forecasters without number, belied repeated prophecies of a 'new era of prosperity' and outlived repeated forebodings of 'chronic depression.'" The same observations could be made today.

While every business cycle is different, business cycles share common elements that make them interesting for analysis. This paper puts the current fluctuations of aggregate economic activity in a transition economy into perspective by answering the following questions:
- Does the aggregate economic activity exhibit fluctuations, which correspond to the definition of Mitchell and Burns (1946)?
- Do the characteristics of business cycles in a transition economy change?

As noted by Brada (2002) there are two important issues, which are to be considered when analyzing business cycles in a transition economy. First important issue is, whether a cycle of fixed periodicity is appropriate, when measuring business cycles. Second important issue is, whether there are only internal factors, which are responsible for cyclical behavior of economic activity. Recent studies (Artis and Zhang 1999) found that business cycles of the ERM countries have became more synchronized with German cycle. In our paper we follow the same assumption by answering the following questions:
- Does the aggregate economic activity of a transition economy have the same cyclical frequency as in Germany?
- Is the cyclical component synchronized with German cycle?

Supporting results would confirm a general view in the business cycle literature that business cycles in the approach phase of the integration are becoming more synchronized with the target integration bloc as a result of increased international trade, openness of financial markets and global capital flows. Artis and Zhang (1999) suggest a high degree of synchronization of business cycles between EU and Germany. Therefore we have decided to choose Germany as an anchor country.

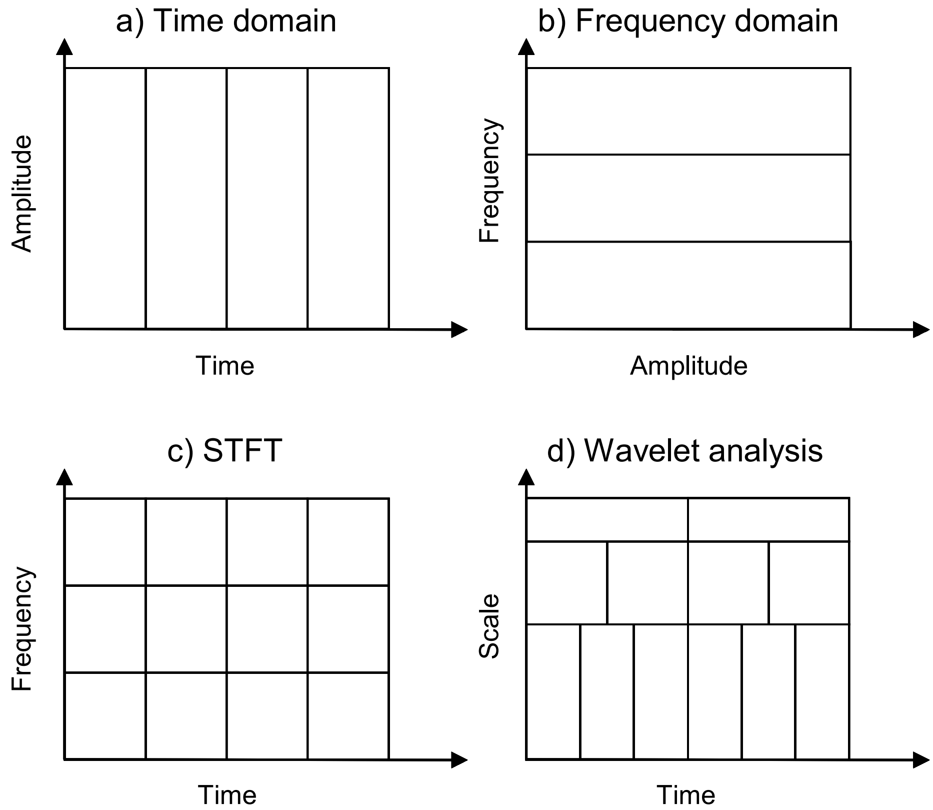
To address these issues it is necessary to introduce a dynamic perspective into methodological framework. We will present a new econometric approach, which will be then used on the data for Slovene economy.

The outline of the paper is the following. The methodological framework is given in section two. In section three the database is presented. The database is then used in section four, where we apply suggested econometric procedures. In the last part of the paper the conclusions and implications for economic modeling are presented.

2. METHODOLOGICAL FRAMEWORK

When analyzing cyclical behavior of a time series, Fourier analysis is extremely useful. But the Fourier analysis has also a serious drawback. In transforming to the frequency domain, time information is lost (Figure 1, plot a and b). When looking at a Fourier transform of a time series, it is impossible to tell when a particular event took place. If the time series properties do not change much over time - that is, if it is what is called a stationary time series - this drawback isn't very important. However, most interesting time series contain numerous nonstationary or transitory characteristics: drift, trends, abrupt changes, and beginnings and ends of events. These characteristics are often the most important part of the time series, and Fourier analysis is not suited to detecting them.

Figure 1: Time-based, frequency-based, stft and wavelet views of a signal



In an effort to correct this deficiency, Gabor (1946) adapted the Fourier transform to analyze only a small section of the time series at a time - a technique called windowing the time series (*figure 1*, plot c). Gabor's adaptation, called the Short-Time Fourier Transform (STFT), maps a time series into a two-dimensional function of time and frequency. The Fourier transform is performed on a sliding segment of length $N\delta t$, thus returning frequencies from T^{-1} to $(2\delta t)^{-1}$ at each time step. The segments can be windowed with an arbitrary function such as a boxcar (no smoothing) or Gaussian window (Kaiser 1994).

As Discussed by Kaiser (1994), the STFT represents an inaccurate and inefficient method of time-frequency localization, as it imposes a scale or "response interval" T into the analysis. The inaccuracy arises from the aliasing of high- and low-frequency components that do not fall within the frequency range of the window. The inefficiency comes from the $T/(2\delta t)$ frequencies, which must be analyzed at each time step, regardless of the window size or the dominant frequencies present. In addition, several window lengths must usually be analyzed to determine the most appropriate choice. For analyses where a predetermined scaling may not be appropriate because of a wide range of dominant frequencies, a method of time-frequency localization that is scale independent should be employed.

The wavelet transform (*Figure 1*, plot d) can be used to analyze time series that contain nonstationary power at many different frequencies (Daubechies 1990). Assume that one has a time series x_n, with equal time spacing δt and $n = 0,..., N-1$. Also assume that one has a wavelet function $\psi_0(\eta)$, that depends on a nondimensional time parameter η. To be admissible as a wavelet, this function must have zero mean and be localized in both time and frequency space (Percival and Walden 2000). An example is the Morlet wavelet, consisting of a plane wave modulated by a Gaussian:

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\eta^2/2} \tag{1}$$

where ω_0 is the nondimensional frequency. The term wavelet function is used to refer to either orthogonal or nonorthogonal wavelets. The term wavelet basis refers only to an orthogonal set of functions. The use of an orthogonal basis implies the use of discrete wavelet transform, while a nonorthogonal wavelet function can be used with either the discrete or the continuous wavelet transform (Farge 1992). In this paper, only the continuous transform is used.

The continuous wavelet transform of a discrete sequence x_n is defined as the convolution of x_n with a scaled and translated version of $\psi_0(\eta)$:

$$W_n(s) = \sum_{n'=0}^{N-1} x_{n'} \psi^* \left[\frac{(n'-n)\delta t}{s} \right] \tag{2}$$

where the * indicates the complex conjugate and s scale. The subscript 0 on ψ has been dropped to indicate that the function has been normalized. This is necessary in order to ensure that wavelet transforms at each scale s are directly comparable to each other and to the transforms of other time series:

$$\psi \left[\frac{(n'-n)\delta t}{s} \right] = \left(\frac{\delta t}{s} \right)^{1/2} \psi_0 \left[\frac{(n'-n)\delta t}{s} \right] \tag{3}$$

Because the wavelet function $\psi(\eta)$ is in general complex, the wavelet transform $W_n(s)$ is also complex. The transform can then be divided into real part $\Re\{W_n(s)\}$, and imaginary part $\Im\{W_n(s)\}$, or amplitude $|W_n(s)|$, and phase $\tan^{-1}[\Im\{W_n(s)\}/\Re\{W_n(s)\}]$. The wavelet power spectrum is defined as $|W_n(s)|$. For real-valued wavelet functions the imaginary part is zero and the phase is not defined.

A common question is, what is the relationship between scale and frequency? The answer can only be given in a broad sense, and it's better to speak about the pseudo-frequency (F_s) corresponding to a scale (s). In order to determine the pseudo-frequency, one should first compute the center frequency of the wavelet (ω) and then use the following relationship:

$$F_s = \frac{\delta t \omega}{s} \tag{4}$$

The center frequency-based approximation captures the main wavelet oscillations. So the center frequency is a convenient and simple characterization of the leading dominant frequency of the wavelet.

Since the wavelet transform is a bandpass filter with known response function, it is possible to reconstruct the original time series using either deconvolution or the inverse filter. By the redundancy in time and scale in continuous case, it is possible to reconstruct the time series using completely different wavelet function. The easiest way is by using a delta function (δ):

$$x_n = \frac{\delta j \delta t^{1/2}}{C_\delta \psi_0(0)} \sum_{j=0}^{J} \frac{\Re\{W_n(s_j)\}}{s_j^{1/2}} \tag{5}$$

In this case, the reconstructed time series is the sum of the real part of the wavelet transform over all scales. The factor $\psi_0(0)$ removes the energy scaling, while the $s_j^{1/2}$ converts the wavelet transform to an energy density. The factor C_δ comes from the reconstruction of a δ function from its wavelet transform using the function $\psi_0(\eta)$.

As known from the Fourier analysis, jointly using two time series with coherent signals can reveal additional information on analyzed time series. Therefore we introduce the wavelet cross-spectrum or more formally the wavelet cross-covariance. The wavelet cross-covariance is defined as the expected value over time of the product of the wavelet transform of one time series with the conjugate of the wavelet transform of a another time series, in both discrete and continuous time. This can be expressed as:

$$W_n^{xy}(s) = E\{W_n^x(s) W_n^y * (s)\} \tag{6}$$

where $E\{\ \}$ stands for the expected value over time, $W_n^x(s)$ and $W_n^y(s)$ are the wavelet transforms of a two different time series, and '*' represents the complex conjugate operator. The result yields one value for each wavelet scale.

Another useful quantity from Fourier analysis is the coherence, defined as the square of the cross-spectrum normalized by the individual power spectra. This gives a quantity between 0 and 1, and measures the cross-correlation between two time series as a function of frequency. In the case of wavelet transform, we can define a similar concept – wavelet coherence or more formally wavelet cross-correlation:

$$WC_n^{xy}(s) = \frac{E\{W_n^x(s) W_n^y * (s)\}}{\sqrt{E\{|W_n^x(s)|^2\} E\{|W_n^y(s)|^2\}}} \tag{7}$$

The wavelet cross-correlation is defined as the wavelet cross-covariance divided by the square root of the product of the wavelet power spectra of two time series.

3. DATABASE

There are two alternative strategies for obtaining a time series that represents current business activity on a monthly level (Dias 1994): either adopt a single series as the variable of interest or use a function of several variables. Both approaches have long traditions in empirical macroeconomics. For example, the empirical literature on the monthly money-income relationship focuses on the predictability of monthly industrial production. Alternatively, Burns and Mitchell (1946) constructed a reference series by averaging several different major aggregate time series; this reference series was then used to date their reference cycles.

In our example we use monthly index of industrial production. The data was obtained from Bank of Slovenia (2002) and Deutsche Bundesbank (2002). Data cover the time-span from January 1992 to March 2002. In contrast to the previous study (Jagrič 2002), we will use an alternative concept of business cycle fluctuations known as growth cycles. Growth cycles are fluctuations in growth rates of economic activity around long-run trend (Moore 1983, Zarnowitz 1992). This concept has some advantages, but also disadvantages, relative to the conventional business cycle concept (Stock and Watson 1999):

- Growth cycles are better suited for business cycles analysis in countries with high trend growth rates, including many emerging market economies, which tend to experience sharp contractions and expansions in rates of growth rather than levels.
- Growth cycles are often more helpful in understanding the relationship between output, inflation, and unemployment (Boone et. al. 2002). However, growth cycles depend on an arbitrary distinction between trend and cycle, on which there is no consensus in literature. Moreover, key cyclic characteristics vary considerably depending on the detrending method used (Canova 1998, Burnisde 1998).
- Growth recessions are sometimes minor in size, while level recessions are usually associated with major adverse macroeconomic events, which usually makes them more relevant from a policy perspective.

Analyzing growth cycles rather than classical business cycles requires a transformation of original data by following equation:

$$x_t^* = \frac{x_t}{x_{t-12}} - 1 \qquad (8)$$

As Charemza and Deadman (1992) noted, normal differenciation can affect long-term relationships between economic variables. To avoid this affect, we use annual growth rates. No additional procedures like seasonal adjustment will be used, since we do not want to introduce false signals into observed time series.

Nonstationarity of time series is a common phenomenon, especially in periods with unstable conditions like in a transition economy. Such time series can have an impact on the results of classical econometric procedures like spectral analysis, where a “typical spectral shape” of Granger (1966) may be found. By applying wavelet analysis we can avoid such problems as described in Section 2. This also goes for detrending, which can emphasize different frequency ranges in data (Canova 1998, Burnside 1998).

4. RESULTS

Before one can perform the wavelet transform of a selected time series, it is necessary to select an appropriate mother wavelet – this also applies to traditional transforms such as the Fourier, Bessel, Legendre, etc. In choosing the wavelet function, there are several factors which should be considered (Farge 1992):

- Orthogonal or nonorthogonal. In orthogonal wavelet analysis, the number of convolutions at each scale is proportional to the width of the wavelet basis at that scale. This produces a wavelet spectrum that contains discrete blocks of wavelet power and is useful for signal processing. The nonorthogonal transform is useful for time series analysis, where smooth, continuous variations in wavelet amplitude is expected.
- Complex or real. A complex wavelet function will return information about both amplitude and phase and is better adapted for capturing oscillatory behavior. A real wavelet function returns only a single component and can be used to isolate peaks or discontinuities.

- Width. The width of a wavelet function is defined here as the e-folding time of the wavelet amplitude. The resolution of a wavelet function is determined by the balance between the width in real space and the width in Fourier space. A narrow function will have good time resolution but poor frequency resolution, while a broad function will have poor time resolution, yet good frequency resolution.
- Shape. The wavelet function should reflect the type of features presented in the time series. If one is primarily interested in wavelet power spectra, then the choice of wavelet function is not critical.

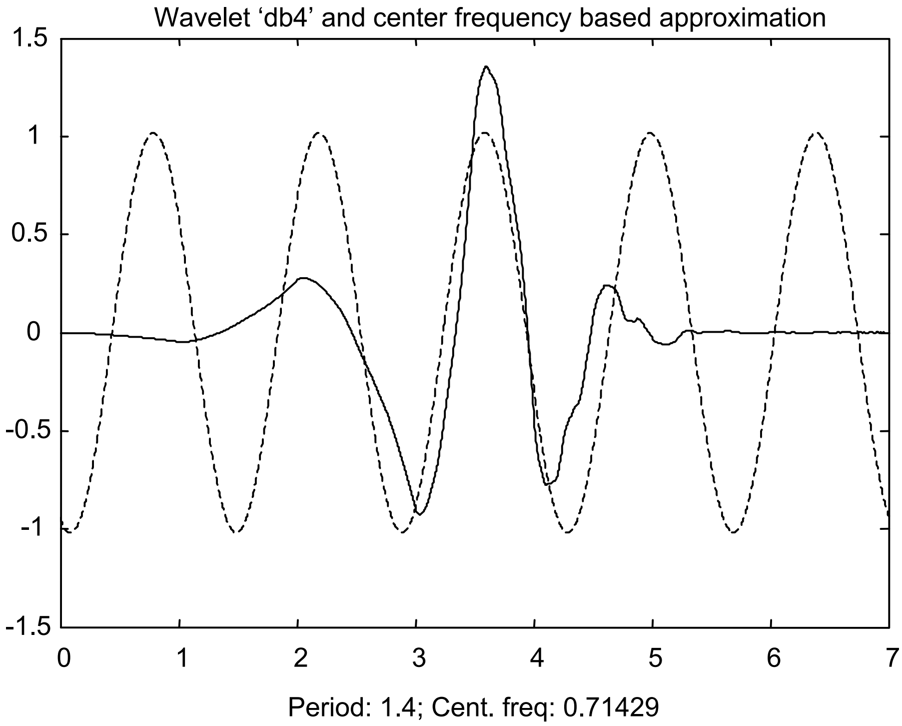
Table 1: Properties of selected wavelets

Wavelet type	'db4'		'gaus4'	
Scale	Frequency	Period*	Frequency	Period*
5	0.1429	7.0	0.1000	10.0
10	0.0794	14.0	0.0500	20.0
15	0.0476	21.0	0.0333	30.0
20	0.0357	28.0	0.0250	40.0
25	0.0286	35.0	0.0200	50.0
30	0.0238	42.0	0.0167	60.0
General characteristics	Compactly supported wavelet with extreme phase and highest number of vanishing moments for given support width. Associated scaling filters are minimum-phase filters.		Derivative of the Gaussian probability density function: gaus(x,n)=Cn*diff(exp(-x^2),n) where diff denotes the symbolic derivative and Cn is such that the 2-nor of gaus(x,n)=1.	
Additional information	Family: Daubechies (db) Orthogonal: yes Biorthogonal: yes Compact support: yes DWT: possible CWT: possible Support width: 2N-1 Symmetry: far from		Family: Gaussian (gaus) Orthogonal: no Biorthogonal: no Compact support: no DWT: no CWT: possible Support width: infinite Symmetry: yes (for n = even)	

Note: *Period is given in months.
Reference: Daubechies (1994, 194-202)

According to the above factors, we selected two different mother wavelets: Daubechies wavelet of order 4 ('db4') and Gaussian wavelet of order 4 ('gaus4'). Both functions are presented on *figure 2*, where we also approximated the center frequencies. Since we will apply continuous wavelet transform, we needed nonorthogonal wavelet function. Both functions are real. The Daubechies wavelet covers a narrow frequency space, which enables us to isolate dominant frequencies more precisely. Both wavelet types have a shape, which is close to the shape of a theoretical business cycle.

Figure 2: Center frequencies of 'db4' and 'gaus4' wavelets



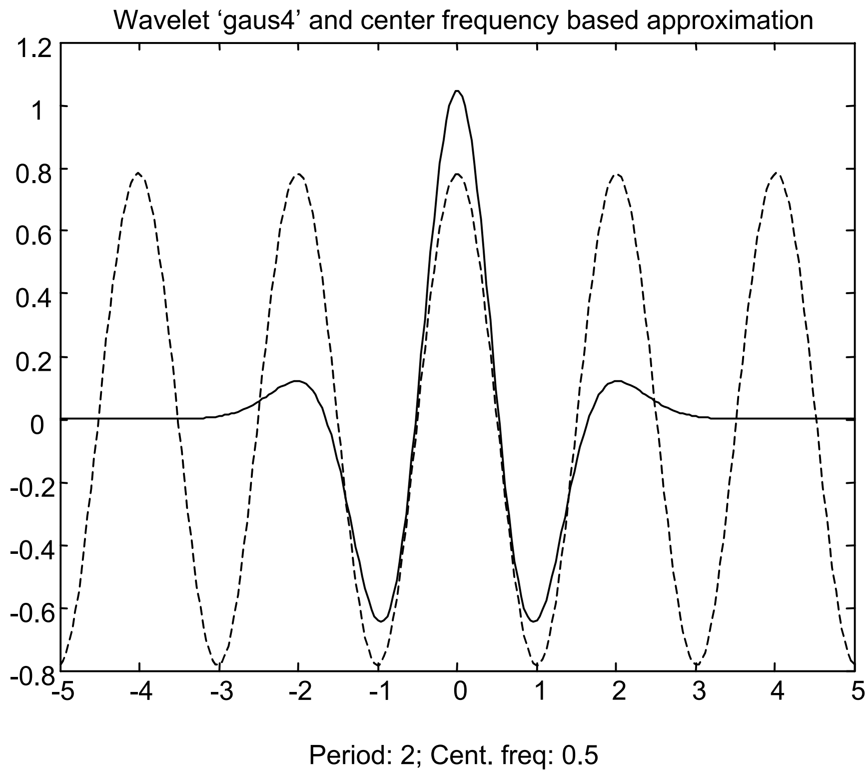
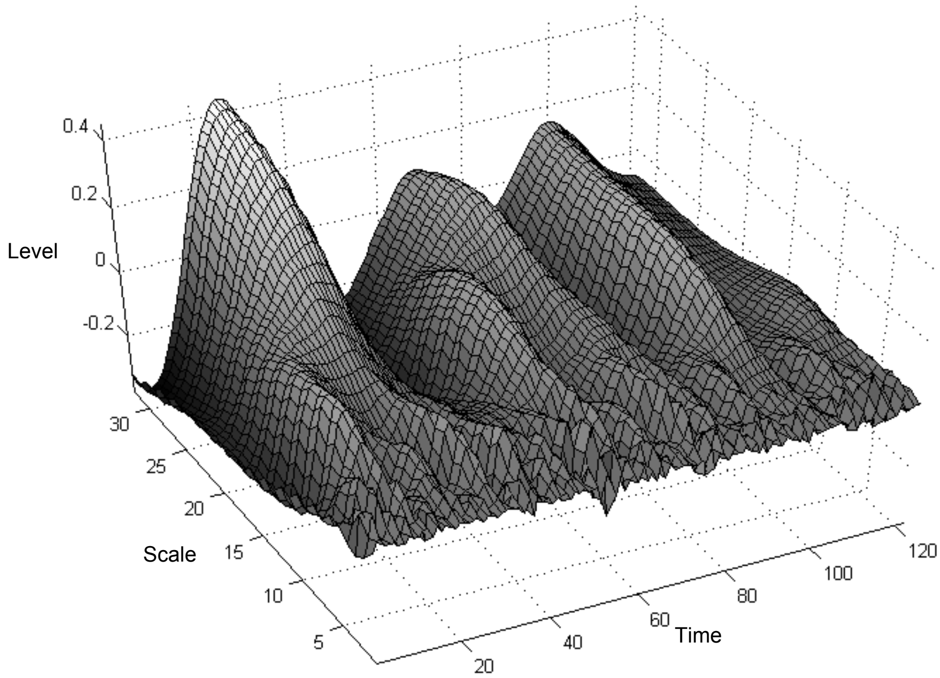
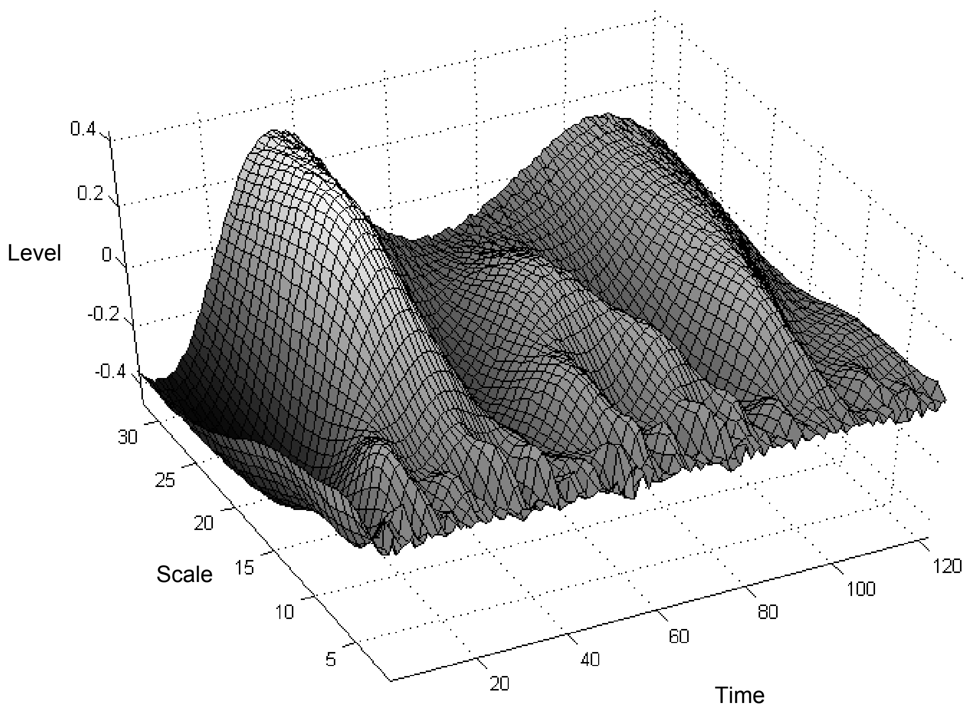


Figure 3: Wavelet coeffients for cwt with ‘db4’ and ‘gaus4’

a) CWT for ‘db4’



b) CWT for ‘gaus4’



Note: Time is given in months (1992:01=0).

The estimated center frequencies in *figure 2* are needed to calculate pseudo-frequency (F_s'), which correspond to a selected scale (s). The pseudo-frequencies are then used to calculate the time period in months. The results for ‘db4’ and ‘gaus4’ wavelets are presented in *table 1*. As one can see, the ‘gaus4’ wavelet covers larger Fourier space as the ‘db4’ wavelet. But we have to note, that the cone of influence (frequency space, where edge effects are important) is bigger than in the case of ‘db4’ wavelet.

In what follows, we use CWT (continuous wavelet transform) to analyze the fluctuations of aggregate economic activity of Slovene economy. As already mentioned, the Fourier transform is based on periodic functions in the time domain, thus capturing weekly, monthly, or annual cycles. However, many economic phenomena, such as business cycles, do not follow this strict periodicity, favoring the more flexible wavelet approach.

The analysis of wavelet coefficients for ‘db4’ and ‘gaus4’ wavelet shows that there is significant cyclical component, which can be identified as a business cycle (*figure 3*). The cyclical component oscillates with an average frequency of three years. These are similar results as in our previous study (Jagrič 2002). However, there is an asymmetry between levels of coefficients representing an expansion and recession phase of a cycle. The results seem to confirm the tendency that recessions are becoming less severed (Zarnowitz 1992). Only one deep recession could be identified in the period from 1992 to 2002. This recession, however, is a result of transformation depression, and can therefore not be classified as normal business cycle recession.

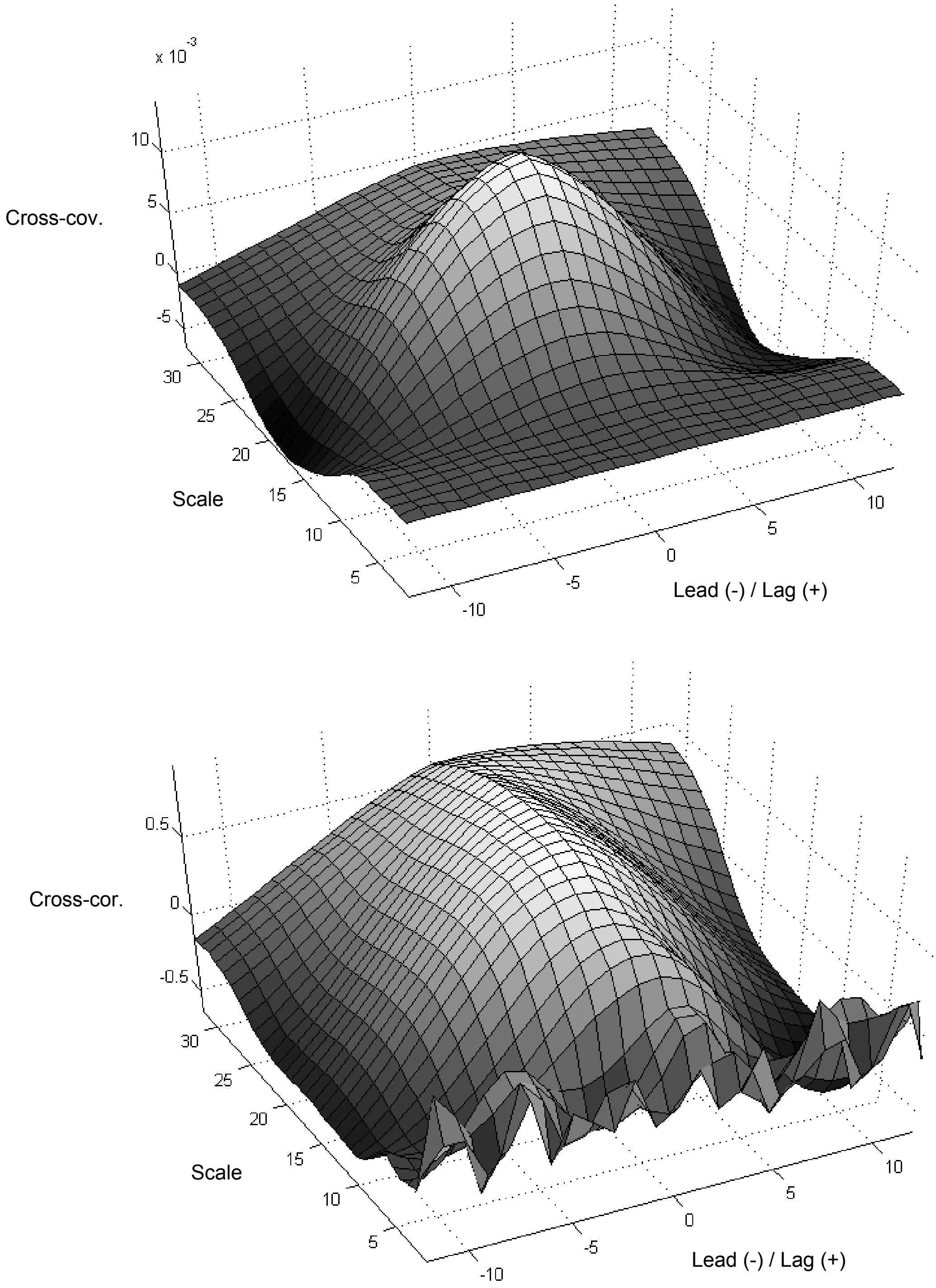
Additionally to a three-year cycle, a cyclical component with lower frequency can also be identified. This cyclical component is present only in the spectrum of ‘gaus4’ wavelet transform (*Figure 3*, plot b) and has a frequency, which corresponds to a period of five to six years. Due to the sample size this frequency falls in to the zone of influence, where edge effects are important when performing wavelet analysis. Therefore, we can not with certainty conclude that a five year cycle is present. On the other hand, such finding would be in line with results of Artis, Kontolemis, and Osborn (1997) who defined an average business cycle of a length between five to six years.

If we consider both cycles, then the three-year cycles can be a result of transition process in Slovenia. Similar episodes of short cycles were also reported in Austria, Denmark, Greece, New Zealand, Norway, and Switzerland, where they were related to structural rigidities that hold back the adjustment to adverse shocks. This seems to be confirmed also by CWT (‘gaus4’), where the three-year cycle is becoming less distinctive and is merging into scale range of longer cycle.

In the case of Slovenia an important role had the impulses from major trading partners. Therefore the adjustment process was marked not only by internal factors. Especially important is also the fact that Slovenia is in the process of adjusting to the European Union. Therefore we expect that the cycles in Slovenia should be highly synchronized with EU cycle.

To test this hypothesis, we applied wavelet cross-covariance and cross-correlation analysis. We use Germany as a proxy for the EU cycle. Since the first recession in Slovenia is not a typical business cycle recession, we performed the analysis on the data for the period from 1994 to 2002. The analysis was performed with ‘db4’ and ‘gaus4’ wavelet. Since the results were similar we will only present the analysis for ‘gaus4’ wavelet. It is also important to note that the ‘gaus4’ wavelet covers broader frequency space, which enables us to more clearly identify major regularities.

*Figure 4: W*avelet cross-covariance and –correlation with ‘gaus4’ for Slovenia and Germany (1994-2002)

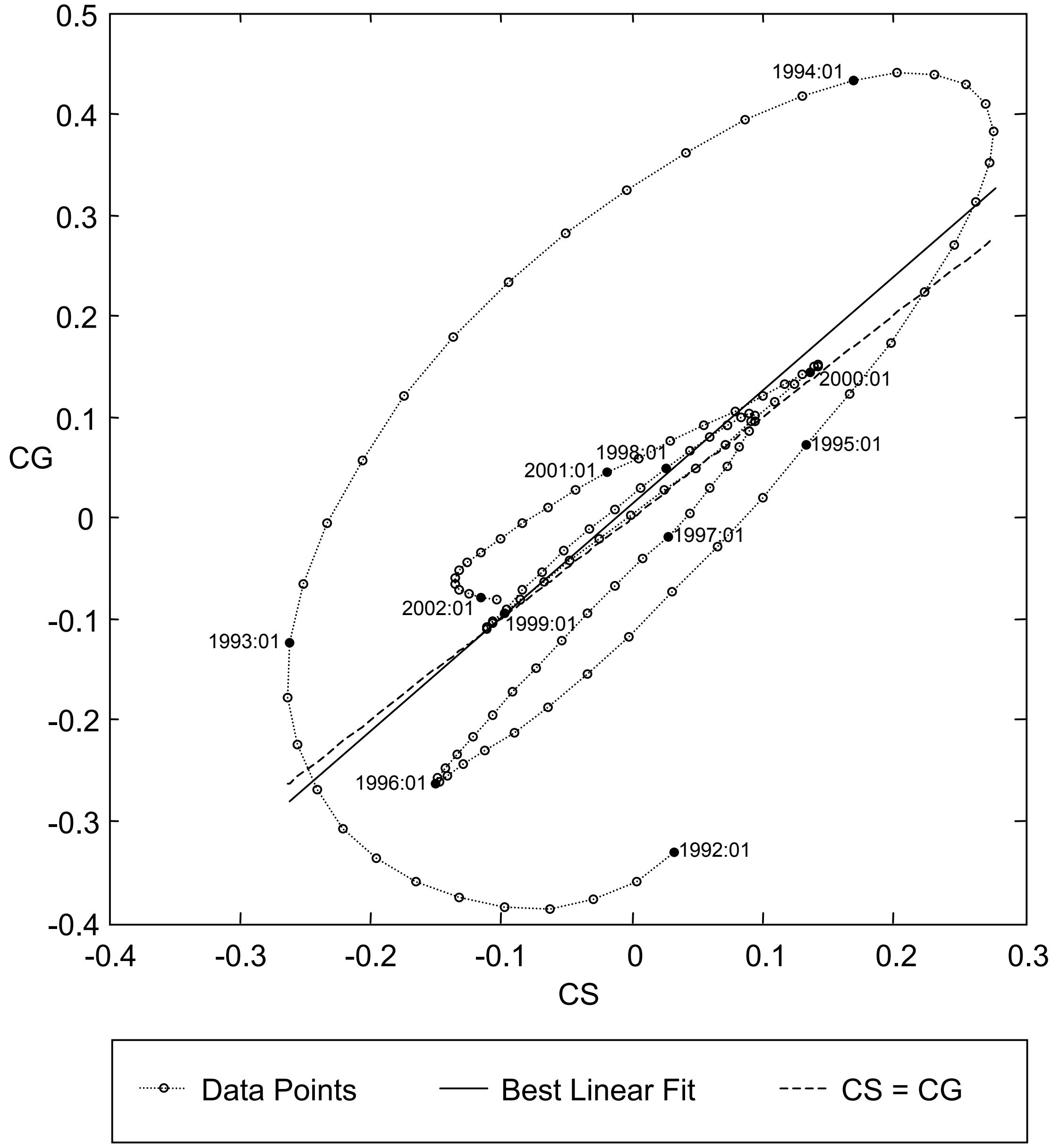


Note: Analysis was performed with ‘gaus4’ mother wavelet.
Lead means that a turn in Slovenian business cycle occurs earlier than in the German cycle. Lead / lag relationship is given in months. Scale can be converted in time periods by using Table 1.

The results of wavelet cross-covariance and cross-correlation analysis are presented in *figure 4*. The synchronization was tested with lags between -12 to +12 months. The results for wavelet cross-covariance show one major peak, with lag 0 and central frequency of 36 months. High levels of cross-covariance are also achieved with lower frequencies.

In order to test, whether the isolated peak is significant, we applied wavelet cross-correlation. The second graph in *figure 4* suggests that isolated peak has the highest level of cross-correlation in observed period. High levels of cross-correlation were also detected for lower frequencies. Such results suggest a high degree of synchronization between Slovenia and Germany.

Figure 5: Scatter plot of business cycle components for Slovenia and Germany (1992-2002)



Note: Best Linear Fit: CG = (1.12) CS + (0.0122)
R = 0.736
CS – Business cycle component for Slovenia
CG – Business cycle component for Germany

In order to give additional support for the results of wavelet cross-covariance and cross-correlation analysis, we also applied inverse wavelet transform. We reconstructed the original time series from wavelet coefficients. Only business cycle frequencies were used for reconstruction process. The results of such transformation are business cycle components of original time series.

Estimated business cycle components were used in the scatter plot in *figure 5*, where a least square regression was performed. In contrast to the wavelet cross-covariance and cross-correlation analysis, we used all available data (1992:01-2002:02). If a total synchronization with lag 0 would be present, the all points would be on CS=CG line and the movement through time would be similar to the pendulum, where the weight is moving from one critical point to another and back. The results, however, suggest that there are three distinctive periods:

- An approach phase (1992-1997), where business cycle in Slovenia is becoming synchronized with German cycle. This period was marked by a deep depression and a rebound, which was mainly driven by internal factors. All major reforms in economic system were accomplished during this phase.
- A phase of high synchronization (1997-2000), where business cycle in Slovenia is totally synchronized with German cycle. In this phase the main factors, which influenced the economic activity, were the impulses from major trading partners. Since Slovenia has first build up the export markets in EU, the main impulses came from this region.
- A phase of acquiring additional markets (2000-2002), where there is still high degree of synchronization, but in the recession phase the recovery is faster, due to impulses outside EU. Slovenia has managed to build up export markets in the region of former Yugoslavia, which are not highly synchronized with EU cycle. Therefore in the recession phase of a business cycle, these markets seem to act as automatic stabilizers.

These findings are also confirmed by least square regression. The estimated linear relationship between Slovenian and German business cycle component is extremely close to the best fit, where the movements of cyclical component of Slovenia would be equal to the German.

5. CONCLUDING REMARKS

A major advantage of wavelet techniques is their ability to decompose a time series locally both in frequency and time. We utilize this property to investigate behavior of aggregate economic fluctuations in a transition economy. The wavelet cross-covariance and wavelet cross-correlation are defined as alternative to the Fourier-based cross-spectrum and magnitude cross-covariance or coherence. Both stationary and nonstationary processes are easily handled by this methodology. This enables us to separate complicated patterns of association between time series into several much simpler patterns, each one associated with a physical time scale.

Recent analyses of modern business cycles suggest the following main points:

- The typical or average cycle lasts about five to six years (Artis, Kontolemis, and Osborn 1997).
- Recessions have become less sever and less frequent over time. Unlike recessions, expansions clearly became longer (Backus and Kehoe 1992).
- Several studies, including Backus and Kehoe (1992) and Bergman, Bordo and Jonung (1998), examined output volatility and generally found a decrease in volatility.
- In some countries (Austria, Denmark, Greece, New Zealand, Norway, and Switzerland) a sequence of short cycle could be recorded. These short cycles were related to structural rigidities that impede adjustment to adverse shocks.

- Synchronization of recessions has been a persistent feature of the historical record (Zarnowitz 1992).

Our empirical analysis seems to confirm these stylized business cycle facts also in the case of transition economy. We found a typical business cycle component. This cyclical component is asymmetric and is becoming less volatile. Additionally to the three-year cycle, we found a cycle with the frequency of five to six years. Therefore we expect that the shorter cycle is a result of a transition process.

Additionally to the findings above, we could also detect a high synchronization with German cycle. Several factors seem to affect the degree of synchronization of business cycles. First, business cycles in small open economies, which have strong trade links with major economies, are likely to be more synchronized with them than is the case for larger, more closed economies. This fact seems to be confirmed in the case of Slovenia. High degree of synchronization with German cycle could be attributed to the increased openness of Slovene economy since independence and rising share of EU in Slovenian foreign trade.

Second, the extent to which domestic demand movements are correlated across countries depends on whether there are common pressures affecting all economies, and the extent to which countries adopt a common policy stance (OECD, 1995). The process of approaching to EU is deepening the economic integration between Slovenia on one side and present members of EU on the other. The need to adopt a common policy stance will undoubtedly increase, so some synchronization of business cycle is expected also from this factor.

Third, the shift to an exchange rate regime in which the currencies float against each other has been an important facilitation of desynchronization. Fixed rates or a single currency is therefore a factor of synchronization. The exchange rate system and movements in the next years in Slovenia will be in the function of adjustment to EU and EMU, so we may expect synchronization with German and EU cycle also from this point of view. Such trends would be in line with current trends in Europe, where ERM membership has promoted a shift of business cycle affiliation to that of the anchor country of the system.

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