

METHOD OF ANALYZING BUSINESS CYCLES IN A TRANSITION ECONOMY: THE CASE OF SLOVENIA

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In this paper, we studied cyclical patterns in a transition economy. We introduced a dynamic perspective into the analysis by applying multivariate wavelet analysis. The wavelet covariance and wavelet correlation were defined and applied to the analysis of business cycles as an alternative to the traditional cross-spectrum analysis. The main findings indicated that there is a significant business cycle component in aggregate economic activity and that business cycles are asymmetric and highly synchronized with the EU cycle. Additionally, it was found that three distinctive periods of business cycle synchronization exert an important impact on the properties of a business cycle.

I. 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. In this paper, the current fluctuations of aggregate economic activity in a transition economy were put into perspective by answering the following questions:

- Does the aggregate economic activity in a transition economy exhibit fluctua-

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Empirical work was performed with MATLAB R12. The code for wavelet cross-covariance and cross-correlation is available upon request from the authors.

tions which correspond to the definition of Burns and Mitchell (1946)?

- Do the characteristics of business cycles in a transition economy change?

As noted by Brada (2002), two important issues must be considered when analyzing business cycles in a transition economy: whether a cycle of fixed periodicity is appropriate when analyzing business cycles and whether only internal factors are responsible for the cyclical behavior of economic activity. In recent studies (Artis and Zhang 1999) on the relationship of the exchange rate mechanism (ERM) of the European monetary system (EMS) with the international business cycle in terms of linkage and synchronization of cyclical movements, it was found that business cycles of ERM countries have become more synchronized with the German cycle. In our paper we adopted 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 the German cycle?

Supporting results would confirm the general concept in the business cycle literature that business cycles in the approach phase of 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) suggested the existence of a high degree of synchronization of business cycles between the EU and Germany. Additionally, as data in Table I indicate, the largest trading partner for Slovenia is Germany. Therefore we have chosen Germany as an anchor country.

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

TABLE I
REGIONAL COMPOSITION OF FOREIGN TRADE FOR SLOVENIA
(Average Values for the Period 1993–2002)

	Exports (in % of Total Exports)	Imports (in % of Total Imports)
EU (15)	66.11	67.74
Germany	30.73	19.88
Italy	13.76	16.60
France	5.74	10.84
Austria	7.28	7.93
CEFTA ^a	7.27	8.37

Source: Bank of Slovenia, <http://www.bsi.si> (accessed May 2002).

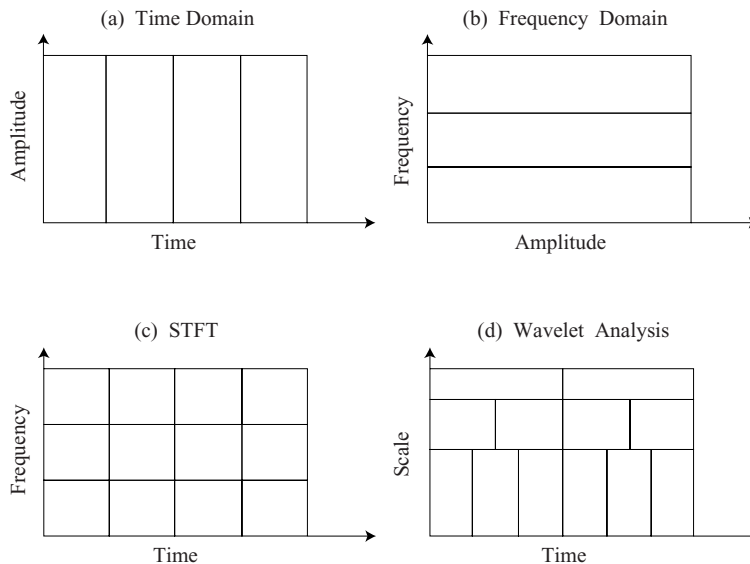
^a CEFTA = Central European Free Trade Agreement.

The outline of the paper is as follows. The methodological framework is given in Section II. The major characteristics of the transition period in Slovenia are outlined in Section III. In Section IV, the database is presented. The database is then used in Section V, where we apply suggested econometric procedures. In the last part of the paper, the conclusions and implications for economic modeling are presented.

II. METHODOLOGICAL FRAMEWORK

When analyzing the cyclical behavior of a time series, although Fourier analysis is extremely useful, it also has a serious drawback, because time information is lost in the transformation to the frequency domain (Figure 1, plots a and b). When looking at a Fourier transform of a time series, it is impossible to determine when a particular event took place. If the time-series properties do not change appreciably over time—that is, if one deals with a so-called stationary time series—this drawback is not very important. However, the 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 detect them.

Fig. 1. Time-Based, Frequency-Based, STFT, and Wavelet Views of a Signal



In an effort to alleviate this shortcoming, 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 on 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 is due to the $T/(2\delta t)$ frequencies, which must be analyzed for 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 a time series x_n shows equal time spacing δt and $n = 0, \dots, N-1$. Also assume that the wavelet function $\psi_0(\eta)$ depends on a nondimensional time parameter η . To be considered as a wavelet, this function must have a 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 function:

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

where ω_0 is the nondimensional frequency. The term wavelet function refers 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 a discrete wavelet transform (DWT), 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 was used.

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

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

where the * symbol denotes the complex conjugate and s scale. The subscript 0 on ψ was dropped to indicate that the function was normalized. This is necessary

to ensure that wavelet transforms on each scale s are directly comparable to each other and to the transforms of other time series:

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

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 a real part $R[W_n(s)]$, and an imaginary part $I[W_n(s)]$, or amplitude $|W_n(s)|$, and phase $\tan^{-1}\{I[W_n(s)]/R[W_n(s)]\}$. The wavelet power spectrum is defined as $|W_n(s)|^2$. For real-valued wavelet functions, the imaginary part is zero and the phase is undefined.

A common question may be raised, namely, what is the relationship between scale and frequency? The answer can only be given in a broad sense, and it is preferable to refer to 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:

$$F_s = \frac{\delta t \omega}{s}. \quad (4)$$

Since the center frequency-based approximation captures the main wavelet oscillations, 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 a 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 the continuous case, it is possible to reconstruct the time series using a completely different wavelet function. The easiest way is by using a delta function (δ):

$$x_n = \frac{\delta j \delta t^{1/2}}{C_\delta \psi_0(0)} \sum_{j=0}^J \frac{R[W_n(s_j)]}{s_j^{1/2}}. \quad (5)$$

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 factor $s_j^{1/2}$ converts the wavelet transform to an energy density. The factor C_δ is derived from the reconstruction of a δ function from its wavelet transform using the function $\psi_0(\eta)$.

Based on Fourier analysis, jointly using two time series with coherent signals can reveal additional information on analyzed time series. Therefore, we introduced 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 a one-time series with the conjugate of the wavelet transform of a second-time series, in both discrete and continuous time. This can be expressed as:

$$W_n^{xy}(s) = E[W_n^x(s)W_n^{y*}(s)], \quad (6)$$

where $E[\]$ stands for the expected value over time, $W_n^x(s)$ and $W_n^y(s)$ are the wavelet transforms of 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 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:

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

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.

III. SOME CHARACTERISTICS OF THE TRANSITION PERIOD IN SLOVENIA

Before discussing the database, let us first observe the transition period in Slovenia (1991 to 2002), which started with the declaration of independence in 1991. This is necessary in order to point out some of the major events which occurred during the transition.

The most important part of the transition period was the transformation depression during the years 1991 to 1993. This is not surprising since the economy in Slovenia was hit by a series of market losses: the collapse of Council for Mutual Economic Assistance (CMEA) markets, the Gulf War, and the collapse of the Yugoslav internal market. This collapse heavily influenced the economic activity and the financial position of the economy. Production declined rapidly, by 9.3 per cent in 1991 and 6.0 per cent in 1992.

In the middle of 1993, Slovenia suddenly reached the bottom of its depression. The recovery which followed can be explained by an increase in the aggregate demand in which the moderate growth of the foreign demand coincided with the fast growth of the domestic demand. A new slowdown occurred in 1995,¹ which can be attributed to “Dutch disease”² and to a debt crisis in the Slovenian economy. Several factors contributed to developments in Slovenia that could be referred to “Dutch disease,” mainly during the period 1991–95:

¹ The period between 1994 and 1995 was also marked by the Mexican crisis, which affected mainly the U.S. economy and Europe to a lesser extent.

² The orthodox use of the term “Dutch disease” normally applies to a case where positive terms of trade disturbances or (what is almost equivalent) natural resource discoveries led to the appreciation of the exchange rate, resulting in the decline of the non-export sector of the country, causing

- Due to the collapse of Yugoslavia, the Slovenian home market was reduced by two-thirds. At the same time, business in the CMEA markets deteriorated sharply due to the disintegration of the former national states in the area. Therefore, most companies had to reorient trade to western markets.
- Foreign markets required higher productivity, which contributed to the development of the international competitiveness of Slovenian producers, thus leading to a growth in exports. As a consequence of these developments, from 1993, the exchange rate of the German mark began to permanently lag behind the growth of domestic prices.
- The Slovenian export structure more closely resembled former sales on the Yugoslav market than sales on the Slovenian market. However, prices which could be obtained on Western markets were lower in relation to those once obtained on the Yugoslav market, implying that the compensation effect for lower export prices, when subsidizing exports to the West, was no longer present.
- The appreciation of the domestic currency described above and the missing compensation effect led to cost pressures. The “Dutch disease” therefore caused a reduction in the GDP in sectors which were not able to cope with the exchange-rate development presented above.

The economic growth rate increased in the second part of the year 1996 mainly due to the economic recovery in Europe and enhanced export competitiveness. Export competitiveness (measured in terms of unit labor costs in the basket of currencies) increased in 1996 by 7.3 per cent after a marked drop of 11.9 per cent in 1995. Competitiveness improved as a consequence of increased productivity, the lower tax burden on wages, and the real depreciation³ of the tolar.

The improved economic performance of the main economic partners was the primary factor enabling exports to rise in 1997. That year, a compromise among the social partners on wages⁴ in the public sector was reached in time. Thus, due

inflation, etc., ultimately making the country's economy less active (Benjamin, Devarajan, and Weiner 1989; Edwards and Wijnbergen 1989; Corden 1984). In the case of Slovenia, we used a more attenuated definition of the term “Dutch disease.” The term indicates a situation in a national economy when, for whatever reason, the balance of payments is in equilibrium but the value of foreign currency decreases. In Slovenia we could use the term “Dutch disease” after the introduction of the Slovenian tolar on October 8, 1991.

³ The real depreciation is calculated by adjusting the nominal effective exchange rate in order to incorporate inflation rate differences. We used two types of price indices: consumer price indices, and producer price indices for Slovenia and major trading partners. In both cases, there was a significant real depreciation of the tolar.

⁴ After the independence, the Yugoslav model of social bargaining was replaced by a system of collective bargaining between government, management, and labor unions. The first collective agreement for the public sector was signed in 1991, as a basis for collective agreements for individual industries and professions. In the year 1997, the government tried to improve its bargaining position of employer and social partner by limiting salaries and other incomes of state officials in proportion to the increase of prices (IMAD 1997). The government also limited employment, new allowances to salaries, and career advancement in the public sector (IMAD 1998).

to the adoption of adequate income policy mechanisms, the growth in wages lagged behind the growth in labor productivity.

The slowdown in economic growth and export market growth in the countries of the major trading partners in the last quarters of 1997 and 1998 inhibited growth in exports and economic activity in Slovenia as well. A high value of the export multiplier⁵ of the Slovenian economy (0.60), in contrast to that in some other transition countries in Europe, explains the high degree of sensitivity of the Slovenian macroeconomic activity to changes in export growth. The decline in 1998 was therefore not a surprise, since contagion effects of the Asian crisis spread to Europe. The global recession, which started in 2001, also exerted an impact on the Slovenian economy. However, the recession seemed to be less severe than in Europe according to the latest macroeconomic data.

IV. DATABASE

The discussion above clearly indicates that some major events exerted an impact on the Slovenian economy. In order to determine how aggregate economic activity reacted to these events, it is necessary to define a monthly measure of the current level of aggregate economic activity. There are two alternative strategies (Dias 1993): either the adoption of a single series as the variable of interest, or the use of 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 used the monthly index of industrial production. The data were obtained from the Bank of Slovenia and Deutsche Bundesbank.⁶ Data covered the period from January 1992 to March 2002. In contrast to a previous study (Jagric 2002), we used an alternative concept of business cycle fluctuations known as growth cycles. Growth cycles are fluctuations in the growth rates of economic activity around a long-run trend (Moore 1983; Zarnowitz 1992). This concept is associated with some advantages, but also disadvantages in terms of conventional business cycle concept (Stock and Watson 1999):

- Growth cycles are better suited to business cycle analysis in countries with

⁵ The export multiplier is defined as the change in the economic growth rate per unit of change in real exports. In 1992–2002, the export multiplier for Slovenia was 0.60, implying that a 1 per cent rise in exports led to a 0.60 per cent rise in real GDP. A regression analysis for some other countries in transition revealed lower values for export multipliers: 0.33 for the Czech Republic, 0.45 for Slovakia, 0.51 for Poland, and 0.50 for Hungary.

⁶ Bank of Slovenia, <http://www.bsi.si> (accessed May 2002); Deutsche Bundesbank, <http://www.bundesbank.de> (accessed May 2002).

high trend growth rates, including many emerging market economies, which tend to experience sharp fluctuations in the rates of growth rather than levels.

- The use of growth cycles is often more suitable for understanding the relationship between output, inflation, and unemployment (Boone et al., forthcoming). However, growth cycles depend on an arbitrary distinction between trend and cycle, for which there is no consensus among experts. Moreover, key cyclic characteristics vary considerably depending on the detrending method used (Canova 1998; Burnside 1998).
- Growth recessions are sometimes minor in size, while level recessions are generally 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 the following equation:

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

As Charemza and Deadman (1992) noted, normal differentiation can affect long-term relationships between economic variables. To avoid this effect, we used annual growth rates. No additional procedures, such as 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 during periods with unstable conditions as 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 using wavelet analysis, we can avoid such problems as described in Section II.

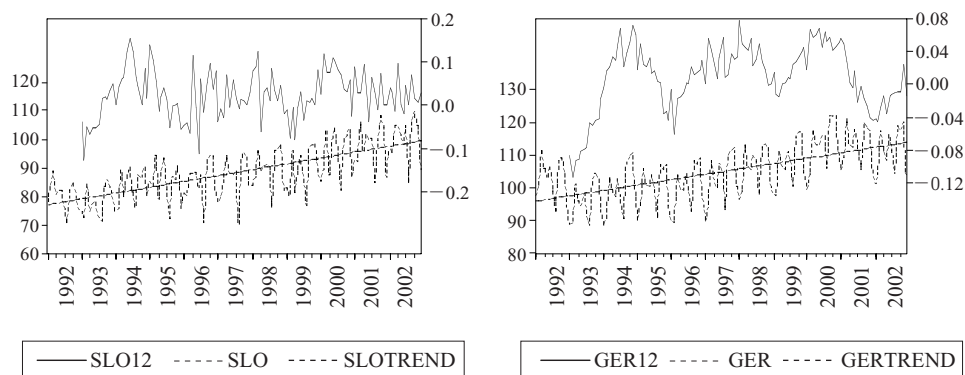
Time trend is an important component for most macroeconomic time series. If a time series has a strong trend component, the results may not be reliable. Therefore, many researchers use detrending, which can however emphasize different frequency ranges in data (Canova 1998; Burnside 1998). As can be seen in Figure 2, both time series (industrial production for Slovenia and Germany) have an extremely strong trend component. By applying transformation (8), we were able to produce time series which did not have a strong trend component.

V. RESULTS

Based on the observations made in Section III, we can conclude, that there should be a cyclical component in aggregate economic activity. However, before we can test this hypothesis by applying the wavelet transform of a selected time series, it is necessary to select an appropriate mother wavelet. In choosing the wavelet function, several factors should be considered (Farge 1992):

- Orthogonal or non-orthogonal analysis. In orthogonal wavelet analysis, the number of convolutions on each scale is proportional to the width of the wave-

Fig. 2. Index of Total Industrial Production for Slovenia and Germany



Note: SLO12: Total industrial production for Slovenia in terms of annual growth rates, SLO: Index of total industrial production for Slovenia, SLOTREND: Linear trend component for the index of total industrial production for Slovenia, GER12: Total industrial production for Germany in terms of annual growth rates, GER: Index of total industrial production for Germany, GERTREND: Linear trend component for the index of total industrial production for Germany.

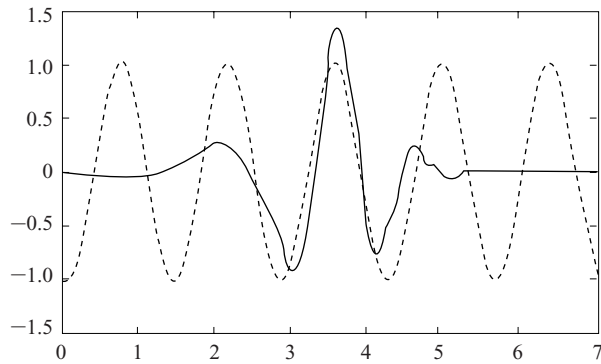
let basis on that scale. This produces a wavelet spectrum that contains discrete blocks of wavelet power and is useful for signal processing. The non-orthogonal transform is useful for time-series analysis, where smooth, continuous variations in wavelet amplitude are expected.

- Complex or real. A complex wavelet function will return information about both amplitude and phase, and is more suitable for capturing an oscillatory behavior. A real wavelet function returns only a single component and can be used to isolate peaks or discontinuities.
- Width. 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 display a good time resolution but low frequency resolution, while a broad function will show a low time resolution, yet a good frequency resolution.
- Shape. The wavelet function should reflect the type of features present in the time series. If one is primarily interested in wavelet power spectra, then the choice of wavelet function is not critical.

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 3, where we also approximated the center frequencies. Since we planned to use a continuous wavelet transform (CWT), we needed a non-orthogonal wavelet function. Both functions are real. The Daubechies wavelet covers a narrow frequency space, which enables us to isolate

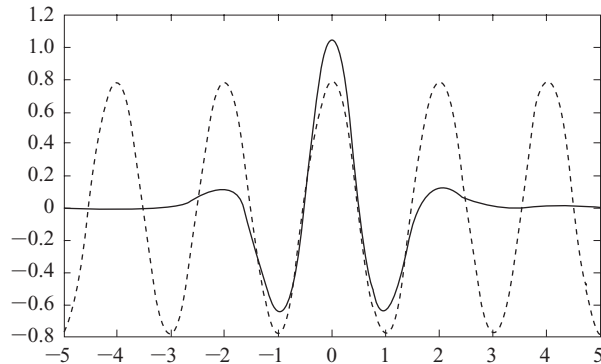
Fig. 3. Center Frequencies of “db4” and “gaus4” Wavelets

Wavelet “db4” and Center-Frequency-Based Approximation



Period: 1.4; Cent. Freq: 0.71429

Wavelet “gaus4” and Center-Frequency-Based Approximation



Period: 2; Cent. Freq: 0.5

dominant frequencies more precisely. The shape of both wavelet types is close to that of a theoretical business cycle.

The estimated center frequencies shown in Figure 3 are needed to calculate the pseudo-frequency (F_s), which corresponds to a selected scale (s). The pseudo-frequencies are then used to calculate the time period in months. The results for the “db4” and “gaus4” wavelets are presented in Table II. As one can see, the “gaus4” wavelet covered a larger Fourier space than the “db4” wavelet. It should be noted, however, that the cone of influence (frequency space, where edge effects are important) was larger than in the case of the “db4” wavelet.

In what follows, we used a CWT to analyze the fluctuations in the aggregate economic activity of the Slovenian economy. As already mentioned, since the Fourier transform is based on periodic functions in the time domain, it captures

TABLE II
CHARACTERISTICS OF SELECTED WAVELETS

Wavelet Type	db4		gaus4	
	Frequency	Period	Frequency	Period
Scale:				
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: $\text{gaus}(x, n) = Cn^* \text{diff}(\exp(-x^2), n)$, where diff denotes the symbolic derivative and Cn is such that the 2-norm of $\text{gaus}(x, n) = 1$.	
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 $n = \text{even}$)	

Source: Daubechies (1992).

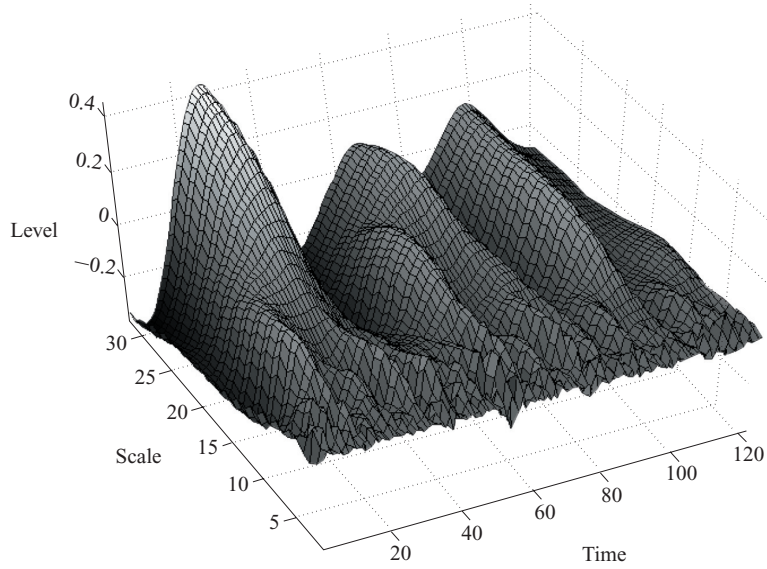
Note: Period is given in months.

weekly, monthly, or yearly cycles. However, since many economic phenomena, such as business cycles, do not follow this strict periodicity, a more flexible wavelet approach is preferable.

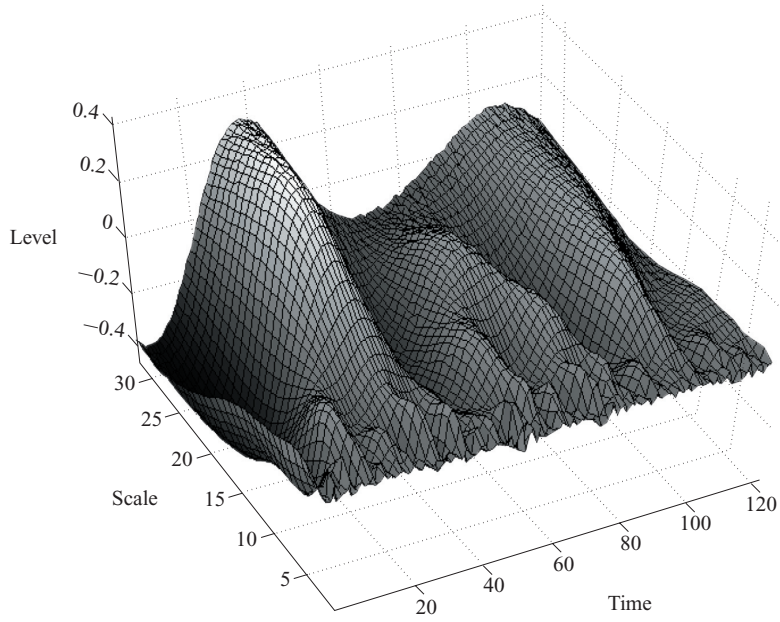
The analysis of wavelet coefficients for the “db4” and “gaus4” wavelets showed that there was a significant cyclical component, which could be identified as a business cycle (Figure 4). The cyclical component oscillated with an average frequency of three years. These are similar results to those obtained in our previous study (Jagrič 2002). However, in contrast to our previous study, where we assumed that the cycles would be constant and symmetric due to the methodology applied, the current results suggested the existence of an asymmetry between the levels of the coefficients representing an expansion and recession phase of a cycle. The results seemed to confirm the tendency that recessions are becoming less severe (Zarnowitz 1992). Only one deep recession could be identified during the period from 1992 to 2002. This recession, however, resulted from transformation depression, and could therefore, not be classified as a normal business cycle recession.

Fig. 4. Wavelet Coefficients for CWT with “db4” and “gaus4”

(a) CWT for “db4”



(b) CWT for “gaus4”



In addition to a three-year cycle, a cyclical component with a lower frequency was also identified, which we could not have detected using classical spectral analysis. This cyclical component was present only in the spectrum of the “gaus4” wavelet transform (Figure 4, plot b) and showed a frequency corresponding to a period of five to six years. Due to the sample size, this frequency fell into the zone of influence where edge effects are important when performing wavelet analysis. Therefore, we cannot conclude with certainty that a five-year cycle was present. On the other hand, such a finding would be in line with the results obtained by Artis, Kontolemis, and Osborn (1997), who defined an average business cycle as one with a length between five and six years.

If we consider both cycles, then the three-year cycles can result from the 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 held back the adjustment to adverse shocks. This seemed to be confirmed by CWT (gaus4), where the three-year cycle became less distinctive and merged into the scale range of a longer cycle. Such changes could only be detected by a dynamic approach where no prior assumptions about the properties of the cyclical component were made. In our previous study, where we applied spectral analysis, we were not able to detect these developments.

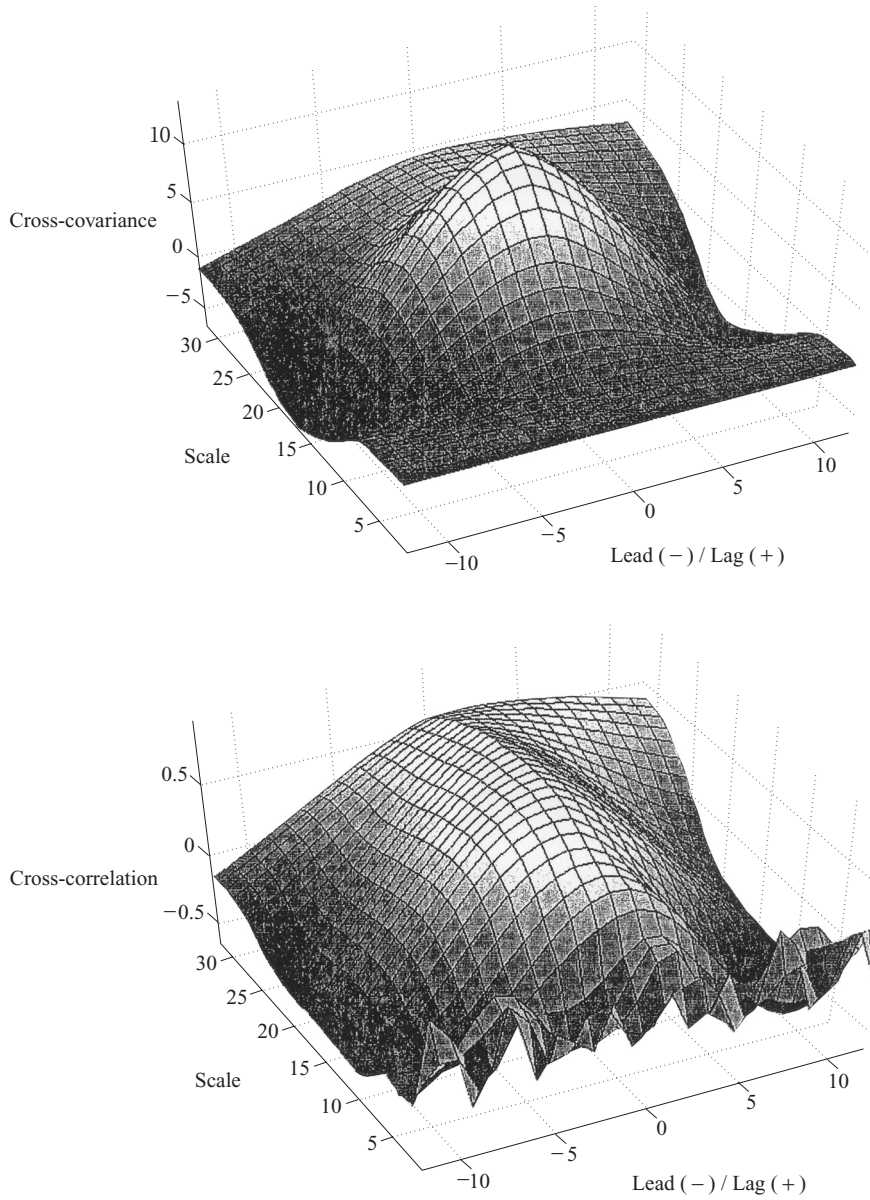
In the case of Slovenia, impulses from the major trading partners played an important role. Therefore, the adjustment process was not characterized by internal factors alone. It is especially important to note that Slovenia is in the process of adjusting to the market conditions prevailing in the EU. Therefore, we expect that the cycles in Slovenia should be highly synchronized with the EU cycle.

To test this hypothesis, we applied wavelet cross-covariance and cross-correlation analysis. We used Germany as a proxy for the EU cycle. Since the first recession in Slovenia was 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 the “db4” and “gaus4” wavelets. Since the results were similar, we will only present the analysis for the “gaus4” wavelet. It is also important to note that the “gaus4” wavelet covered a broader frequency space, which enabled us to identify more clearly major regularities.

The results of wavelet cross-covariance and cross-correlation analysis are presented in Figure 5. The synchronization was tested with lags between -12 and $+12$ months. The results for wavelet cross-covariance revealed one major peak, with lag 0 and a central frequency of 36 months. High levels of cross-covariance were also obtained with lower frequencies.

In order to test whether the isolated peak was significant, we applied the wavelet cross-correlation. The second graph in Figure 5 suggests that the isolated peak showed the highest level of cross-correlation during the observed period. High

Fig. 5. Wavelet Cross-Covariance and Cross-Correlation with “gaus4” for Slovenia and Germany, 1994–2002



- Notes: 1. Analysis was performed with “gaus4” mother wavelet.
 2. Lead implies that a turn in the Slovenian business cycle occurred earlier than in the German cycle. Lead/lag relationship is given in months. Scale can be converted to time periods by using Table II.

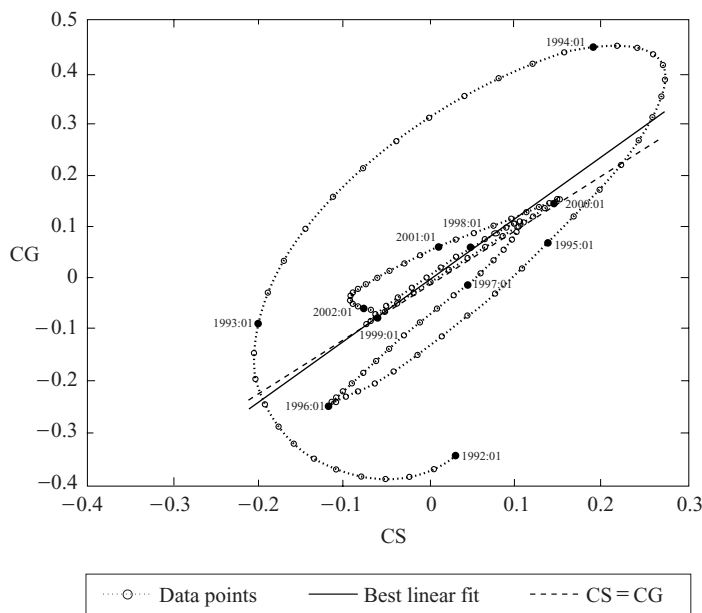
levels of cross-correlation were also detected for lower frequencies. Such results suggest the existence of a high degree of synchronization between Slovenia and Germany.

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

Estimated business cycle components were used in a scatter plot shown in Figure 6, where a least square regression was performed. In contrast to the wavelet cross-covariance and cross-correlation analysis, we used all the available data (1992:01–2002:02). If a total synchronization with lag 0 were to be present, then all the points should be on the $CS=CG$ line, and the movement through time should be similar to that of a pendulum, where the weight is moving from one critical point to another and back. The results, however, revealed three distinctive periods:

- An approach phase (1992–97), where the business cycle in Slovenia was be-

Fig. 6. Scatter Plot of Business Cycle Components for Slovenia and Germany, 1992–2002



- Notes: 1. Best linear fit: $CG = (1.12) CS + (0.0122)$.
 2. $R = 0.736$.
 3. CS: Business cycle component for Slovenia,
 CG: Business cycle component for Germany.

coming synchronized with the German cycle. This period was marked by a deep depression and a rebound, which was mainly driven by internal factors. All the major reforms in the economic system were accomplished during this phase.

- A phase of high synchronization (1997–2000), where the business cycle in Slovenia became totally synchronized with the German cycle. In this phase, the main factors which influenced the economic activity were the impulses from major trading partners. Since Slovenia first built up the export markets in the EU, the main impulses came from this region.
- A phase of acquisition of additional markets (2000–2002), where there was still a high degree of synchronization, but in the recession phase the recovery was faster due to impulses outside the EU. Slovenia had managed to build up export markets in the region of former Yugoslavia, which are not highly synchronized with the EU cycle. Therefore, in the recession phase of a business cycle, these markets appeared to act as automatic stabilizers.

These findings were also confirmed by least square regression. The estimated linear relationship between the business cycle components in Slovenia and Germany was very close to the best fit, where the movements of the cyclical component of Slovenia would be equal to those of Germany.

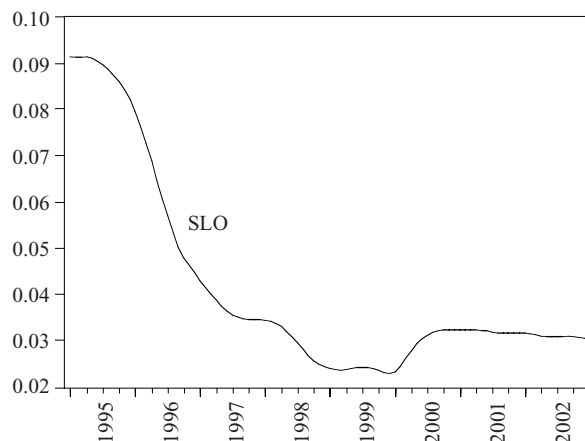
Another important question in the evolution of the business cycle in a transition economy is whether the cycle has become more or less volatile over time. The general evidence of the evolution of the business cycle suggests that its amplitude has significantly declined for most OECD countries over the past decade or more (Dalsgaard, Elmeskov, and Park 2002; Bergman, Bordo, and Jonung 1998; Backus and Kehoe 1992). It is likely that part of the reduction in volatility stemmed from the fact that the size and nature of the shocks have changed over time (IMF 2001; Stock and Watson 2002). In order to test whether similar observations could be made for Slovenia, we used the business cycle component for Slovenia. The results are presented in Figure 7.

The results suggested that volatility declined after transformation depression. To be more specific, volatility not only decreased after transformation depression, but also remained at a lower level for the rest of the observed period (up to 2003). If we take this property together with the results above, we can conclude that, for the observed period, the cyclical component of aggregate economic activity in Slovenia exhibited patterns similar to those of most OECD countries.

VI. CONCLUDING REMARKS

A major advantage of wavelet techniques is their ability to decompose a time series locally in both frequency and time. We utilized this property to investigate the behavior of aggregate economic fluctuations in a transition economy. The wavelet

Fig. 7. Volatility of the Business Cycle Component for Slovenia, 1991–2003



Note: Volatility is measured according to IMF (2001) methodology as the standard deviation of the business cycle component (denoted as SLO in the plot). We used a four-year moving window from 1991:01 to 2003:02.

cross-covariance and wavelet cross-correlation were defined as alternatives to the Fourier-based cross-spectrum and magnitude cross-covariance or coherence. Both stationary and nonstationary processes can be easily handled by this methodology. This enabled us to separate complex 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 severe and less frequent over time. Unlike recessions, expansions have clearly become longer (Backus and Kehoe 1992).
- Several studies, including those of 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 cycles could be observed. These short cycles were related to structural rigidities that impeded adjustment to adverse shocks.
- Synchronization of recessions has been a persistent feature of the historical record (Zarnowitz 1992).

Our empirical analysis seemed to confirm these stylized business cycle facts also in the case of a transition economy. We identified a typical business cycle

component. This cyclical component was asymmetric and became less volatile. In addition to the three-year cycle, we found a cycle with a frequency of five to six years. Therefore, we consider that the shorter cycle resulted from the transition process.

In addition to the findings described above, we could also detect a high synchronization with the German cycle, which can be attributed to several factors. First, business cycles in small open economies which have strong trade links with major economies are likely to be more synchronized with the major economies than is the case of larger, more closed economies. This fact seemed to be confirmed in the case of Slovenia. Synchronization with the German cycle could be attributed to the increased openness of the economy in Slovenia since independence and the important share of the EU in trade (especially during the second period of transition: 1997–2000).

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 1994). Since the process of EU accession is deepening the economic integration between Slovenia, on one side, and the present members of the EU on the other, some synchronization of the business cycle can be attributed to this factor. Since Slovenia will become a full member of the EU, we can expect that this factor will be extremely important in coming years.

Third, the shift to an exchange rate regime in which currencies float against each other has been an important factor in facilitating desynchronization. Fixed rates or a single currency may, therefore, act as a factor of synchronization. As the exchange rate system and movements in the coming years in Slovenia are likely to be related to the function of adjustment to the EU and the EMU, we may expect an even stronger synchronization with the German and EU cycles from this point of view as well. The process of acquisition of new export markets in the region of former Yugoslavia, which are not highly synchronized with the EU cycle, can therefore, exert only a transitory effect on the linkage between the business cycles in Slovenia and the EU, especially due to the fact that the former Yugoslav republics are also trying to become members of the EU.

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