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Economic Theory

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COMOVEMENTS OF ECONOMIC ACTIVITY IN THE POST-COMMUNIST ECONOMIES

Abstract

This paper studies the cyclic patterns in transition economies with multivariate spectral analysis. It examines whether the transition in Slovenia and Croatia was marked by a significant shift in aggregate economic activity, which corresponds to the definition of the business cycle, and whether the cycles are synchronized with the cycle of the EU. For Slovenia, we find very close synchronization. The testing for Croatia, however, suggests that there is no typical EU component in its business cycle. To additionally support the results obtained with multivariate spectral analysis, we also employed the Granger causality test. According to lag selection criteria, economic activity in Slovenia lags behind the EU economic activity for 1 month. Granger causality test also supports the results for Croatia. We could not find any significant connection between economic activity in Croatia and the EU.

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Key words

Business cycle, multivariate spectral analysis, Granger causality synchronization.

1. Introduction

Recent studies (Artis and Zhang, 1999) of the relationship of the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS) to the international business cycle in terms of linkage and synchronization of cyclical movements found that the business cycle of the ERM countries have become more synchronized with the German cycle. In our paper, we follow the same assumption as we analyze the business cycles in Slovenia and Croatia. Therefore, we set up the following hypothesis:

H1: The series for Slovenia and Croatia should contain the cyclical component, which corresponds to the definition of the business cycle proposed by Mitchell and Burns, and it should have the same frequency as the business cycle in Germany.

H2: The business cycles of Slovenia and Croatia should be synchronized with the German cycle.

Such findings would confirm a general view in the business cycle literature that business cycles in the approach phase of integration become 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 high degree of business cycle synchronization between the EU and Germany. Therefore, we decided to choose Germany as an anchor country.

We test the hypothesis of synchronization of cyclical movements on the basis of monthly data for the period 1991–2001. As it can be seen in some applications, spectral analysis can be a valuable tool for studying business cycles, see for example Sargent (1987), Englund, Persson, and Svensson (1992), Reiter (1995), and Woitek (1997). Spectral analysis has been used to study the existence of cycles in RBC models by Watson (1993), Söderlind (1994), Cogley and Nason (1995), and Wen (1998), and it has been suggested as an econometric method for measuring the goodness-of-fit for RBC models (Watson, 1993). We choose the multivariate spectral analysis to study the relationship between business cycles of Germany, Slovenia and Croatia. The selected method is used to estimate the strength of wavelength relationship of economic indicators.

The remainder of the paper is organized as follows: after Introduction, we set out the analytical framework in Section II. In Section III we present basic procedures to be applied on selected time series. Section IV summarizes main findings and concludes.

2. The Analytical Framework

The task of quantifying comovements with the business cycle is conceptually difficult. Burns and Mitchell (1946) quantified comovements in terms of leads or lags at turning points of each series relative to the reference cycle and in terms of their index of conformity. More recent work has focused on the second moment of the joint distribution of the series of interest. For example, Hymans (1973) summarized cyclical timing by estimating phases in the frequency domain at business cycle frequencies. This perspective – focusing on the second moment properties of the series – is adopted here.

To apply the multivariate spectral analysis, it is desirable to have a minimum of 200 observations, and economic indicators must be stationary. Let $\{y_t\}_{t=-\infty}^{\infty}$ be stationary, stochastic n-dimensional vector process with mean vector $E(y_t) = \mu$ and the τ 'th autocovariance matrix given by:

$$\Gamma(\tau) \equiv E\left[(y_t - \mu)(y_{t-\tau} - \mu)\right] \tag{1}$$

If the sequence of matrix autocovariances $\{\Gamma_\tau\}_{\tau=-\infty}^{\infty}$ is absolutely summable, and if z is complex scalar, the matrix autocovariance generating function of y_t is given by:

$$F_y(z) = \sum_{\tau=-\infty}^{\infty} \Gamma(\tau) z^{\tau}, \tag{2}$$

where $F_y(z)$ is $(n \times n)$ – dimesional matrix of complex numbers.

If we evaluate the matrix autocovariance generating function at the value $z = e^{-i\omega\tau}$, and divide it by 2π, we have the multivariate spectrum – the cross-spectral density function:

$$S_y(\omega) = \frac{1}{2\pi} \sum_{\tau=-\infty}^{\infty} \Gamma(\tau) e^{-i\omega\tau}, \tag{3}$$

where $S_y(\omega)$ is an $(n \times n)$ matrix. The diagonal elements are the power spectrum of the individual processes, which are real-valued and nonnegative for all ω. The off-diagonal elements are the cross-spectra. The cross-spectrum is, in general, a complex number at each frequency. If we consider the case for $y = [y_t, x_t]$, where $\{y_t\}_{t=-\infty}^{\infty}$ and $\{x_t\}_{t=-\infty}^{\infty}$ are the two jointly stationary stochastic processes with continuous power spectra, then the multivariate spectrum is given by:

$$S_y = \begin{bmatrix} S_{yy}(\omega) & S_{yx}(\omega) \\ S_{xy}(\omega) & S_{xx}(\omega) \end{bmatrix} = \frac{1}{2\pi} \begin{bmatrix} \sum\limits_{\tau=-\infty}^{\infty} \gamma_{yy}(\tau) e^{-i\omega\tau} & \sum\limits_{\tau=-\infty}^{\infty} \gamma_{yx}(\tau) e^{-i\omega\tau} \\ \sum\limits_{\tau=-\infty}^{\infty} \gamma_{xy}(\tau) e^{-i\omega\tau} & \sum\limits_{\tau=-\infty}^{\infty} \gamma_{xx}(\tau) e^{-i\omega\tau} \end{bmatrix}. \quad (4)$$

As it was stated above, the cross-spectrum is a complex quantity. In order to estimate it, we will use polar decomposition. So it is possible to reformulate the cross-spectrum in terms of two real quantities, the co-spectrum and the quadrature spectrum:

$$S_{yx}(\omega) = co_{xy}(\omega) + i\ qu_{yx}(\omega) = \frac{1}{2\pi} \sum_{\tau=-\infty}^{\infty} \gamma_{yx}(\tau) \cos(\omega\tau) + i \frac{1}{2\pi} \sum_{\tau=-\infty}^{\infty} \gamma_{yx}(\tau) \sin(\omega\tau). \quad (5)$$

The cospectrum between y_t and x_t at frequency ω has the interpretation of the covariance between y_t and x_t that is attributable to cycles with frequency ω. The quadrature spectrum from x_t to y_t at frequency ω is proportional to the portion of the covariance between x_t and y_t due to cycles of frequency ω. Cycles of frequency ω may be important for both x_t and y_t individually as reflected by large values for $S_x(\omega)$ and $S_y(\omega)$ yet fail to produce much contemporaneous covariance between the variables because at any given date the two series are in different phases of the cycle. For example, the variable x_t may respond to economic recession later than y_t. The quadrature spectrum looks for evidence of such out-of-phase cycles.

Business cycles are characterized by strong correlation of several macroeconomic variables over the business cycle. Multivariate time series analysis in the frequency domain can be used to analyze this phenomenon by using coherence (*Coh*) and phase (*Ph*):

$$\begin{aligned} Coh(\omega) &= \frac{\left|S_{yx}(\omega)\right|^2}{S_{yy}(\omega) S_{xx}(\omega)}, \qquad 0 \le Coh(\omega) \le 1 \\ Ph(\omega) &= \operatorname{atan}\left(\frac{qu(\omega)}{co(\omega)}\right), \qquad lead / lag = \frac{Ph(\omega)}{\omega} \end{aligned} \quad (6)$$

The coherence between two or more time series can be used to measure the extent to which multiple time series move together over the business cycle. The phase gives the lead of *y* over *x* at frequency ω. There is close relationship between the concept of the phase of two time series and the business cycle research of isolating leading, coincident and lagging indicators. Furthermore, the concept of phase is closely connected to the concept of Wiener-Granger causality (Granger, 1980; Granger, 1988).

It is common that the cross-spectrum shows no regularities. This is because there is not enough information in the original signals to obtain a well-behaved curve. Using a longer series does nothing to help this problem. The answer is to use smoothing and filtering procedures. Filters are normally applied on the input signals. They are used for two general purposes: separation and restoration. Signal separation is needed when a signal has been contaminated with noise. Signal restoration is used when a signal has been distorted in some way. An example of this problem can be observed in Lucas (1972), where rational agents solve the signal separation and restoration problem in order to react optimally to an observed price change, where it is unknown whether the price change reflects the change in general price level or the change in real demand on the individual market.

Although the spectral density diagram is an asymptotically unbiased estimate of the spectrum, it is not consistent. A whole set of literature has been developed on smoothing methods for the spectral density function, which are referred to as spectral windows. Care, however, must be exercised not to introduce a cyclical peak solely due to smoothing technique.

When analyzing economic variables, it is a common problem to have short and particularly volatile time series. To check whether the spectrum of individual variables is stable (for cross-spectrum we use Welch estimation procedure which belongs to nonparametric methods), we introduce subspace methods, also known as super-resolution methods. They generate frequency component estimates for a signal based on eigenanalysis or eigendecomposition of the correlation matrix. These methods are best suited for short signals and effective in the detection of sinusoids buried in noise, especially when the signal-to-noise ratios are low. In our example, we selected the multiple signal classification method (MUSIC), which is normally used in digital signal processing. To additionally confirm the results obtained by estimation of coherence and phase, we will also use Granger causality test.

3. The Data

The monthly indices of industrial production were obtained from the Bank of Slovenia (2001), European Central Bank (2001), Deutsche Bundesbank (2001), and the Economic Institute of Zagreb (2001). Data cover the time-span from January 1991 to September 2001.

Almost each time series includes the impact of seasons in its movement. The use of such original monthly series can bring us to absolutely wrong conclusions about further development of the observed phenomenon. It is therefore reasonable to employ special procedures in order to separate the seasonal component from the other components. Of course, it is desired as well as necessary that the series does not lose its characteristics in this process. A well-known example of the use of the method of moving averages is the Method II – version X11 from 1968. The main weakness of this method (as well as all other traditional procedures) lies in neglecting the fact that the seasonal component is stochastic in character and that it is related to other components. It is thus better to use seasonal models ARIMA (Bundesbank, 1999). Despite the fact that numerous programmes, which enable the use of the mentioned methods, have been developed, we use the X11ARIMA programme (Statistics Canada, 1999) in the empirical part of our research.

Table 1.

Results of the Stationarity Test for Industrial Production

Coefficient:	$(\rho-1)$	Λ	α	*ADF*
SLOSA	–0.102138 (–1.705967)	–0.486705 (–5.624749)	9.945391 (1.726474)	–1.705967
SLOSAHP	–0.680244 (–5.744431)	–0.205232 (–2.227017)	–0.122836 (–0.405501)	–5.744431
CROSA	–0.125676 (–2.080821)	–0.398333 (–4.379440)	13.54788 (2.090006)	–2.080821
CROSAHP	–0.622601 (–5.256318)	–0.157049 (–1.612279)	–0.001295 (–0.003852)	–5.256318
GERSA	0.014685 (0.420257)	–0.521215 (–5.881761)	–1.263067 (–0.378521)	0.420257
GERHP	–0.375271 (–4.174619)	–0.364768 (–4.138464)	–0.061358 (–0.415437)	–4.174619

Critical values by MacKinnon (N = 106):
–3,4928 at 1% significance level;
–2,8887 at 5% significance level;
–2,5811 at 10% significance level.

Note:
Each field contains, first, the value of coefficient and then, t-statistics.
SLOSA Industrial production (Slovenia) – de-seasoned data.
SLOSAHP Industrial production (Slovenia) – de-seasoned data and HP trend removed.
CROSA П Industrial production (Croatia) – de-seasoned data.
CROSAHP Industrial production (Croatia) – de-seasoned data and HP trend removed.
GERSA Industrial production (Germany) – de-seasoned data.
GERSAHP Industrial production (Germany) – de-seasoned data and HP trend removed.

Stationarity of time series is a common phenomenon, especially in periods with stable conditions. Nonstationary time series may have the «typical spectral shape» of Granger (1966), which makes impossible to detect business cycle frequencies. Differentiation of time series can eliminate the presence of nonstationarity, but it also has its drawbacks (Charemza and Deadman, 1992). Differentiation does also affect the long-term relationships among economic variables.

The testing of stationarity was done in two steps. As the first step, we tested the original series. The second step was to remove the trend. The testing of de-seasoned data showed that the series are not stationary if the model does not include the trend. With the inclusion of trend, the series become stationary. This is why the observed series need to be remodeled in the consequent testing. As the use of different forms of differentiation may bring negative influence on the results of further testing, we decided to eliminate the long-term linear trend by using the Hodrick-Prescott filter ($\lambda = 14400$, suggested value for monthly data).

The discussion in Canova (1998) and Burnside (1998) makes clear that different detrending methods emphasize different frequency ranges in the data, and that many stylized facts are sensitive to the choice of the detrending method. As we apply the same procedure on all series, it seems that in our application this method gives good results.

4. Results and Concluding Remarks

A major impression from recent studies (Bergman, Bordo, Jonung 1998) of contemporaneous correlations of output for developed countries is that the correlations tend to increase over time. Most of the significant correlations are reported from the post-Bretton Woods period. The cyclical comovements for real GDP across countries suggest growing international linkages over time. Some authors have researched changes over time in correlation patterns. Angeloni and Dedola (1998) find that GDP correlations between Germany and other EU countries were much higher in 1993–97 than 1986–92. As noted by Clark and Shin (2000); Imbs (1998); and Krugman (1993), among others, greater similarity in production structures is likely to increase business cycle correlations. Industry-specific shocks will create more comovement among regions with similar production structures than among regions with dissimilar structures. Industry structures of transition economies are increasingly adapting to the structures of the developed economies. Slovenia and Croatia are the outliners among them in this process of synchronization.

Virtually all economies experience recurrent fluctuations in economic activity, which persist from several quarters to several years. There is a definite tendency for the business cycles of the developed countries to move together. In our research, we try to find out whether Slovenia and Croatia correspond to this trend.

In our analysis we employed the monthly industrial production index (1999 = 100) under the assumption that the selected series represent the economic activity. Such a choice provided us with a sufficient number of observations for empirical testing. Since time series have to be stationary and must not include the trend, the long-term trend was subtracted from the original time series.

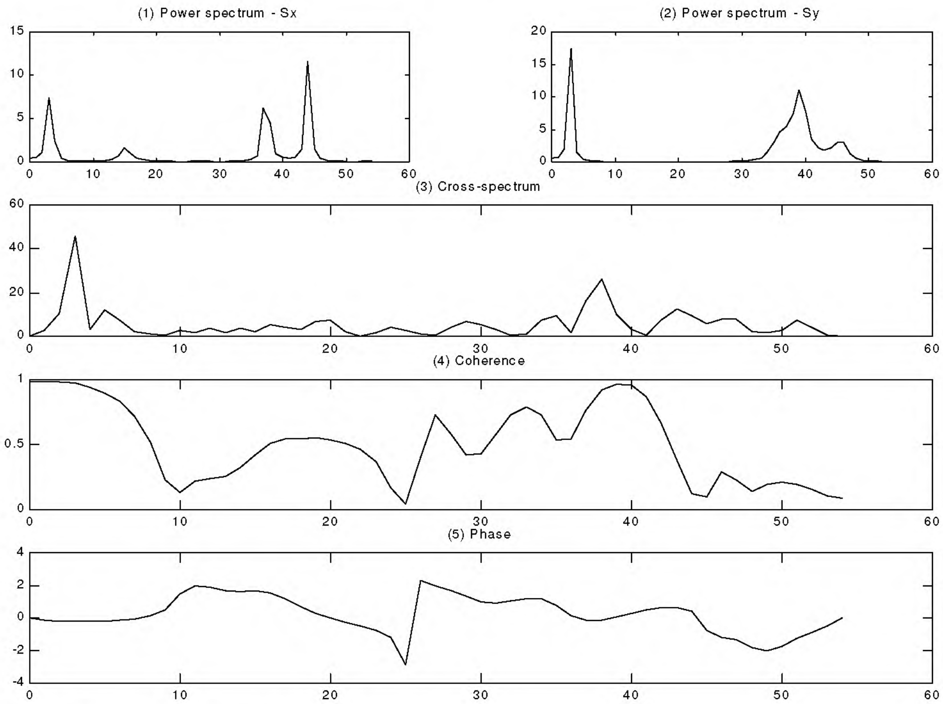
The results of testing data for Slovenia are presented in Figure 1. The first graph presents spectral density diagram for index of industrial production in Slovenia (1999 = 100). We find one spectral peak at the frequency of 36 months. The spectrum of industrial production has also two additional peaks at higher frequencies, which can be attributed to the strong stochastic component of the selected time series. In the second graph the spectral density diagram for German industrial production is presented. We find again one spectral peak with the same frequency, but the peak diverges stronger. As in the case of Slovenia, additional spectral peak can be found at the frequency range, which is typical for the stochastic component. In this way, the first hypothesis for Slovenia is confirmed - the frequency of the cyclical component corresponds to the length of typical business cycle proposed by Mitchell and Burns and is significant for both countries.

By using the spectral analysis, we were able to estimate the length of the business cycle in Slovene economy in the years from 1991 to 2001. Following the results from our analysis, we can conclude that first years of Slovenian transition were marked by typical transformational depression. This is not surprising, since Slovenian economy was hit by a series of market losses: the collapse of 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. The production was pushed down rapidly to a decline of 9.3 percent in 1991 and 6.0 percent in 1992.

Our analyses determine June 1993 as a through and as a start of the new cycle (we used inverse real discrete Fourier transformation). This was confirmed by Mencinger (1995), who also found that in the middle of 1993 Slovenia suddenly reached the bottom of the depression. The revival that followed can be explained by an increase in aggregate demand, whereby a moderate growth of foreign demand coincided with fast growth of domestic demand. The peak was reached in January 1995. The turnaround could be attributed to the Dutch disease and the debt crisis in Slovene economy. The peak was also preannounced by Surveys on Business Trends published by the Statistical office of the Republic of Slovenia (1994), which reported on continued worsening of export demand since October 1994 (the diffuse index was steadily growing from 34 percent in October to 43 percent in December).

Figure 1.

Results of Cross-Spectral Analysis (Slovenia – Germany)



Note: *X*-axes contain frequency values.

The end of the first cycle was reached in June 1996. After reaching a through, economic developments improved in the second part of the year mainly due to economic recovery in Europe and contributed to growth of export competitiveness. According to the Institute of Macroeconomic Analysis and Development (1997), export competitiveness (measured in terms of unit labour costs in the basket of currencies) improved in 1996 by 7.3 percent after the market drop of 11.9 percent in 1995. Competitiveness improved as a consequence of increased productivity, lower tax burden on wages, and real deprecation of the Tolar.

Acceleration in the rate of growth of the world economy as a whole, and the European Union in particular, allowed Slovene economy to extend growth into 1997. Improved economic performance of the main economic partners was the primary factor enabling exports to rise in 1997 without an increase in export competitiveness. That year social partners reached timely consensus on wages. This allowed to adopt adequate income policy mechanisms, which succeeded in keeping growth in wages behind growth in labour productivity.

The slowdown in economic and export market growth of the most important trade partners during the last quarters of 1997 and 1998 held back the growth in Slovenian exports and (with some lag) economic activity as well. An extremely high value of export multiplier for the Slovene economy (0.6) explains high degree of sensitivity of Slovene macroeconomic activity to changes in export growth. The deceleration of cycle in 1998 was therefore not a surprise, since the contagion effects of the Asian crisis spread over to Europe.

The cross-spectral density diagram (third graph in Figure 1) confirms the hypothesis about the relationship between the cyclical component of industrial production in Slovenia and Germany. The spectral peak is again at frequency of 36 months. The peak is statistically significant, which is confirmed by the maximum value of coherency at the selected frequency (statistically significant values of coherency are all values over 0.5) (see fourth graph in Figure 1).

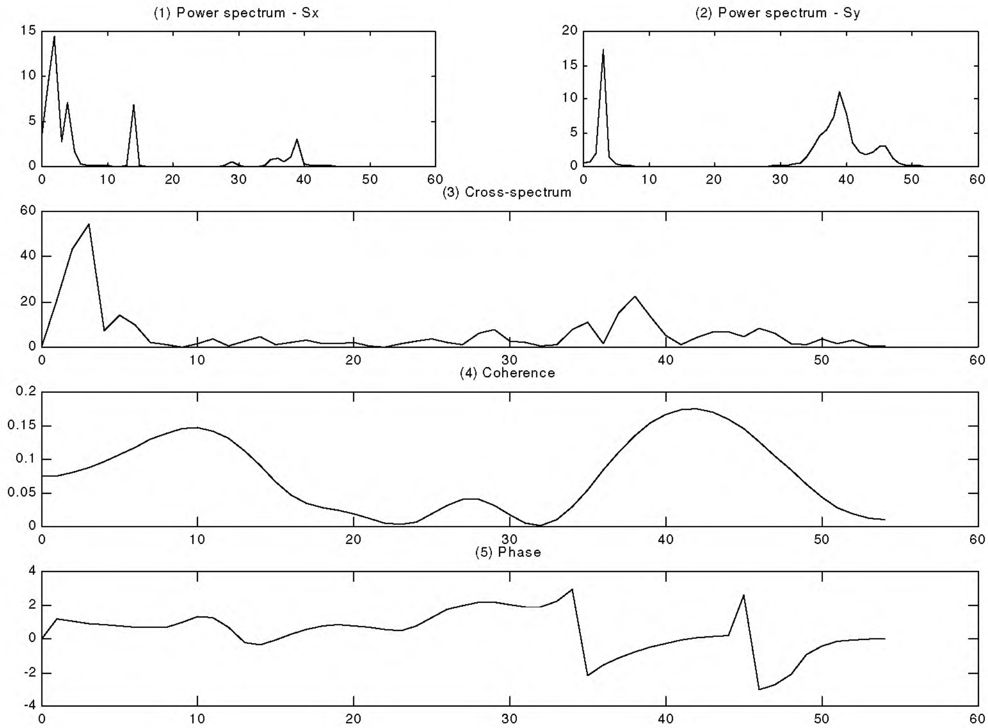
The fifth graph shows the time lag in the oscillations of cyclical components of Slovenia and Germany. At the significance frequency of 36 months, the Slovenian cyclical component lags with an average lag-time of 1.2 months. The time lag between cyclical components is short, so our results seem to provide strong support to our second hypothesis.

The results of testing the data for Croatia are presented in Figure 2. Spectral density diagram for the industrial production index in Croatia (1999 = 100) suggest that there are two significant spectral peaks at the frequencies of 54 and 27 months. The spectrum of industrial production has also additional peaks at higher frequencies, which can be attributed to the strong seasonal and stochastic components of the selected time series. These results seem to confirm the presumption, that the Croatian business cycle is heavily influenced by tourism activity. In the second graph the spectral density diagram for German industrial production is presented. We can isolate one spectral peak with the frequency of 36 months. Therefore, the first hypothesis for Croatia can be confirmed only partially – there are two strong cyclical components, which correspond to the length of the typical business cycle proposed by Mitchell and Burns, but the length is not the same as in the case of Germany.

The cross-spectral density diagram (third graph in Figure 2) confirms that there is no strong relationship between business cycles in Croatia and Germany. The spectral peak is at frequency of 36 months, but it is not statistically significant, which is confirmed by the low value of coherency (less than 0.5) at the selected frequency (fourth graph in Figure 2).

Figure 2.

Results of Cross-Spectral Analysis (Croatia – Germany)



The fifth graph shows the time lag between the oscillations of cyclical components of Croatia and Germany. As there is no significant frequency, it is not worth to determine the lead/lag relationship. The results only suggest that the Croatian economic activity lags behind the German at all business cycle frequencies. Blanchard and Watson (1986) draw attention to large shocks, which contribute to macroeconomic instability along with the small ones. Large shocks presumptively occur at irregular intervals – war is a typical case. Such events and their direct and indirect effects are likely to increase the diversification and irregularity of the business cycle over time.

The initial conditions for transition were considerably different in Croatia as compared to other former socialist countries. Unlike the case of Slovenia, the most disadvantageous characteristic imposed on economic growth in the independent Croatia was the war. Economic events in Croatia in the early 90's resembled a typical agenda of transformational depression: contraction of output surpassing stabilization expectations, drop in employment and living standard, high inflation. Accumulated fiscal problems, fast liberalization of trade and prices, dramatic reduction of trade with former Yugoslav republics resulted in 1993 in one of the highest levels of inflation in transition economies (1149.7%), and serious cumulative downfall of output (37%) in 1989–1993. Economic recovery started in 1994, with the lag of one year behind Slovenia. The economic damages inflicted on Croatia by the war conditions dampened its economic activity so that the GDP and industrial production levels in 1995 equalled respectively 71.4% and 61.1% of their 1990 performance (WIIW, 1996). The unusually long through of the business cycle is undoubtedly related to these facts.

Several factors affect the degree of synchronization of business cycles in different economies. First, business cycles in small open economies that have strong trade links with major economies are likely to be more synchronized with them than it would be the case with larger, more closed economies. This fact seems to be confirmed in the case of Slovenia. High degree of synchronization with the German cycle could be attributed to the increased openness of Slovene economy since its independence and the rising share of THE EU in the Slovenian foreign trade (Table 2). We presume that lower synchronization of the Croatian cycle can be explained by the war conditions which prevailed in the early 90's and affected the Croatian economy for the rest of the 90's.

Second, the extent to which domestic demand shifts 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 the EU deepens economic integration between Slovenia and Croatia, on the one side, and the current EU members, on the other. The need to adopt a common policy stance will undoubtedly increase, so this factor is expected to contribute to the synchronization of the business cycles.

Table 2.

Regional Composition of Foreign Trade for Slovenia and Croatia (2000)

Region	Export (in % of total export)		Import (in % of total import)	
	Slovenia	Croatia	Slovenia	Croatia
THE EU (15)	66.11	54.51	67.74	55.59
Germany	30.73	14.25	19.88	16.37
Italy	13.76	22.31	16.60	17.01
France	5.74	2.47	10.84	5.03
Austria	7.28	6.61	7.93	6.67
CEFTA	7.27	13.80	8.37	14.77

Sources: Bank of Slovenia (2001); the Institute of Economics, Zagreb, (2001).

Third, the shift to floating exchange rate regime facilitated de-synchronization considerably. Fixed rates or single currency is, therefore, a factor of synchronization. The exchange rate systems and movements in the following years in Slovenia and Croatia will function as a mechanism of adjustment to the EU and the EMU. Thus, we may expect synchronization with the German and the EU cycles from this point of view as well. Such trends would be in line with the current trends in Europe, where the ERM membership has promoted a shift in the business cycles' affiliation to that of the anchor country.

The conclusions made in this paper are based on the results of empirical testing. As mentioned earlier, we adopted the multivariate spectral analysis in our example. These types of tools work best when analysing long series of high-frequency data in stable regimes. In our case, the data can cover only the period from 1990. Since in 1990 the former Yugoslavia broke apart, this year could not be included in the sample. On the other hand, the results seem to be very stable. We tested the single spectrum for each time-series with two different methods: the non-parametric Welch method, and the Multiple Signal Classification (MUSIC) method which belongs to parametric methods. All these procedures produced similar results (results are available upon request).

To additionally support the results obtained with multivariate spectral analysis, we also employed the Granger causality test. The results are presented in Table 3. According to lag selection criteria presented in Table 3, the economic activity in Slovenia lags behind the German economic activity for 1 month. Additional significant lags were discovered, however, the value of *F*-statistics is significantly lower. Granger causality test also supports the results for Croatia. We could not find any significant connection between economic activity in Croatia and Germany.

An important assumption of the applied method is time-invariance. The data come from economies in transition, where economic structures are being changed. When more data are available, it seems useful to proceed our testing with procedures used by Sargent and Cogley (2001), where they use Bayesian methods to estimate vector autoregressions with drifting parameters and impute drift in spectral densities from the VAR estimates. The application of such methods would enable us to analyse how the coherence across selected countries has changed in the observed period.

Table 3.

Granger Causality Test for the Period of 1991–2001.

Null Hypothesis:	Lags					
	1	2	3	4	5	6
SLO does not Granger Cause GER	1.38727 (0.24190)	1.18045 (0.31190)	0.67938 (0.56703)	0.54216 (0.70519)	0.43592 (0.82222)	0.61354 (0.71878)
GER does not Granger Cause SLO	8.32234 (0.00488)	2.11344 (0.12685)	1.33921 (0.26700)	2.17244 (0.07917)	2.73332 (0.02484)	2.55124 (0.02630)
CRO does not Granger Cause GER	0.01715 (0.89611)	0.61365 (0.54365)	0.85827 (0.46603)	1.56926 (0.19015)	1.40618 (0.23099)	1.22004 (0.30527)
GER does not Granger Cause CRO	1.98100 (0.16265)	1.36546 (0.26056)	1.54365 (0.20905)	1.53074 (0.20080)	1.78101 (0.12616)	1.50703 (0.18707)
	7	8	9	10	11	12
SLO does not Granger Cause GER	0.80490 (0.58587)	1.14268 (0.34614)	0.92287 (0.51107)	0.97720 (0.47179)	0.87371 (0.56988)	0.77864 (0.66963)
GER does not Granger Cause SLO	4.60091 (0.00026)	3.84072 (0.00084)	4.15609 (0.00027)	3.34080 (0.00148)	2.70915 (0.00646)	2.20308 (0.02301)
CRO does not Granger Cause GER	1.01854 (0.42547)	0.87960 (0.53797)	0.69059 (0.71492)	0.59668 (0.81085)	0.50827 (0.89061)	0.41309 (0.95267)
GER does not Granger Cause CRO	1.78001 (0.10404)	1.66300 (0.12274)	1.60219 (0.13221)	1.13168 (0.35309)	1.22044 (0.29297)	1.11893 (0.36278)

Note: Each field contains, first, the value of *F*-statistics and then, the significance level.
SLO Industrial production – Slovenia.
CRO Industrial production – Croatia.
GER Industrial production – Germany.

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