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LEADING INDICATORS OF AGGREGATE ECONOMIC ACTIVITY OF SLOVENIA[1]

Key words: leading indicator, business cycle, Granger causality, spectral analysis

ABSTRACT

The report presents the development of the first composite and diffuse index of leading indicators (CLI, DLI) for Slovene economy. To construct a forecasting model it is necessary to select an indicator of economic activity, as well as a group of variables that, when adjusted construct the CLI and DLI that forecast the reference series. We are developing a model, where NBER method is modified with elements of Stock-Watson approach. Current results suggest, that in the period from 1992 to 2002, CLI and DLI forecasted all turning points of aggregate economic activity. The average lead-time is 8 months, which is comparable with the performance of leading indicators in other countries. There are, however, numerous structural changes going on in Slovenia and such composite leading indicator should be closely followed and re-estimated as more data becomes available in order to capture ongoing changes in transition process.

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1. INTRODUCTION

Business cycle indicators convert complex economic dynamics into one-dimensional figures that are easily tractable. Although the indicators are effective in the ex-post description of the cycles, the main strength of the indicators lies in the forecasting.

Construction of business cycle indicators has become a common practice. The system of leading, coincident and lagging economic indicators developed in the proceeding research project was developed in 1930s by the National Bureau of Economic Research (NBER). For recent advances in the field of leading indicators one can consult Lahiri and Moore (1991), Zanrnowitz (1992) and Stock and Watson (1993).

A system of leading indicators is an indispensable tool for a macroeconomic research; it complements macroeconomic policy analysis using large-scale models, which by their nature cannot be adapted to new information quickly. Since Slovenia has passed a period of disintegration of Yugoslavia and the radical reform following that period, it is time to construct a system of business cycle indicators. The need for the system is present despite the fact that the available data cover a short time span and are dominated by impacts of the market economic reform. Especially in the economies of transition economic policy makers are interested in the short-run consequences of their actions. That is why a system of leading indicators is a perfect tool. It provides a rapid information about the consequences of the economic policy decisions.

The remainder of the chapter is organized as follows: in section 2, we describe some methodological aspects. In section 3 we show how to measure economic activity and perform analysis of cyclical movements of economic activity in Slovenia. Section 4 is devoted to the description of the database. Then we present the construction of the model. In the last part we discuss results and comment on the fundamental findings.

2. METHODOLOGICAL ASPECTS

The construction of composite (CLI) and diffuse (DLI) index of leading indicators has long tradition, starting with the work of Moore and Shishkin in 1967. The main purpose of this approach is to address a problem that is particularly serious in developing countries. Economic time series, in particular real gross domestic product (GDP), are reported with important time lags. In addition, the series are revised frequently to incorporate new information. This leaves policy makers and investors without objective measures of the current situation and direction of economic activity.

The two most commonly used methodologies to construct leading indicators are NBER and Stock-Watson (1989) (SW) approach. The former is based on the work by Moore and Shishkin (1967), while the latter adds an econometric foundation to the NBER approach. Both of them rely on an abstract concept of economic activity, which is referred as “the state of the economy”. The state of the economy is an unobservable variable that must be estimated out of several available series. The estimate of the unobservable state of economy is called a composite index of coincident indicators, and is a measure of economic activity used by these approaches. Leading indicators aim to forecast the behavior of this composite index of coincident indicators.

NBER and SW methodologies differ in the strategies used to construct the CLI and DLI. The selection of individual candidate series in the NBER approach is based on a scoring system, which weights in an arbitrary manner certain desirable characteristics that time series should have. This is done by assigning each characteristic a maximum possible score. The candidate series are then scored according to how close they are to possessing each characteristic and the final score is taken as an orientation of which variables to select. It is acknowledged though the series selected are not always those with a higher score; this is to allow informal judgment in the selection process. Composite index is obtained by taking weighted averages of chosen series.

SW approach however, uses time series econometric concepts, like regression analysis and Granger Causality, for the selection process. Composite index is again weighted average of selected series but the weights are estimated using econometric techniques.

In the case of Slovenia, there are some important limitations to be considered:

- Time-series can cover only the period of nine years.
- Slovenia has faced a deep transformation depression. In the process of restructuring its economy wild swings in time-series occur, which may have a significant impact on chosen indicators.
- In the observed period, Slovene economy is in the process of transforming from former semi command socialist economy to market oriented economy. The former regional market has changed to the state market. The ownership structure is changing rapidly and hence it may have important impact on changed behavior of investment and consumption.

Due to these facts, we are not able to fully adopt NBER approach. On the other hand, short and extremely volatile time-series are not enough to solely relay on econometric SW approach. Therefore we decided to modify NBER methodology by using econometric techniques, which are used in SW method. With this methodology, the composite index of leading indicators will be constructed, which should from an econometric standpoint, produce satisfactory forecast of aggregate economic activity. From an economic standpoint, the series that are used in composite index, should also be broadly consistent with what many economists believe is the main source of fluctuations in Slovenia.

3. MEASURING CURRENT ECONOMIC ACTIVITY

Measuring current economic activity demands that the researcher addresses some crucial issues:

- definition of current economic activity;
- business cycles properties of aggregate economic activity;
- turning points of economic activity;
- main sources of fluctuations.

The reference variable is the benchmark that indicates fluctuations in the economic activity, and is the variable to be forecast. The variable must have the advantage of being a monthly reported variable, available for many countries, and measures the real sector of the economy. Real GDP is directly considered to be the relevant measure of economic activity for two reasons. The first is that it is the most commonly discussed measure of economic activity in practice and in the literature. The second is that in papers that use the SW methodology (Dias 1994), a common practice is to compare the estimated coincident indicator with real GDP to evaluate, if it accurately describes economic activity. On the other hand, GDP is not published on monthly bases and is often revised. What is more, the aim of this research was not to construct a perfect composite coincident indicator, but to construct composite leading indicator.

3.1 Definition of Current Economic Activity

There are two alternative strategies for obtaining a time series that represents current business activity on a monthly level: 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.

There are two main reasons why should one adopt the second of these two approaches. First, all aggregate time series are measured with error and this measurement error is arguably more important at the monthly level than at longer sampling intervals. For example, Miron and Zeldes (1987) describe the difficulty of reconciling industrial production with another measure of production derived from the monthly statistics on inventories and sales. If measurement error is imperfectly correlated across series, then using average of several series can in principle reduce this source of inaccuracy. Second, the business cycle is generally viewed as reflecting common movements in multiple series, not just movements in a single measure of output (Burns and Mitchell 1946, Lucas 1977).

The construction of leading economic indicators however, demands a monthly and up-to-date series. Another important issue is the fact, that in Slovenia time series cannot be longer then nine years, since Slovenia got independence in October 1991. This makes it difficult to determine, whether the selected time series has the characteristics of coincident indicator. In order to check industrial production as a single monthly series that describes economic activity, we decide to test following hypothesis:

H: The industrial production should posses the same cyclical characteristics as gross domestic product (GDP).

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). It 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 multivariate spectral analysis to study the relationship between industrial production and current business activity. The selected method is used to estimate the strength of wavelength relationship between economic indicators.

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 the economic indicators must be stationary. Let $\{y_t\}_{t=-\infty}^{\infty}$ be a 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[2] $\{\Gamma_\tau\}_{\tau=-\infty}^{\infty}$ is absolutely sumable and if z is complex scalar[3], the matrix autocovariance generating function[4] of y_t is given by:

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

where Fy(z) is (n×n)-dimensional matrix of complex numbers.

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

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

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[2] Consider the case, where n=2, and $y' = \begin{bmatrix} y_t & x_t \end{bmatrix}$. The cross covariance between the two covariance stationary stochastic processes $\{y_t\}_{t=-\infty}^{\infty}$ and $\{x_t\}_{t=-\infty}^{\infty}$ is defined as $\gamma_{yx}(\tau) \equiv E\left[(y_t - Ey_t)(x_{t-\tau} - Ex_t)\right]$, or written out fully

$$\Gamma_y(\tau) = E\begin{bmatrix} (y_t - \mu_y)(y_{t-\tau} - \mu_y) & (y_t - \mu_y)(x_{t-\tau} - \mu_x) \\ (x_t - \mu_x)(y_{t-\tau} - \mu_y) & (x_t - \mu_x)(x_{t-\tau} - \mu_x) \end{bmatrix}$$

$$= \begin{bmatrix} \gamma_{yy} & \gamma_y \\ \gamma_y & \gamma_{xx} \end{bmatrix}$$

[3] Of particular interest as an argument for the autocovariance generating function is any value of *z* that lies on the complex unit circle, using de Moivre's theorem

$$z = \cos(\omega) - i\sin(\omega) = e^{-i\omega}$$

where ω is the radian angle that *z* makes with the real axis.

[4] A generating function is a way of recording the information of some sequence. Consider the sequence $a_0, a_1, a_2, \ldots$ of possibly infinite length, then the generating function is defined as

$$a(z) = \sum_{j=0}^{\infty} a_j z^j$$

The quantity *z* does not necessarily have any interpretation and may be considered as the carrier of information in the sequence. The concept of generating function is useful because it can be manipulated in simpler ways than the whole sequence a_j.

where $S_y(\omega)$ is an (n×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 n=2, where $\{y_t\}_{t=-\infty}^{\infty}$ and $\{x_t\}_{t=-\infty}^{\infty}$ are two jointly stationary stochastic processes with continuous power spectra, then the multivariate spectrum is given by:

$$y = [y_t \quad x_t]$$

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

By using trigonometric rules and Euler's relations, the multivariate spectra for n=2 can be formulated as:

$$S_y = \frac{1}{2\pi}\begin{bmatrix} \sum_{\tau=-\infty}^{\infty}\gamma_{yy}(\tau)\cos(\omega\tau) & \sum_{\tau=-\infty}^{\infty}\gamma_{yx}(\tau)\{\cos(\omega\tau) - i\sin(\omega\tau)\} \\ \sum_{\tau=-\infty}^{\infty}\gamma_{xy}(\tau)\{\cos(\omega\tau) - i\sin(\omega\tau)\} & \sum_{\tau=-\infty}^{\infty}\gamma_{xx}(\tau)\cos(\omega\tau) \end{bmatrix} \tag{5}$$

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

$$\begin{aligned} S_{yx}(\omega) &= co_{xy}(\omega) + i\, qu_{yx}(\omega) \\ co_{yx}(\omega) &= \frac{1}{2\pi}\sum_{\tau=-\infty}^{\infty}\gamma_{yx}(\tau)\cos(\omega\tau) \\ qu_{yx}(\omega) &= \frac{1}{2\pi}\sum_{\tau=-\infty}^{\infty}\gamma_{yx}(\tau)\sin(\omega\tau) \end{aligned} \tag{6}$$

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 phase 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 a high correlation between 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):

$$Coh(\omega) = \frac{\left|S_{yx}(\omega)\right|^2}{S_{yy}(\omega)S_{xx}(\omega)} \qquad ,0 \le Coh(\omega) \le 1$$

$$Ph(\omega) = \operatorname{atan}\left(\frac{qu(\omega)}{co(\omega)}\right) \qquad ,lead/lag = \frac{Ph(\omega)}{\omega} \tag{7}$$

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 seen in Lucas (1972), where rational agents solve a signal separation and restoration problem in order to react optimally to an observed price change where it is unknown whether the price change reflects a change in the general price level or 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 the smoothing technique.

Results

In our analysis we employed the monthly index of industrial production (1992=100) and monthly index of GDP (1992=100) under the assumption, that the latter represents the current business activity. Such a choice enabled us 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 original time series.

The cross-spectral density diagram confirms hypothesis of relationship between cyclical component of GDP and cyclical component of industrial production. There is only one spectral peak, which is in the range of business cycle frequencies. The peak is statistically significant, which is confirmed with the maximum value of coherency at the selected frequency (second graph in Figure 1).

FIGURE 1: CROSS-SPECTRAL ANALYSIS (GDP, INDUSTRIAL PRODUCTION)

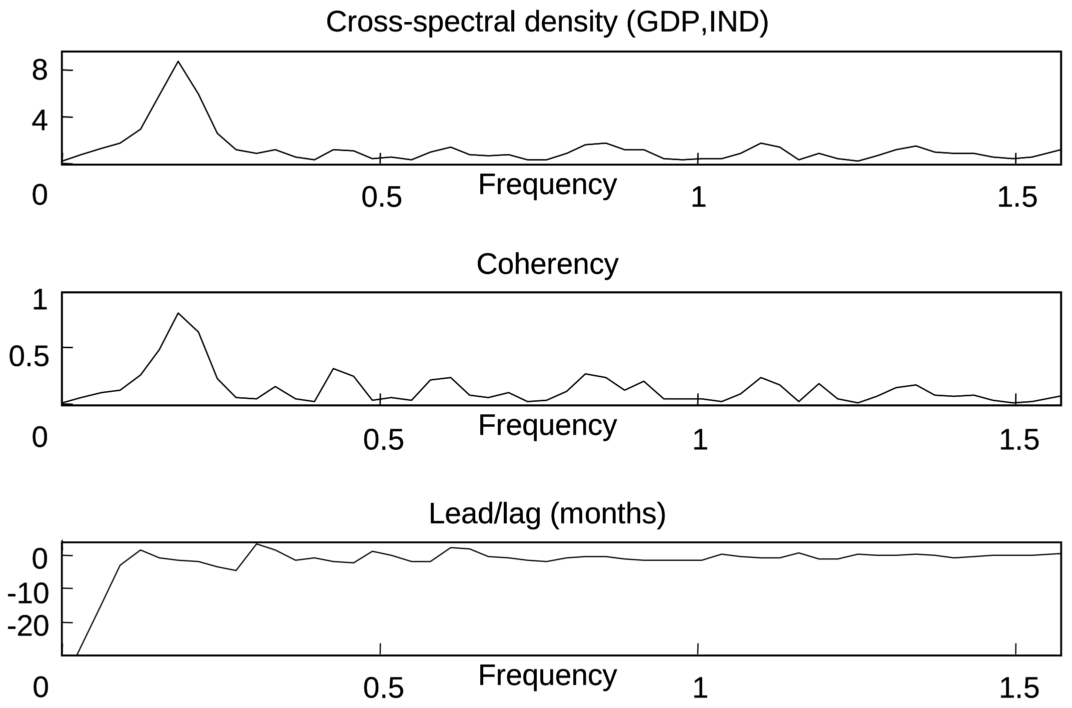


TABLE 1: GROSS DOMESTIC PRODUCT (STRUCTURE IN VALUE ADDED IN %)

	95	96	97	98	99	00	01	02	03
							Estimate		
Agriculture, forestry, fishing (A+B)	4.6	4.5	4.3	4.2	3.7	3.3	3.3	3.2	3.1
Industry and construction (C+D+E+F)	38.5	28.5	38.2	38.5	38.3	38.3	37.5	37.0	36.5
Industry (C+D+E)	33.4	32.8	32.5	32.8	32.0	32.1	31.6	31.2	30.8
Construction (F)	5.1	5.7	5.7	5.7	6.3	6.2	5.9	5.8	5.7
Services (G…O)	59.2	59.5	59.8	59.7	60.3	60.6	61.4	62.0	62.4

Source: Spring report, UMAR (2001, 114-115)

The third graph shows the time lag between oscillations of cyclical components of GDP and industrial production. At the significant frequency of 34.3 months, the GDP leads with an average lead-time of 1.6 months. The time lag between industrial production and GDP is small, so our results seem to provide strong support to our hypothesis.

Due to the results of our empirical testing and confirmations of hypothesis, we may conclude, that the index of industrial production in Slovenia seems to be a good coincident indicator of current business activity.

3.2 Business Cycles Properties of Aggregate Economic Activity

A stylized fact for virtually all reforming ex-socialist economies is the deep output contraction in the early years of transformation. Within a period of three years, from 1989 to 1992, gross domestic product in Slovenia fell by 19%. The turnaround to positive real growth was achieved in the second half of the year 1993. In the course of 90's a process of stabilization continued and allowed Slovenia to make substantial progress towards stabilizing and transforming the economy. With spectral analysis however, we want to research if the transition in Slovenia was marked by statistically significant movement of aggregate economic activity which corresponds to the definition of business cycle proposed by Mitchell and Burns (1946).

3.2.1 Analytical Framework

The first true definition of business cycles was given by Mittchell and Burns (1946). The definition captures some important characteristics about business cycles:

- Business cycles are fluctuations in the economic activity of marked oriented economies and sectors.
- Business cycles are characterized by a high covariation between a large number of macroeconomic time series, and are not measured by a single series.
- Business cycles have recurrent but not strictly periodic phases (expansion, recession, contraction, recovery).
- Business cycles are limited to cycles with period, which varies from more than 1 to 12 years.
- Business cycles cannot be reduced to a combination of shorter cycles.

The dynamic or cyclical pattern of an economic time series is summarized by the autocovariance function or autocorrelation function, which contains all the information about the time dependence of individual observations in the time series. Analysis of the autocovariance forms the basis for the analysis of the cyclical properties in time and frequency domain.

A generating function is a way of recording the information of some sequence. Let a_0, a_1, a_2, … be a sequence of infinite length, then the generating function is defined by:

$$a(z) = \sum_{j=0}^{\infty} a_j z^j \tag{8}$$

The term z does not necessarily have any interpretation. It may be considered as the carrier of information in the sequence. The concept of generating function is useful because it can be manipulated in simpler ways then whole sequence a_j. It is seen that the polynomial in the lag operator is a generating function with z=L.

Let $\{y_t\}_{t=-\infty}^{\infty}$ be a real-valued stochastic process with variance equal to γ_0 and the τ'th autocovariance equal to γ_τ. Let $\{\gamma_\tau\}_{\tau=-\infty}^{\infty}$ be the sequence of autocovariances. If the sequence of autocovariances is absolutely summable, then the autocovariance generating function is given by:

$$g_y(z) \equiv \sum_{\tau=-\infty}^{\infty} \gamma_\tau z^\tau \tag{9}$$

where term z is complex scalar. It is seen that replacing z with the lag operator, the sequence of autocovariances can be formulated as:

$$\{\gamma_\tau\}_{\tau=-\infty}^{\infty} = \sum_{\tau=-\infty}^{\infty} \gamma_0 L^\tau \tag{10}$$

Of particular interest as an argument for the autocovariance generating function is any value of z that lies on the complex unit circle, using de Moivre's theorem:

$$z = \cos(\omega) - i\sin(\omega) = e^{-i\omega} \tag{11}$$

where ω is the radian angle that z makes with the real axis. The period of a cycle is the minimum number of periods between two reference points of the cycle and can be determined by:

$$period = \frac{2\pi}{\omega} \tag{12}$$

The highest frequency about which we have direct information is π. This is known as the Nyquist frequency. With monthly data, we cannot detect cycles with a higher frequency than two months. This is related to the problem of time aggregation or sampling. The process of converting a continuous time signal to a discrete time sequence of numbers such as monthly industrial production is called sampling in the signal processing literature (or time aggregation). This leads to distortions of the underlying continuous time stochastic process, of which aliasing is the most serious problem (Porat 1997). If actual time series contains cycles at higher frequency than monthly, then these will be imputed to cycles with frequency between zero and π. This is known as aliasing.

Let us now introduce the spectral representation theorem (Cramer's representation), which says that any covariance-stationary stochastic process can be given an alternative representation in terms of infinite weighted sum of orthogonal functions:

$$y_t = \mu + \int_0^\pi \alpha(\omega)\cos(\omega t)d\omega + \int_0^\pi \delta(\omega)\sin(\omega t)d\omega \tag{13}$$

If we replace the term z in the autocovariance function, which was defined above, with the value $e^{-i\omega}$ and divide by 2π, the resulting function of ω is called the population spectrum of yt for $-\pi < \omega < \pi$:

$$S_y(\omega) = \frac{1}{2\pi} g_y(e^{-i\omega}) = \frac{1}{2\pi}\sum_{\tau=-\infty}^{\infty} \gamma_\tau e^{-i\omega\tau} = \frac{1}{2\pi}\left(\gamma_0 + 2\sum_{\tau=1}^{\infty}\gamma_\tau \cos(\omega\tau)\right) \tag{14}$$

Assuming that the sequence of autocovariances $\{\gamma_\tau\}_{\tau=-\infty}^{\infty}$ is absolutely summable, the spectrum exists. A peak in the spectrum of a series can be an indicator of a cyclical component in the series with almost constant period. There are some special cases, which are worth to consider (Brockwell and Davis 1996):

- If the estimated spectrum is flat without any peaks and without any clear tendency to follow a smooth curve, then the time series is close to a white noise. The white noise process $y_t = \varepsilon_t$ has variance $\gamma_0 = \sigma_\varepsilon^2$ and autocovariance $\gamma_\tau = 0\ (\tau \neq 0)$. The covariance generating function is $g_y(z) = \sigma_\varepsilon^2$ and the spectrum is constant.
- If the time series contains a clear cyclical component at some frequency, as a deterministic second order difference equation with complex roots, the spectrum has a tall, narrow peak (infinitely tall, infinitely narrow peak, having finite area). Business cycles are not periodic and no sharp peaks at any frequencies should be expected.
- A time series with an important trend component will have a strong peak at very low frequencies – typical spectral shape of Granger (1966). If the time series contains an autoregressive unit root, the peak will be infinite at zero frequency.

We can compute the spectrum of a covariance stationary stochastic process when we know the stochastic process, which has generated the time series. It was mentioned above that any covariance stationary stochastic process can be given an infinite moving average representation or Wold representation:

$$y_t = \psi(L)\varepsilon_t = \sum_{j=0}^{\infty} \psi_j L^j \varepsilon_t$$
$$\psi_0 = 1$$
$$\psi(L) = 1 + \psi_1 L^1 + \psi_2 L^2 \qquad (15)$$

The spectrum of the white noise process is:

$$S_\varepsilon(\omega) = \frac{1}{2\pi}\sigma_\varepsilon^2 \qquad (16)$$

and shows that y_t is generated by filtering the white noise process where $\psi(L)$ are filter weights. The spectrum of y_t is thus the spectrum of white noise process multiplied by the effect of the filter. This can be computed if we first formulate the model in terms of its moving average representation by using lag operator. Then substitute the lag operator with $e^{-i\omega}$ to receive the transfer or frequency response function. The square of the absolute value of the frequency response function is called the power transfer function of the filter, which is multiplied by the spectrum of the white noise process.

Another way to compute the spectrum of a time series is Fourier analysis (Priestley 1981). The fundamental idea in Fourier analysis is that any deterministic function of ω can be approximated by an infinite sum of trigonometric functions called Fourier series representation.

Let $\{y_t\}_{t=-\infty}^{\infty}$ be a sequence of real or complex numbers with $\sum_{t=-\infty}^{\infty} |y_t| < \infty$, then there exists a complex-valued function called the Fourier transform belonging to the interval $[-\pi, \pi]$, such that

$$f(\omega) = \int_{t=-\infty}^{\infty} y_t e^{-i\omega t} = \int_{t=-\infty}^{\infty} y_t (\cos(\omega t) - i \sin(\varpi t)) \tag{17}$$

The spectrum is the Fourier transform of the covariogram. If the frequencies take values in a discrete state space with T equally spaced valued in the range $[0, 2\pi]$, where T is the number of observations in the signal, so the sampling interval is $2\pi / T$, using the frequencies:

$$\omega(k) = \frac{2k\pi}{T}, \quad 0 \le k \le T - 1 \tag{18}$$

the result is the discrete Fourier transform (DFT):

$$f(\omega) = \sum_{t=0}^{T-1} y_t e^{\frac{-i2k\pi t}{T}} \tag{19}$$

Now we transform our basic notation in to rectangular form:

$$f(\omega) = \sum_{t=0}^{T-1} y_t \left(\cos\left(\frac{2\pi\omega t}{T} \right) - i \sin\left(\frac{2\pi\omega t}{T} \right) \right) \tag{20}$$

Since in further analysis we do not need all characteristics of complex discrete Fourier transform (especially the analysis of negative frequencies), we shall transform the last notation into real form. This procedure changes the conditions of the analysis.

First, the real Fourier transform converts a real time domain signal, y_t, into two real frequency domain signals, ReY(ω) and ImY(ω). By using complex substitution, the frequency domain can be represented by a single complex array, f(ω). In the complex Fourier transform, both yt and f(ω) are arrays of complex.

Second, the real Fourier transform only deals with positive frequencies. That is, the frequency domain index, ω, only runs from 0 to T/2. In comparison, the complex Fourier transform includes both positive and negative frequencies (the frequency spectrum of a discrete signal is periodic, which makes the negative frequencies between T/2 and T-1 the same as between –T/2 and 0).

Third, the real Fourier transform requires special handling of two frequency domain samples: ReY(0) an ReY(T/2), but the complex Fourier transform does not. The real Fourier transform also requires and additional scaling step: ReY(0) and ReY(T/2) must be divided by two.

There are some more differences between real and complex transformation. As these differences are not crucial for the use of selected model, we can proceed with a notation of a real forward discrete Fourier transform:

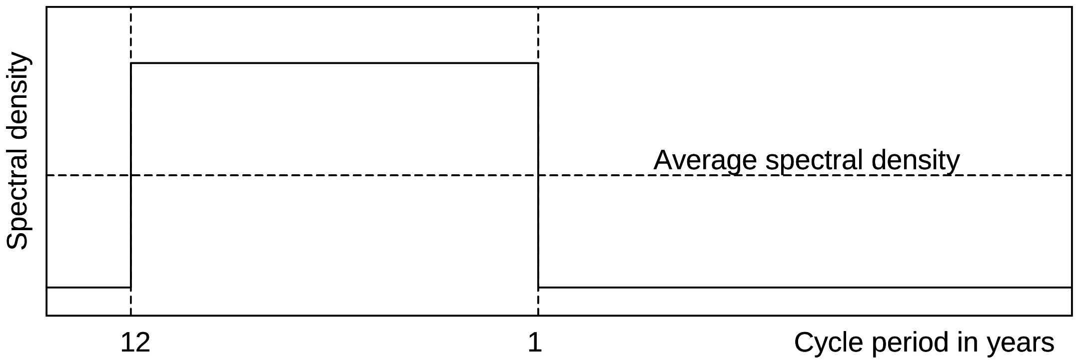
$$\operatorname{Re} Y(\omega) = \frac{2}{T}\sum_{t=0}^{T-1} y_t \cos\left(\frac{2\pi t\omega}{T}\right)$$
$$\operatorname{Im} Y(\omega) = -\frac{2}{T}\sum_{t=0}^{T-1} y_t \sin\left(\frac{2\pi\omega t}{T}\right) \tag{21}$$

Alternatively, the frequency domain can be expressed in polar form, which is necessary to form spectral density diagram. It is common that the spectral density diagram shows no regularities. This is because there is not enough information in the original signal to obtain a well-behaved curve. Using a longer DFT does nothing to help this problem, because the longer DFT provides only better frequency resolution, but the same noise level. The answer is to use smoothing and filtering procedures.

3.2.2 Results

To engage in formal econometric testing, it is necessary to define precisely what is meant by a cycle in the classical sense. Since classical writers saw business cycles as recurrent phenomena with typical frequencies, one could define the existence of a cycle as a peak in the spectrum of a time series in the specified range.

FIGURE 2: SPECTRAL DENSITY OF HYPOTHETICAL ECONOMIC TIME SERIES

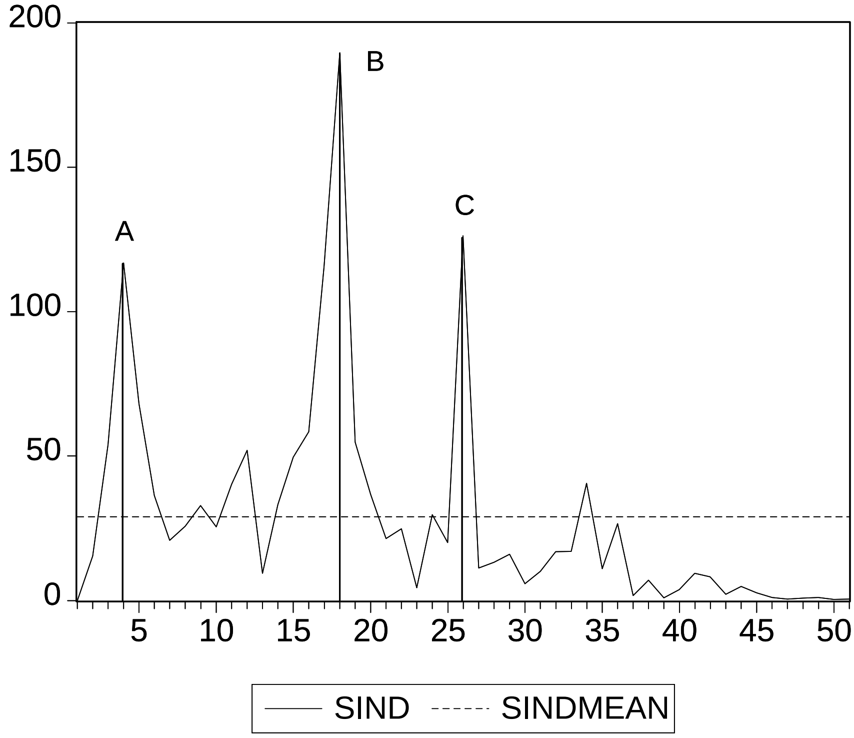


Definition: An economic time series exhibits a classical cycle if there is a clear spectral peak in the business cycle range between 1 to 12 years.

The definition is illustrated in Figure 2, which displays the stylized graph of the spectral density of a hypothetical economic time series. The x-axis in the picture measures frequency, but the numbers on the axis indicate the cycle period, for convenience. If the selected time series has a significant cyclical component, which corresponds to the stated definition, a spectral peak will appear in the range between 1 and 12 years. This is the case in the Figure 1.

In completing the spectral analysis we employed different models. First we will present the results for real discrete Fourier transformation.

FIGURE 3: SPECTRAL DENSITY DIAGRAM (ORIGINAL DATA)



Note: The true frequency value can be calculated, if the selected value on x-axis is subtracted by 1 and divided by 100.

SIND - the value of spectral density function for industrial production

SINDMEAN - average value of spectral density for industrial production

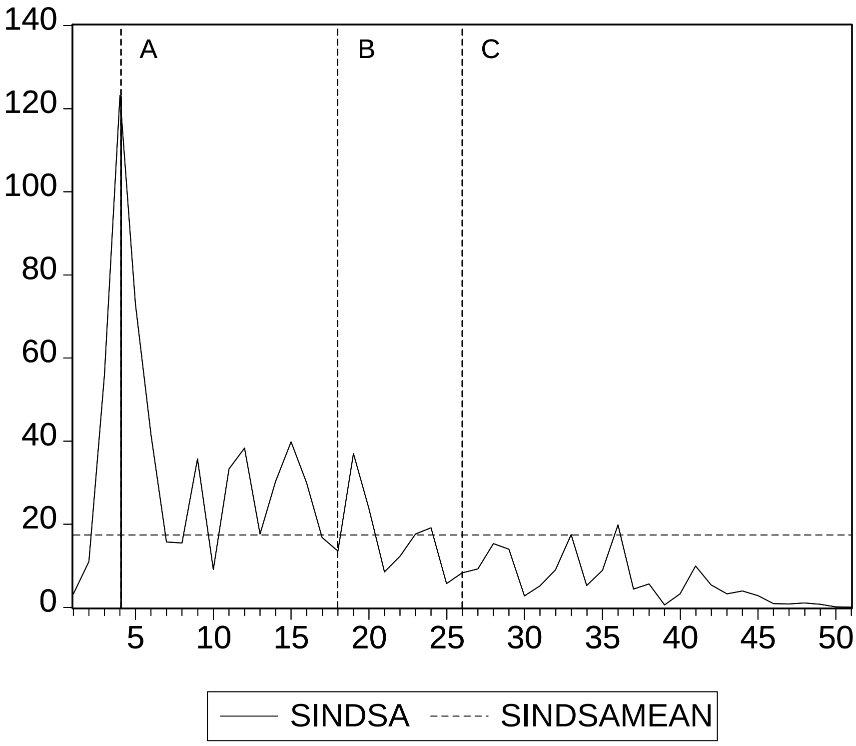
In the first step we tested the basic data, which we remodeled with the calculated trend. The results are given on Figure 3, where the diagram of spectral density or polar diagram can be seen. As it has been mentioned in the presentation of the methodology employed, we used a special method for smoothing the spectrum, which partly eliminates the noise from the specter. Due to the small amount of data we used a modified Parzen procedure.

On spectral density diagram in Figure 3 three spectral peaks can be found:

- Peak A – the first spectral peak, which reaches its maximum at frequency of 0.03, which corresponds to the oscillation with frequency of 33.3 months.
- Peak B – the second spectral peak, which reaches its maximum at frequency of 0.17, which corresponds to the oscillation with frequency of 5.9 months.
- Peak C – the third spectral peak, which reaches its maximum at frequency of 0.26, which corresponds to the oscillation with frequency of 4 months.

Taking into account the isolated frequencies, we could assume that the spectral peak A represents a cyclic component of the observed variable. Spectral peaks B and C can represent the seasonal component of the observed variable. If the stated assumption holds true, then there is a cyclic oscillation with the frequency 33.3 months in the Slovene industrial activity (presuming that the industrial production is a subsequent indicator of the aggregate economic activity).

FIGURE 4: SPECTRAL DENSITY DIAGRAM (DESEASONED DATA)



Note: The true frequency value can be calculated, if the selected value on x-axis is subtracted by 1 and divided by 100.
SINDSA - the value of spectral density function for deseasoned industrial production
SINDSAMEAN - average value of spectral density for deseasoned industrial production

In order to confirm the stated assumption it is necessary to carry out an additional test. Here we start with the presumption that the quality of data deseasoning can eliminate the seasonal influence from the observed series. Thus, spectral analysis should show only one spectral peak, with the frequency equal to the frequency of the spectral peak A.

Spectral analysis has confirmed our assumptions (Figure 4). With deseasoned data, it is possible to isolate only one spectral peak, with the frequency of 0.03, which corresponds the frequency of the spectral peak A. Thus we can assert (taking into account the set assumptions) that a statistically significant cyclic component is present. The length of the average cycle is 33.3 months.

As stated earlier, we present also results for autoregressive spectral estimation. The sample spectrum of industrial production (we use deseasoned data) is computed using the autoregressive spectral estimation technique of Parzen (1969) and Berk (1974). The procedure follows two steps. First we estimate the coefficients of an AR(p) process by OLS:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t \qquad (22)$$

where p is chosen so that the AR(p) process is an adequate approximation to the true data generating process. The lag length can be determined by the use of information criteria, or by using the standard t statistics. The estimated spectrum is sensitive to overparameterization. If we select the lag length, which is too small, the estimated spectrum may be badly biased.

After the estimation of parameters in AR(p) process, we can compute the estimator of the spectrum:

$$S_y(\omega) = \frac{1}{2\pi}\left(\frac{1}{1-\phi(e^{-i\omega})}\right)\left(\frac{1}{1-\phi(e^{i\omega})}\right)\sigma^2 = \frac{1}{2\pi}\left(\frac{1}{\left|1-\phi(e^{-i\omega})\right|}\right)^2\sigma^2 \tag{23}$$

where

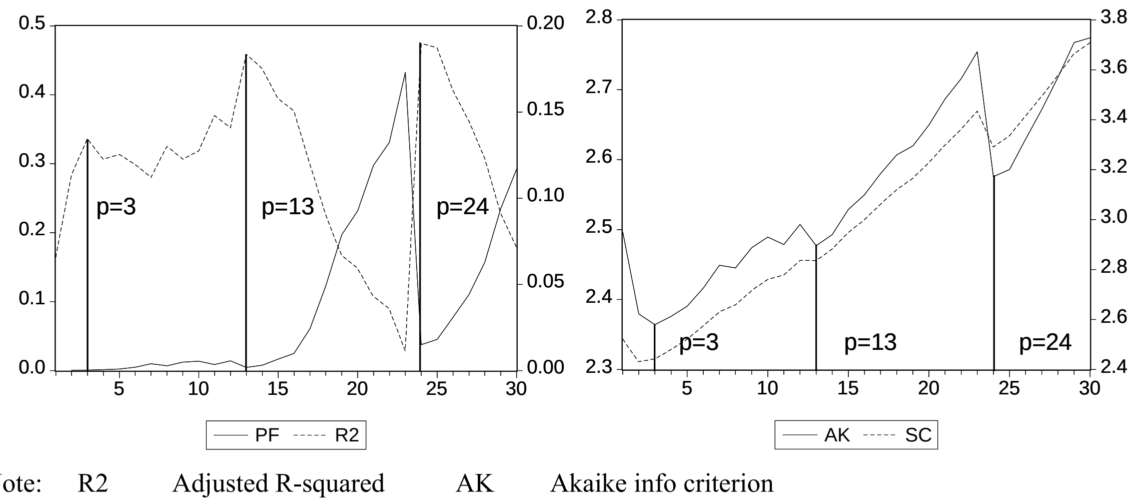
$$1-\phi(e^{-i\omega}) = 1-\phi_1 e^{-1i\omega} - \ldots - \phi_p e^{-pi\omega} \tag{24}$$

Since the variance of the spectrum increases with p, p should be chosen no larger than is necessary for the AR-model to be an adequate approximation to the underlying true data generating process.

Berk (1974) shows that the autoregressive spectral estimator is unbiased, consistent, and asymptotically normal. Because the spectrum is a theoretical spectrum, it will tend to be smoother than a spectrum produced by standard methods using windowing techniques but it also seems to have high resolution, in that it is able to pick out narrow peaks.

The results for the first step of autoregressive spectral estimation are presented in Figure 5. We have selected three autoregressive processes by considering four information criteria. The selected AR processes are for p=3, p=13 and p=24.

FIGURE 5: INFORMATION CRITERIA FOR AR(p) PROCESS



Note: R2 Adjusted R-squared AK Akaike info criterion
PF Prob(F-statistics) SC Schwarz criterion

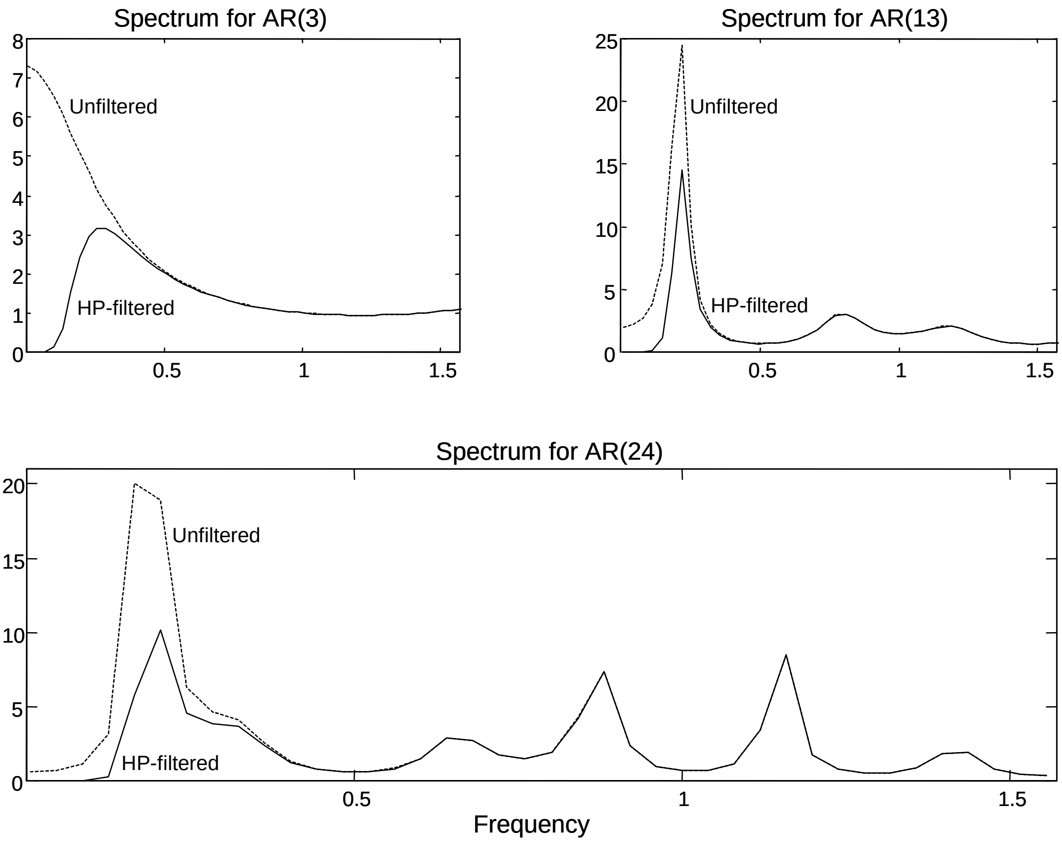
In the next step we have computed the theoretical spectra. The results are presented in Figure 6. We have computed two types of spectrum for each AR process: spectrum for unfiltered data and spectrum for filtered data. We have used standard Hodrick-Prescott-filter (HP-filter).

The value of term λ implies the cutoff frequency. We decided that the filter removes cycles, which last for 16 or more years.

Considering the Figure 6, we can conclude, that the AR(3) process has a typical spectral shape of Granger (1966) with a tall peak at frequency zero, implying the presence of near unit root. After filtering procedure, we receive a spectral peak at frequency of 0.2563, which corresponds to the cycle length of 24.5 months. As it can be seen on Figure 25, the AR(3) process is not a good approximation of real AR process, therefore the computed cycle length is not reliable.

AR(13) process shows better results as AR(3) process. We can isolate one distinctive spectral peak for unfiltered and filtered data. The spectral peak is at the frequency of 0.2144, which corresponds to the cycle length of 29.3 months. The isolated frequency is near the frequency of spectral peak A, which was estimated with real DFT.

FIGURE 6: AUTOREGRESSIVE SPECTRAL ESTIMATION (DESEASONED DATA)



The best results were achieved with AR(24) process. We can see a clear peak at frequencies between 0.1641 and 0.2038 for unfiltered data, which correspond to the cycle length between 30.8 and 38.3 months. By using HP-filter, we receive a cycle length of 38.3 months. Also additional cycle peaks were detected, which have almost the same frequency as cycle peaks B and C.

The results of the analysis suggest that the data for Slovene economy support the prediction of the classical writers: in the aggregate economic activity (under the assumption that industrial production is coincident indicator of aggregate economic activity) exists significant cyclic component with the frequency between 1 and 12 years.

3.3 Turning Points of Economic Activity

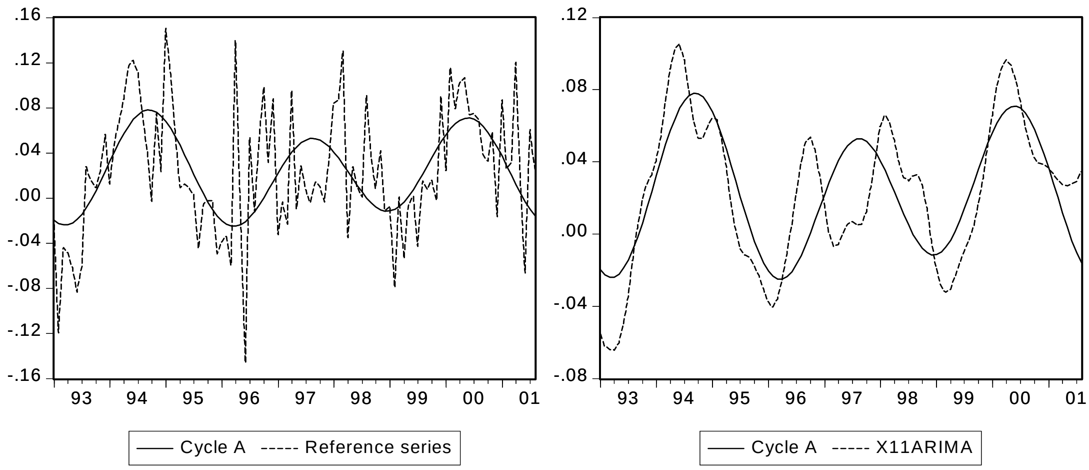
A specific cycle is a set of turning points observable in a particular series. The criteria for cycle dating are based on detecting these turning points. The traditional NBER method of determining cyclical turning points was developed by Burns and Mitchell (1946). The selection of a turn must meet the following criteria:

- The cycle duration must be at least 15 months, as measured from either peak to peak or trough to trough.
- If the peak or trough zone is flat, then the latest value is selected as the turn.
- Strike activity or other special factors generally are ignored, if their effect is brief and fully reversible.

In 1971, these decision rules were formalized by Bry and Boschen (B-B) and incorporated into a computerized routine for determining cyclical turning point dates. The main steps in the final adjusted version of the B-B computerized routine are:

- Smooth the data after first adjusting the time series for any outliers.
- Select preliminary turning points using the smoothed series and then search for turning points in the raw series around the dates found in smoothed series.
- Once theses tentative dates are selected in the raw series, a check is made of the duration. If the duration criteria are not met, then one pair of cyclical dates is eliminated.
- A final check of the amplitude is made using the Haywood amplitude criterion, which is based on the moving standard deviation of the series.
- After the series has passed through all theses tests, a statement of the turning point is given.

FIGURE 7: SELECTION OF TURNING POINTS



Note: Cycle A – Estimated business cycle using frequency of spectral peak A in Figure 24.
Reference series – seasonally adjusted total industrial production.
X11ARIMA – estimated cyclical component using X11ARIMA procedure.

A related concept in the selection of specific cycle turning point dates is determination of the reference business cycle. The conceptual basis for the reference cycle is to select turning point dates from a basket of economic indicators that represent the central tendency of a group of indicators reflecting aggregate supply-and-demand conditions. These are coincident indicators and often include: real GDP, real disposable personal income, real final sales, real manufacturing and trade sales, industrial production, and employment. A reference cycle chronology is then established based on the central tendency of individual turning points in the basket of indicators.

As described earlier, we selected total industrial production as a reference series. The selection of turning points is than performed using some of the procedures described above:

- The reference series is first transformed into annual growth rates using the following formula:

$$S_{y_t} = \frac{y_t}{y_{t-12}} - 1 \tag{25}$$

- Transformed reference series is then seasonally adjusted using the X11ARIMA procedure.
- The estimated cyclical component is then used to determine the reference points, which are later used to analyze the performance of the model. The turning points are defined in the same manner as in original NBER methodology. To check if the selected turning points meet business cycle criteria, we estimated business cycle component with inverse Fourier transformation, by using the results of spectral analysis.

The final results are presented in Figure 6. As already noted, the main difference between estimated business cycle and cyclical component using X11ARIMA, is in the period from 1996 to 1999. If we follow the NBER criteria, only one cyclical peak can be present in this period. As we try to develop an econometric model, which forecasts actual reference series, we will use X11ARIMA cyclical component, since this makes easier to analyze the forecast performance of the model.

3.4 Main Sources of Fluctuations

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 became more synchronized with German cycle. Therefore we follow the same assumption as we analyze business cycle in Slovenia. We constructed the following hypothesis:

H: Business cycle of Slovenia should be synchronized with German cycle.

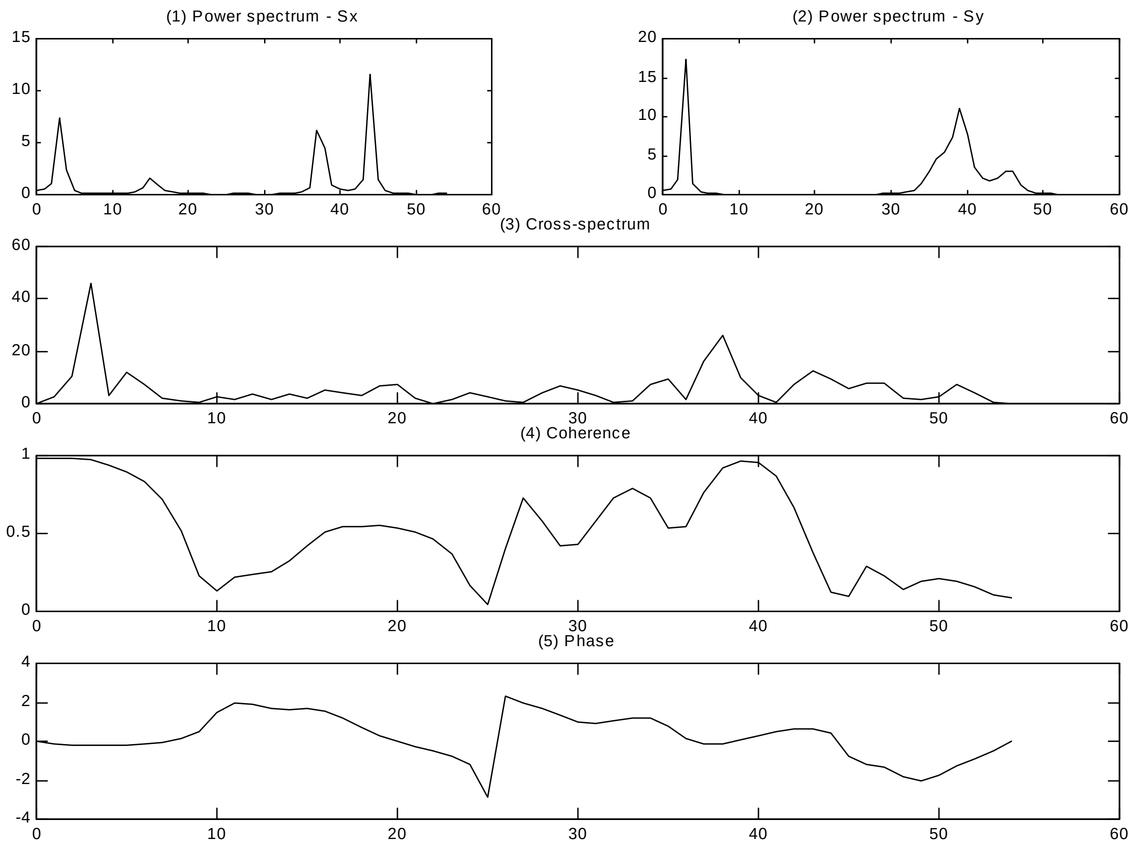
Such findings would confirm a general view in the business cycle literature that business cycles in the approach phase of the integration are becoming more synchronized with the target integration bloc as a result of increased international trade, openness of financial markets and global capital flows.

We test the hypothesis of the synchronization of cyclical movements on monthly data for the period 1992-2000. Artis and Zhang (1999) suggest a high degree of synchronization of business cycle between EU and Germany. Therefore we decide to choose Germany as an anchor country.

3.4.1 Results

Virtually all economies experience recurrent fluctuations in economic activity that persists of several quarters to several years. There is a definite tendency for the business cycle of developed countries to move together. In our research we try to find out, if Slovenia corresponds to these trends.

FIGURE 8: CROSS-SPECTRAL ANALYSIS RESULTS (SLOVENIA – GERMANY)



Note: Sx – reference series for Slovenia
Sy – reference series for Germany

The results of testing data for Slovenia are presented in Figure 8. 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 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 case of Slovenia, additional spectral peak can be found at the frequency range, which is typical for stochastic component. In this way the first hypothesis for Slovenia is confirmed - the frequency of cyclical component corresponds to the length of typical business cycle proposed by Mitchell and Burns and is significant for both countries.

The cross-spectral density diagram (third graph in Figure 8) confirms hypothesis of relationship between 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 with the maximum value of coherency at the selected frequency (fourth graph in Figure 8).

The fifth graph shows the time lag between oscillations of cyclical components of Slovenia and Germany. At the significant 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.

Several factors affect the degree of synchronization of business cycles in different economies. 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.

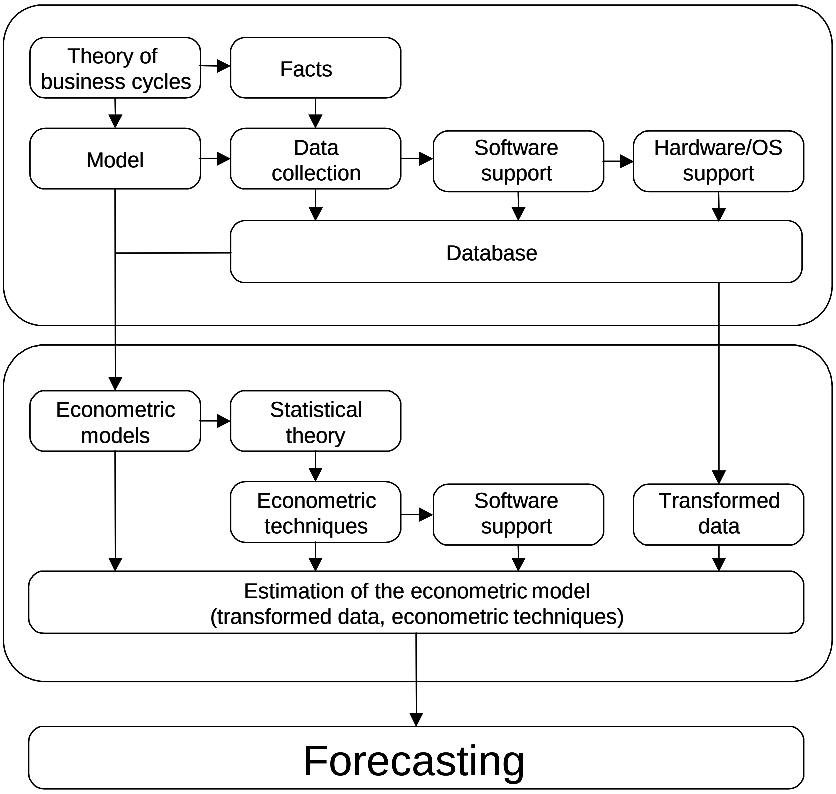
Second, the extent to which domestic demand movements are correlated across countries depends on whether there are common pressures affecting all economies, and the extent to which countries adopt a common policy stance (OECD 1995). The process of approaching to EU is deepening the economic integration 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.

4. DATABASE

Important step in the process of construction the model is development of a broad database, which should cover all crucial fields of economic activity. The development of database does not only include data collecting, but also the development of adequate information system support, which is essential for data storage and processing. Software and hardware is not only in function of the database characteristics, but also in function of the chosen model, hence the whole procedure of construction of the system of leading indicators was divided in two phases (Figure 9).

FIGURE 9: PHASES OF DEVELOPMENT OF SYSTEM OF LEADING INDICATORS



The database, which was used in the model, includes 365 time series, what corresponds to more than 40.000 single observations. To ensure sufficient transparency, the time series are classified in categories, which are presented in Table 2.

Since Slovenia got independence in October 1991, the time series start with January 1992. At the moment the database covers the period 1992:01 – 2001:08. The NBER approach however demands time series for at least twenty years long period. This had important impact on the development of the scoring system.

In the final version of the database, all time series were transformed into growth rates. All series, which are presented in current prices, were converted using CPI (1999=100). This enabled us to compare data in different time periods.

The main sources, which were used for collecting the data, were:
- Central Bank of Slovenia,
- Statistical Office of Republic of Slovenia,
- Institute for Macroeconomic Research and Development,
- Ministry of Finance,
- European Central Bank,
- Bundesbank,
- OECD Statistical Office.

As it can be seen from list of sources and Table 2, the database can be divided in two major groups of time series:

- time series representing Slovene economic activity,
- time series representing foreign economic activity.

TABLE 2: DATABASE STRUCTURE

Code	Category	Number of series included
S01	Industrial production	27
S02	Construction	6
S03	Trade	6
S04	Tourism	15
S05	Transport	8
S06	Export	23
S07	Import	23
S08	Balance of payments	10
S09	Employment	10
S10	Wages	21
S11	Unemployment	5
S12	Labor costs and productivity	16
S13	Money aggregates	5
S14	Bank claims	36
S15	Bank liabilities	45
S16	Interest rates (active)	10
S17	Interest rates (passive)	12
S18	Exchange rates	15
S19	International liquidity	3
S20	Government expenditure	10
S21	Prices	16
S22	Consumption	4
S23	Foreign activity indicators	22
S24	Indicators of German economic activity	17
	Total:	365

5. SCORING SYSTEM FOR BUSINESS CYCLE INDICATORS

The ideal leading indicator should possess the following characteristics (Burns and Mitchell 1946): it must cover a time period of fifty years; it has to lead at least three months; it must be smoothed; it has to be closely connected with the movement of aggregate economic activity; it must allow simple and fast updating; it should not have a seasonal component.

In our study we extended the use of criteria employed by NBER, by adding some elements of Stock-Watson approach in the scoring system. The scoring of each series reflects our desire not only to make as explicit as possible the criteria for selecting indicators but also to increase the amount of information available to the user in order to aid in evaluating their current behavior.

The scoring plan includes five major elements: economic significance, statistical adequacy, promptness of publication, smoothness, and Granger causality. When the subheads under these elements are counted, ten different properties of series are rated in all. This list of properties provides a view of many different considerations relevant to an appraisal of the value of a series for current business cycle analysis.

A high score for economic significance is accorded to a series that succeed to measures a variable, which has an important role in the analysis of business cycle movements. A series that represents a strategic process more broadly is rated higher than one more narrowly defined. Such broadly defined series is also less likely to shift as a result of technological developments, changing consumer tastes, and other similar factors.

Statistical adequacy reflects the requirement that a series continue to measure the same economic process during future business cycle fluctuations, when the selected indicators are put to the hard test of current usage. The main element that has the highest weight is the length of time-series. This characteristic of a time series is important due to demands of X11ARIMA program (Statistical Office Canada, 1999), which was used. Other elements are: type of reporting system, coverage of time unit, measure of revisions, availability of descriptive material, and comparability throughout the period.

For short-run business cycle forecasting a leading indicator can be useful only, if it is up to date. Series that are released promptly, therefore, are assigned higher scores than those that lag in publication.

The smoothness criterion is the same as in original NBER scoring plan. Since the start of a new cyclical phase can be discerned more promptly in a series, which is smoother than in one, which is irregular, smoother series are given higher ratings. Due to the fact, that we only use monthly series, only MCD (months of cyclical dominance) value was used to measure the smoothness. The MCD value is reported by X11ARIMA program.

Conformity of an indicator to past business cycles and timing of its turning points relative to those in aggregate economic activity are obviously essential qualities in an indicator. Since for Slovenia the time-series can only cover a period of up to eight years, we could not apply the NBER approach of a probability test. Therefore we used a criterion, which is based on Granger causality (Jagric 2000a, Jagric 2001). This enabled us to introduce econometric testing into scoring system. Econometric testing was performed on all series in the database twice. First we tested the series for the whole period and in the second step for the period from 1997:01 to 2000:08. This was necessary, since we found out, that many series have changed their characteristics in the beginning of 1997.

6. RESULTS

The described scoring system is a basic methodological step in creation of a forecast. Scoring procedure may be performed in two different ways: the first possibility is, that only a group of potential leading indicators, which were selected on researcher's experience, go in to the scoring procedure; and the second possibility is, that all time-series go in to the scoring procedure. Since for Slovenia the system of leading indicators was not yet developed and since database does not include time-series, which are usually good leading indicators, we decided to score all time-series. In the phase of scoring, graphical analysis was used, which enabled us to compare reference dates with changes in movement of selected time-series. The total score of time-series, theoretical lead-time, and the results of graphical analysis, were than used to form the potential group of leading indicators.

6.1 The list of leading indicators

The list of potential leading indicators comprises 39 time-series from database. The assigned scores must be considered rough rather than precise measure of the relative usefulness of different series in analysing short-term business conditions and prospects. Moreover, the scoring plan for each indicator contains information not revealed by the over-all score alone. Since the scores assigned to each of the considered factors indicate particular merits and limitations of series, the detailed results are of great assistance in the final selection.

The average lead-time is determined by Granger test of causality, where two criteria were used: the value of adjusted determination coefficient, and Akaike information criteria. The average lead-time is only an estimate of actual lead-time for selected time-series. Therefore we have to employ exact graphical analysis when we deal with final selection of leading indicators. Special emphasis in graphical analysis is dedicated to analysis of trend-cycle component in time-series, which is estimated with X11ARIMA program. A reliable leading indicator has to oscillate with the same or similar frequency as the reference series. If this condition is not fulfilled, the selected indicator cannot forecast all turning points in reference series.

The scoring system, we have used, ensure that the selected indicators posses the best characteristics among all time-series in database. They cover different fields of economic activity:

- business and consumer confidence (consumer confidence indicator),
- construction (average net wages),
- labour market (the share of over-hours in gross wages, employment (manufacturing)),
- monetary sector (monetary aggregate M2, real effective exchange rate (production prices), index of production prices (manufacturing)),
- foreign activity (OECD leading economic indicator for EU, OECD leading economic indicator for Italy),
- paying system (incomes of enterprises (financial intermediation)).

The shortcoming of selected indicators is non-presence of three indicators, which are usually used in OECD countries: retail inventories, index of stock exchange, and prices of primary commodities. Retail inventories were not included, since Statistical Office of the Republic of Slovenia does not collect these data on monthly basis. The prices of primary commodities were not selected for two reasons: first, we found significant relationship between reference series and primary commodities for the period 1997-2001 only; second, significance was found in this period only when high price changes have occurred.

Index of leading indicators usually includes index of stock exchange. The idea behind this variable is, that asset prices contain information about future movements in real variables, and in particular that asset prices significantly signal future movements in industrial production. Empirical data (IMF, 2000) suggest that asset prices fluctuations have remained substantial and highly correlated with business cycle in industrial countries. Empirical support for the hypothesis that stock prices affect consumption via its leading indicator properties about the growth of labour incomes is provided by Poterba and Sanwick (1995). Estimates of the magnitude of this effect vary considerably across countries, and are highly depended on the type of asset in question. Stock returns also led output growth in several emerging countries (Mauro, 2001). There is extensive empirical evidence that asset price changes tend to have significant predictive power on output growth (Christoffersen and Slok, 2000). Furthermore, Filer, Hanousek and Campas (1999) using Granger causality test, find evidence of a positive and significant relationship going from stock market development to economic growth, particularly for less developed countries.

We tested stock variables and found that there was no strong link with industrial production in Slovenia. There are some plausible explanations for this finding. The effect from asset prices to real economic activity may come through a number of different channels. In Slovene economy, some of them differ significantly vis a vis developed economies. The development of the Slovenian capital market has been marked by privatization and indirect central bank interference in market movements. A special feature of privatization process in Slovenia was the distribution of privatization vouchers in nominal value SIT 567 million (corresponding to about 40% of the social capital of companies undergoing ownership transformation) to more than 2 million citizens in October 1993, the individual value of vouchers depending on the citizen's age. The vouchers could have been used for purchase of shares of the employer, the shares of Authorized Investment Companies, purchase of shares in public sale and purchase of any other shares offered for sale against vouchers. The behavior of 2 million stockowners is in line with the way they got stocks: they sell whenever they need liquidity, no matter how the price is moving. Therefore, the stockholders are not responding their behavior to macroeconomic situation, so the link of stock movements with industrial output is week or non-existable.

The second reason why asset prices yield no information for future developments in the real economy lies with Bank of Slovenia. Given the small monetary area and consequently limited possibility of the Bank to neutralize any big-scale adverse effects-pressures of such capital inflows on the exchange rate, the Bank required as of February 1997 that non-resident portfolio transactions be channeled through custody accounts with fully licensed domestic banks. Pursuant to revision in July, the requirement exempted committed long-term portfolio investment of at least seven years. The introduction of compulsory custody accounts for foreigners substantially reduced their interest in portfolio investment, which, by then had been the main driving force on Ljubljana Stock Exchange. The uncertainty has made domestic investors more hesitant too. After the introduction, the turnover slumped sharply. The ratio of share, bond and short-term security turnover in total turnover dramatically changed. Share turnover dropped from above three-quarters to 56% of total turnover. Domestic investors moved from the stock exchange market to the short-term security market, were Bank of Slovenia's bond issue coupons represented the majority of the turnover.

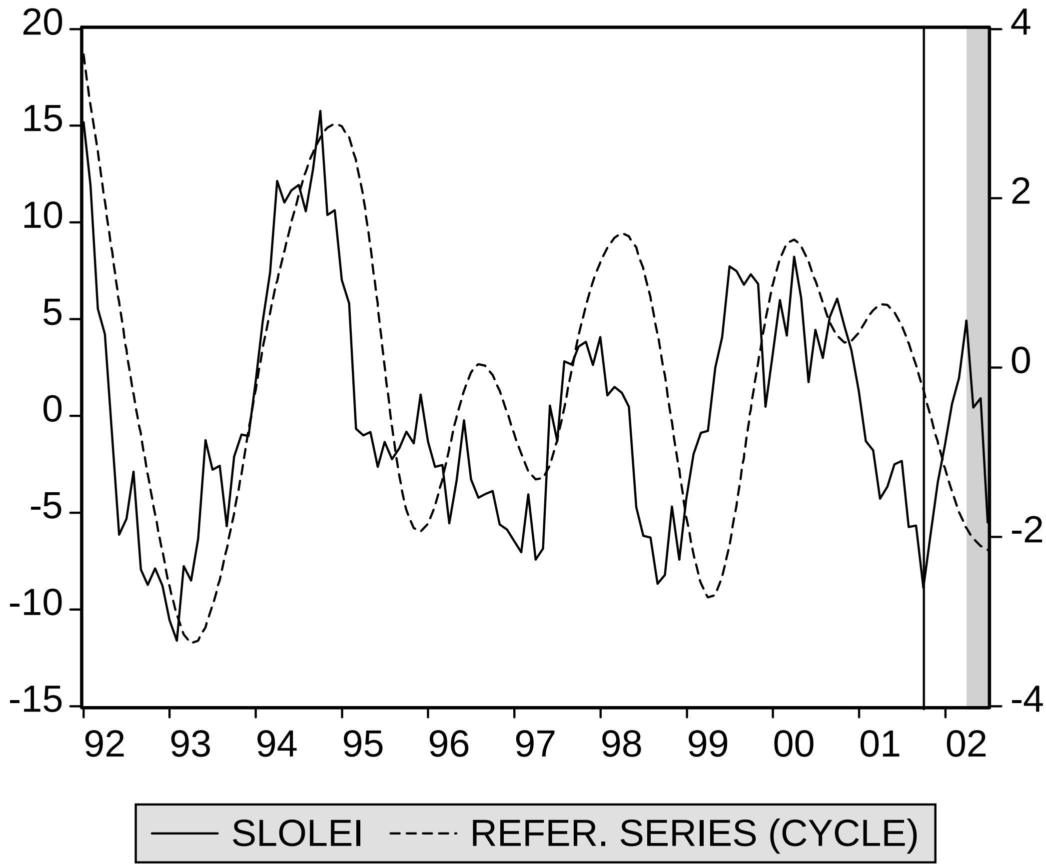
Along with the privatization and custody accounts impact, there has recently been an internationalization of emerging equity markets. This has taken several forms. Ljubljana Stock Exchange is confronted with situation, where some companies have issued depositary receipts that subsequently can be traded on a foreign exchange in parallel with the local exchange. Investors are so becoming concerned that liquidity is drying up and that the price determination is increasingly moving offshore. In this way asset prices are loosing information about future developments in real economy.

6.2 Composite and diffuse index of leading indicators

The forecast of economic activity is based on calculation of SLOLEI composite and diffuse index. The main steps followed by the NBER in compiling the composite indexes are to compute the standardized and weighted average changes, to modify the average changes and to cumulate these changes into an index. Due to procedure it is reasonable to expect, that composite index will be less volatile than single indicator and reference series (Niemira and Klein, 1994).

Burns (1969) observed that a business cycle expansion does not imply that every underlying economic activity is expanding nor does a business cycle contraction mean that every firm has decline sales. He further observed that economic activity has two types of cycles: seen and unseen. One cycle is in the fluctuation of the aggregate measure itself and consequently is seen. But a second cycle – diffusion cycle – exists in the distribution of components within that aggregate based on the number of expanding or contraction segments. This unseen cycle is important because it helps to monitor and forecast the path of the seen cycle.

FIGURE 10: SLOLEI (COMPOSITE INDEX) AND REFERENCE SERIES



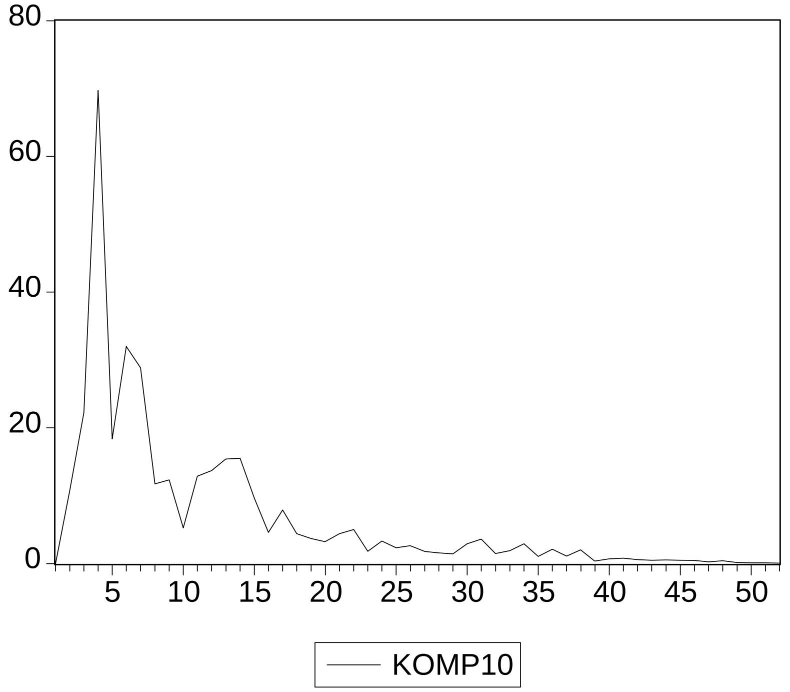
Note: SLOLEI composite index (1992:01=100)
Reference series (1992:01=100) – cycle
Both series are in growth rates.

This concept of diffusion is made operational by defining it as a time-series representing the percentage of the components within an aggregate that are expanding. The major limitation with diffuse index is that its volatility can make interpretation difficult. Therefore we lengthen the span of time over which the diffuse index is calculated (we used a span of six months). Although this method reduces the volatility, we lose some observations. By applying such filter we also have to be aware of a phase-shift in the cyclical component in the index.

To evaluate the performance of the composite and diffuse index of SLOLEI, we use the ex-post analysis. We observed the behavior of indexes in the period from 1992:01 to 2002:06.

Figure 10 shows the first results and documents the behavior of composite index and reference series. Reference data were determined with trend-cycle, which was estimated with X11ARIMA. Considering the analyses of the cyclical behavior of reference series, two full-length cycles could be identified. The movement of composite index confirmed this also. The results suggest that in the observed period our composite index successfully forecasted all turning points in the movement of the reference series.

FIGURE 11: SPECTRAL DENSITY DIAGRAM

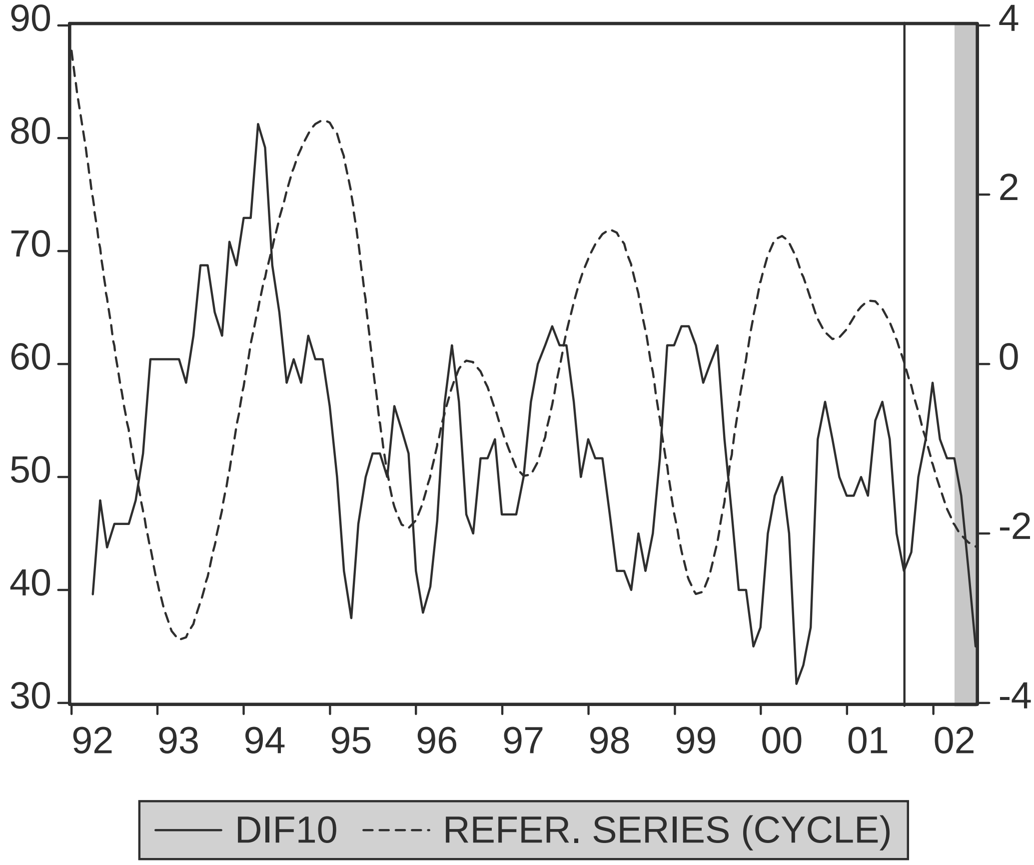


Note: True frequency is calculated by dividing x-axes value by 100.

The analysis of composite index shows high correlation with reference series, which is also confirmed with spectral analysis (Figure 11). We can isolate one spectral peak only. Its frequency is 3/100, which corresponds to the frequency of the spectral peak, which was found in the analysis of reference series. Considering our assumptions, we may conclude that statistically significant cyclical component is present. The length of the average cycle is 33.3 months. The spectrum is smoother in comparison with reference series. This finding confirms our presumption about characteristics of composite index.

The results of diffuse index also confirm our expectations. Its original values are highly volatile. Therefore, we use a three-month average of diffuse index (Figure 12).

FIGURE 12: DIFFUSE INDEX



Note: DIF10 - Diffuse index (three months average)
Reference series (1992:01=100) – cycle (growth rates)

7. CONCLUSION

This report presents the list of Slovenian cyclical indicators and a description of a scoring plan with all modifications that have been developed to help in the evaluation and selection of indicators. More than three hundred series have been evaluated. This study is concerned chiefly with the series quality as leading indicators of business expansion and contractions. It is limited to the role of economic time series as indicators of short-run movements in aggregate economic activity, and may not be relevant to their other uses.

The list of ten leading indicators we have chosen confirms our expectations we had formed in the analysis of cyclical movements of reference series. In particular, indicators suggest foreign economic activity, which showed strong relationship with reference series. We find important that more than half of selected indicators are present also in leading indicators for OECD countries. Serious problem represent time-series, which are shorter than three years. In that case the characteristics of cyclical component of such time-series are not determined with high reliability.

The forecasting power was tested with ex-post analysis also. We found that in observed period composite and diffuse index forecasted all reference points. As it is expected, diffuse index oscillate stronger than composite index, hence diffuse index forecasted a swing also in the period 1995-1998, all-the same the latter cannot be characterized as classical business cycle (spectral analysis also didn’t find any swing in this period). There are, however, numerous structural changes going on in Slovenia and such composite leading indicator should be closely followed and re-estimated as more data becomes available in order to capture ongoing changes in transition process.

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