WORKING PAPERS

No. 1/2011 (41)

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THE COINCIDENT AND THE LEADING BUSINESS CYCLE INDICATORS FOR POLAND

WARSAW 2011

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Abstract

In the paper, two indicators, the coincident and the leading indicator, are proposed to represent the aggregated economic activity in Poland. The indicators are constructed with stochastic cycle and trend model. Not only does the presented approach solve the problem of existence of stochastic trends in the observed series, but it also allows to account for a different data span of each series in dataset.

1 Introduction

The most commonly cited business cycle definition comes from Burns and Mitchell (1946). Business cycles are a type of fluctuation in the aggregate economic activity of a country which organizes its work mainly in business enterprises by taking into account only those types of activities that are systematic and economic in their nature. The series consists of an expansion period, manifesting itself at the same time in many types of economic activity, followed by periods of a weak market, recession and recovery, which connects to the expansion period of the next cycle. The sequence of these changes is repetitive. In their duration, business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar nature with amplitudes approximating their own. According to a definition by Gaudreault et al. (2003), the term cycle refers to common movements in a broad range of economic variables, such as production, employment or retail sales. Accordingly, the business cycle is a common unobservable component, which affects many observable economic series.

The paper presents a model which is in line with this approach. Gomez (2001) showed that Butterworth filters, widely used in engineering, are compatible with the class of unobservable components models. It is worth mentioning that the low-pass filter as well as the band-pass filter can be put into the state space form. The principal advantage of this approach is that the cyclical component is calculated in a way that an ideal band-pass filter can be obtained as a limiting case. The problem connected with the ends of the sample does not occur within this framework. Once the model is put into the state space form, the parameters are estimated by maximum likelihood. The paper presents coincident and leading indicators of aggregate economic activity. Not only can the current and future economic situation be analyzed on the basis of the results, but also investigations of the Polish cycle, including the determination of the peaks and the troughs can be made.

The remainder of this paper is organised as follows. In Section 2 the dataset is described. Section 3 presents the model. The empirical results can be found in Section 4. Section 5 contains conclusions.

2 Data

According to the definition of the business cycle, series with a broad coverage of the economy were selected. The industrial production index is a proxy for total production, the volume of retail trade reflects economic activity in this sector, and exports and imports reflect business fluctuations in demand for

domestic and foreign goods, as after all, the current consumer confidence indicator mirrors the economic situation of households. The set of leading indicators consists of the expected volume of the sold output in manufacturing in the next three months, the WIG20 index and the spread between the yield on five-year treasury bonds and the three-month WIBOR. As these variables cover the data span 1999.03 - 2010.10, they allow to calculate the leading indicator only for that period. Therefore, two special purpose series were included in the set. The series of the expected volume of sold output in industry and the 11-months lagged expected general economic situation in the construction industry were taken from the archival database, and cover the data span 1994.06 − 2008.12. The role of these two series is to model the leading indicator in the sample 1994.06 − 2010.10. In the period before the crisis, which began in 2007, the index of the economic situation in construction was commonly used as the leading indicator. The expected volume of sold output can be perceived as historical data for manufacturing. Table 1 presents the exact names of the variables and their sources, where GUS stands for the Central Statistical Office.

Table 1: Selected series

SERIES	DATA SPAN	SOURCE	INDICATOR
Industrial production (2005 = 100)	1992.06 − 2010.09	OECD	Coincident
Volume of retail trade (2005 = 100)	1992.06 − 2010.09	OECD	Coincident
Imports (billions PLN) − Total	1995.01 − 2010.08	GUS	Coincident
Exports (billions PLN) − Total	1995.01 − 2010.08	GUS	Coincident
Current consumer confidence indicator	1997.04 − 2010.10	GUS	Coincident
Spread pogb5yr - wibo3m	1999.03 − 2010.10	NBP	Leading
WIG20	1999.03 − 2010.10	NBP	Leading
Expected volume of sold production in next 3 months (manufacturing)	1999.03 − 2010.10	GUS	Leading
Expected volume sold production (industry)	1994.06 − 2008.12	GUS	Leading
Expected general economic situation of the the enterprise in construction − lagged 11 months	1994.06 − 2009.11	GUS	Leading

The series of industrial production and volume of retail trade are seasonally adjusted and come from the OECD. Imports and exports as well as series of expected volume of sold production in manufacturing and industry, and the expected general economic situation in construction were seasonally adjusted by TRAMO/SEATS method implemented in DEMETRA program. Seasonal adjustment was performed because of the fact that these series was

not provided in a seasonally adjusted form. Since the current consumer confidence indicator was published on quarterly basis before January 2004, the period 1997.04 – 2003.12 was disaggregated by the digital signal processing method. The choice of the disaggregating method was justified by comparison of disaggregation of a current consumer confidence indicator, as presented in Wozniak (2011). The differences in the data span for the series are not a problem, as long as the model is handled in the state space framework, as presented in Harvey (1989).

3   Model

Let us consider structural time series model in which observable variable y_t is a sum of unobservable trend component $\mu_{m,t}$, unobservable cyclical component $\psi_{n,t}$, and irregular component ϵ_t, i.e. white noise. It can be written as

$$y_t = \mu_{m,t} + \psi_{n,t} + \epsilon_t,$$

where $t = 1, 2, \ldots, T$. Unobservable component $\psi_{n,t}$ is defined as the $m - th$ stochastic trend, for positive values of m,

$$\mu_{1,t} = \mu_{1,t-1} + \zeta_t$$

$$\mu_{i,t} = \mu_{i,t-1} + \mu_{i-1,t}$$

for $i = 2, \ldots, m$, where ζ_t is white noise with zero mean and constant variance σ_ζ^2. The first order stochastic trend is a random process, while the second order trend is an integrated random walk process. If variances equal to zero, the model is called deterministic. If so, the model can be perceived as a classical regression model, with a constant and deterministic trend, see Commandeur and Koopman (2007).

The use of unobservable cyclical component was characterized and developed by Harvey (1989), Harvey and Jaeger (1993), and Trimbur (2003). Unobservable component $\psi_{n,t}$ is $n - th$ order stochastic cycle, for positive values of n, if

$$\begin{bmatrix} \psi_{i,t} \\ \psi_{i,t}^* \end{bmatrix} = \rho \begin{bmatrix} \cos \lambda_c & \sin \lambda_c \\ -\sin \lambda_c & \cos \lambda_c \end{bmatrix} \begin{bmatrix} \psi_{i,t-1} \\ \psi_{i,t-1}^* \end{bmatrix} + \begin{bmatrix} \psi_{i-1,t-1} \\ \psi_{i-1,t-1}^* \end{bmatrix}$$

$$\begin{bmatrix} \psi_{1,t} \\ \psi_{1,t}^* \end{bmatrix} = \rho \begin{bmatrix} \cos \lambda_c & \sin \lambda_c \\ -\sin \lambda_c & \cos \lambda_c \end{bmatrix} \begin{bmatrix} \psi_{1,t-1} \\ \psi_{1,t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix}$$

where $i = 2, \ldots, n$, $\kappa_t \sim WN(0, \sigma_\kappa^2)$, $\kappa_t^* \sim WN(0, \sigma_{\kappa^*}^2)$. Parameter ρ is the damping parameter and it fulfils $0 < \rho \leq 1$.

A state space representation consists of two equations, where the first is an observation equation for y_t, and the second, a transition one, for a vector of state variables, and it determines their dynamics. The vector of state variables $\alpha_t = (\mu_t', \psi_t')'$, where $\mu_t' = (\mu_{m,t}', \mu_{m-1,t}', \ldots, \mu_{1,t}')$ and $\psi_t' = (\psi_{n,t}', \psi_{n-1,t}', \ldots, \psi_{1,t}')$, where $\mu_{j,t}' = (\mu_{j,t}^{1'}, \mu_{j,t}^{2'}, \ldots, \mu_{j,t}^{N'})$, where the superscript stands for $j-th$ order trend component for the $n-th$ observed variable. The measurement equation takes the form

$$y_t = z_t'\alpha_t + \epsilon_t$$

for $t = 1, \ldots, T$, where first $(m+1)$ elements of vector z_t are ones, and the rest of them are zeros. The transition (state) equation for the trend component is as follows:

$$\mu_t = U_m\mu_{t-1} + i_m\zeta_t,$$

where U_m is an $m \times m$, the upper triangular matrix of ones, while i_m is an $m \times 1$ vector of ones. The variance-covariance matrix of irregular vector is equal to $Var(i_t\zeta_t) = i_m i_m' \sigma_\zeta^2$. The transition equation for cyclical component is

$$\psi_t = T_\psi\psi_{t-1} + i_n \otimes \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix},$$

where transition matrix T_ψ can be written

$$T_\psi = I_n \otimes \rho \begin{bmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{bmatrix} + S_n \otimes I_2,$$

where S_n is an $n \times n$ matrix of zeros with the exception of the first super-diagonal with elements equal to one. In case of the second order stochastic cycle the transition matrix T_ψ is

$$T_\psi = \begin{bmatrix} \rho\cos\lambda_c & \rho\sin\lambda_c & 1 & 0 \\ -\rho\sin\lambda_c & \rho\cos\lambda_c & 0 & 1 \\ 0 & 0 & \rho\cos\lambda_c & \rho\sin\lambda_c \\ 0 & 0 & -\rho\sin\lambda_c & \rho\cos\lambda_c \end{bmatrix}$$

A detailed description of the state space models, of the Kalman filter and of the stochastic cycle the interested reader may find in the book by Harvey (1989), and in the papers of Harvey and Jaeger (1993), and Azevedo et al. (2004). The model parameters were set at levels $m = 2$ and $k = 6$. This choice is substantiated in Harvey and Trimbur (2003). Since both the indicators were estimated with $N = 5$ variables, the 4×5 parameters must be estimated with the maximum likelihood method for each indicator. The frequency λ_c was chosen at level $\pi/48$ and it corresponds with fluctuation of the

96-months period. In the coincident indicator model, unit restriction for the common cycle loading was imposed for industrial production. In the leading indicator model, a similar restriction was imposed for the spread between the yield of the five-year treasury bonds and the three-month WIBOR.

4   Results

The estimation was performed in GAUSS 10 on the basis of my own implementation of the model. Two series representing business cycle fluctuations were received. The appendix presents parameters' estimations for both the coincident and the leading indicator models.

The coincident indicator is interpreted as an output gap, which is the difference between the actual output and its potential value, i.e. the long-term trend. The estimated series is the common part of five observed series in desired frequencies, as long as there is no doubt that all the coincident indicators are driven by one common force. Since it represents business cycle, it is not expressed in any units. Therefore, an interpretation should be exactly the same as in the case of the confidence indicator. The indicator points to the deviations from the trend, thus turning points analyses can be performed. Thus conclusions may be drawn about the current economic activity. Consequently, on the basis of the leading indicator one can conclude about the economic activity in the next three months, i.e. real month t is analyzed using $t-3$ month from the leading indicator. Diminishing values of the indicators show contraction, weakening the aggregated business activity. Consequently, rising values indicate that economy is expanding. Figures 1-2 present the normalized estimated indicators and the OECD leading indicator.

The obtained series coincide with turning points of the Polish business cycle published by the OECD. The most interesting feature of the leading indicator is that it is extracted from state variables, thus it can be estimated at any point in time, when the data for whole month is not necessarily available. Published analyses of the Polish business cycle, Skrzypczynski (2006) or Adamowicz et al (2009), focus on the quarterly GDP, therefore direct comparison cannot be made. However, coincident indicator and published quarterly series of cyclical component of the Polish GDP are similar to a large extent.

The stochastic cycle and the trend model reveal superiority over other methods. The OECD composite indicators are a weighted average of the cyclical components of the selected series. The choice of weights is a considerable source of uncertainty. Additionally, the Hodrick-Prescott filter can generate business cycle dynamics, even if none are present in the analyzed

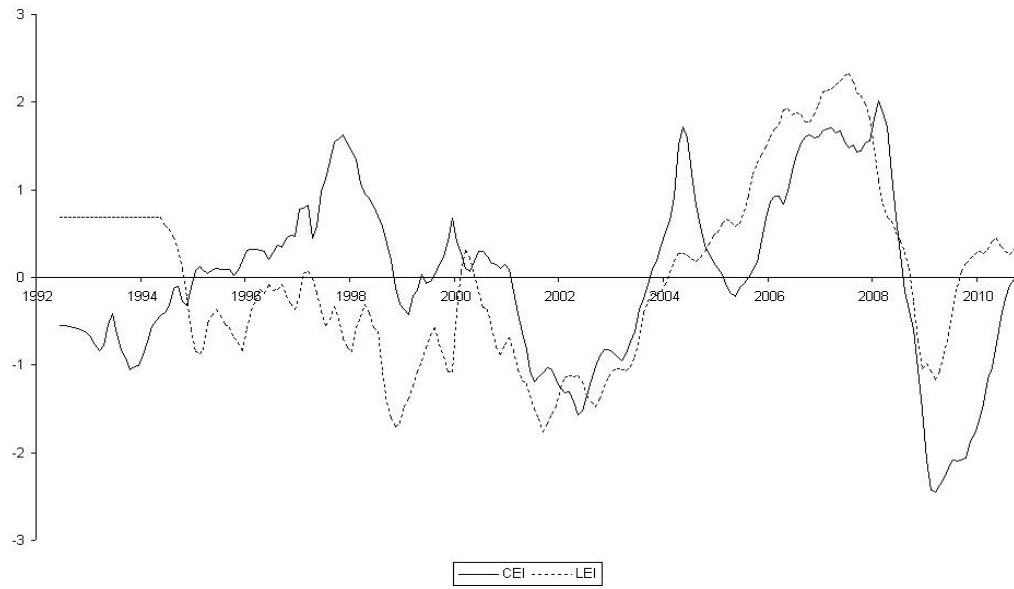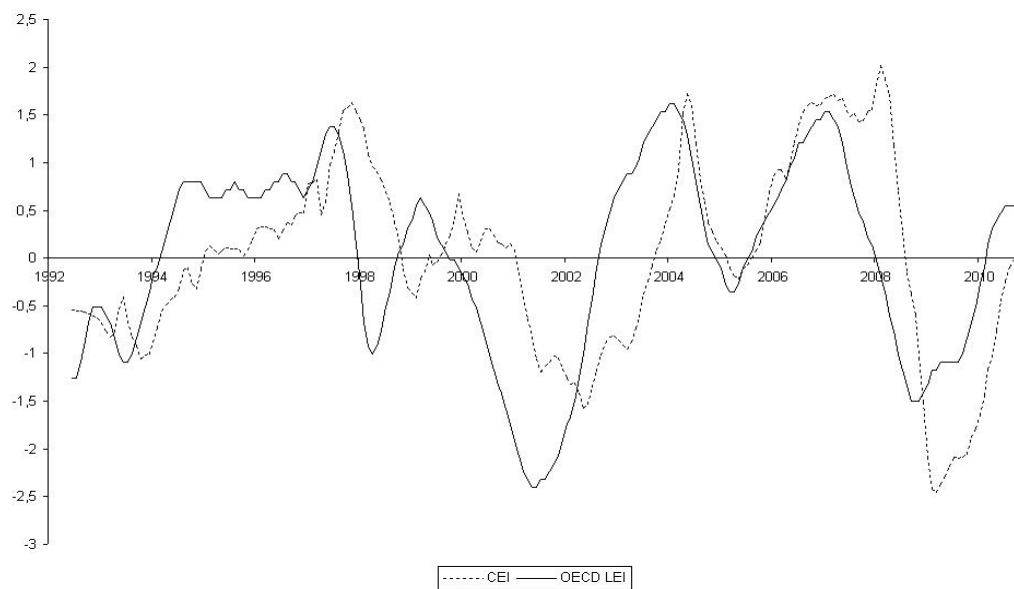Figure 1: The coincident and the leading indicators (normalized)

Figure 2: The leading indicator and the OECD leading indicator (normalized)

series. The stochastic trend approach is not biased by this disadvantage, because of the smooth transfer function.

The methods proposed in Stock and Watson (1990) as well as in Mariano and Murasawa (2002) extract a coincident indicator from the stationary series. Removing the linear deterministic trend can lead to uncertain results. The problem occurs where the observed trend differs from the linear deterministic trend. It is not debatable that the Polish series are characterized by the stochastic trend. What is more, since high frequency fluctuations are not removed, drawing conclusions about the business cycle movements may be distorted.

According to Azevedo et al. (2004), the series resulting from the stochastic cycle and the trend model and from Forni's model (2000) can be compared with each other. It is worth to note that a more circumscribed model is desirable, especially in the case of the Polish economy, for the reason that a considerable number of series begin in 2000 or even 2004.

5 Conclusions

Firstly, the presented method allows to estimate the monthly economic indicator from more than one series. The obtained results are comparable to the published cyclical components of the quarterly GDP, however, it has the advantage of a higher frequency.

Secondly, from the point of view of methodology, the method is superior to other methods of constructing business cycle indicators. It takes into account the existence of stochastic trends in the series and differences in the data span of the time series . What is more, stationary as well as nonstationary series can be incorporated into the stochastic cycle and the trend model without differencing. Additionally, undesirable high frequencies are removed.

Finally, not only the coincident indicator is presented, but also the leading one. The idea of the leading indicator is to present the future business cycle situation. On the basis of the selected series it is possible to calculate the index three months in advance.

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Appendices

Table 2: Results of an estimation of the coincident indicator model

$$\begin{bmatrix} \psi_{1,t} \\ \psi_{1,t}^* \end{bmatrix} = 0.624 \begin{bmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{bmatrix} \begin{bmatrix} \psi_{1,t-1} \\ \psi_{1,t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix}, \text{ where } \sigma_\kappa = \sigma_{\kappa^*} = (0.046)^2$$

$$y_{1,t} = 1.000 * \psi_{6,t} + \mu_t^1 + \epsilon_{1,t},\ \epsilon_{1,t} \sim N(0, (1.340)^2)$$
$$y_{2,t} = 0.430 * \psi_{6,t} + \mu_t^2 + \epsilon_{2,t},\ \epsilon_{2,t} \sim N(0, (3.700)^2)$$
$$y_{3,t} = 0.428 * \psi_{6,t} + \mu_t^3 + \epsilon_{3,t},\ \epsilon_{3,t} \sim N(0, (0.786)^2)$$
$$y_{4,t} = 0.257 * \psi_{6,t} + \mu_t^4 + \epsilon_{4,t},\ \epsilon_{4,t} \sim N(0, (0.668)^2)$$
$$y_{5,t} = 0.680 * \psi_{6,t} + \mu_t^5 + \epsilon_{5,t},\ \epsilon_{5,t} \sim N(0, (3.680)^2)$$

Table 3: Results of an estimation of the leading indicator

$$\begin{bmatrix} \psi_{1,t} \\ \psi_{1,t}^* \end{bmatrix} = 0.599 \begin{bmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{bmatrix} \begin{bmatrix} \psi_{1,t-1} \\ \psi_{1,t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix}, \text{ where } \sigma_\kappa = \sigma_{\kappa^*} = (0.005)^2$$

$$y_{1,t} = 1.000 * \psi_{6,t} + \mu_t^1 + \epsilon_{1,t},\ \epsilon_{1,t} \sim N(0, (1.146)^2)$$
$$y_{2,t} = 1.720 * \psi_{6,t} + \mu_t^2 + \epsilon_{2,t},\ \epsilon_{2,t} \sim N(0, (0.106)^2)$$
$$y_{3,t} = 26.180 * \psi_{6,t} + \mu_t^3 + \epsilon_{3,t},\ \epsilon_{3,t} \sim N(0, (4.638)^2)$$
$$y_{4,t} = 5.800 * \psi_{6,t} + \mu_t^4 + \epsilon_{4,t},\ \epsilon_{4,t} \sim N(0, (5.300)^2)$$
$$y_{5,t} = 6.500 * \psi_{6,t} + \mu_t^5 + \epsilon_{5,t},\ \epsilon_{5,t} \sim N(0, (5.400)^2)$$