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NON-PARAMETRIC AND PARAMETRIC APPROACHES TO THE CZECH BUSINESS CYCLE DATING

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Abstract
When composite indicators are used for business cycle analysis their construction usually consists of five steps: 1. pre-selection phase, which is passed only by long time series of indicators that have justified economic relationship with the reference series, broad coverage of economic activity and high frequency of observations, 2. filtering phase, when the time series are seasonally adjusted and de-trended, 3. evaluation phase, when only the best individual indicators with the strongest relationship with the reference series are selected to be included in the composite indicators, 4. aggregation phase, when the composite indicators are created, and 5. presentation of the results.
This paper focuses mainly on the evaluation phase of the composite indicators construction. In the evaluation phase cyclical components of all the evaluated individual indicators are compared to the reference series. Their relationship can be described by several methods: the average lead (lag) time between the turning points, cross correlations and number of extra and missing cycles. The analyses therefore depends largely on the correct turning points tracking.
This paper describes non-parametric (Bry-Boschan algorithm) and parametric (Markov switching model) approach to tracking the turning points. It applies these methods on several indicators of Czech business cycle and compares their performance.It shows that Bry-Boschan algorithm is more suitable for analyzing the short time series like those analyzed in this paper.

Key words: *business cycle analysis, turning points tracking, Bry-Boschan algorithm, Markov switching model.*

1. Introduction

Composite indicators may serve as one of the methods how to analyze business cycle. They have become widespread because they can be easily interpreted, although they summarize the multidimensional relationships between economic indicators. In this paper, we follow the OECD methodology of the composite indicators construction.

According to OECD, the time series should be de-trended and seasonally adjusted. Then the cycle components of all the individual indicators are found and their turning points are detected. Not every peak or trough of the cycle is considered as the turning point though. Bry-Boschan algorithm (Bry and Boschan, 1971) is used to determine the turning point.

The cycle components of all the individual indicators are compared to the reference series (usually GDP or index of industrial production). OECD uses several methods how to evaluate their relationship: the average lead (lag) times between the turning points, cross correlations and number of extra and missing cycles. Then the selected individual indicators are divided into groups of leading, coincident and lagging ones and the composite indicators are created.

OECD uses Bry-Boschan algorithm to detect the turning points of the time series. Goodwin (1993), Diebold and Rudebusch (1996) and Levanon (2010) also mention regime switching models as alternative to estimate the phases of the cycle. Bruno and Otranto (2004) provides comprehensive overview of several parametric and non-parametric methods for turning points detection.

We will briefly describe the non-parametric Bry-Boschan algorithm and the parametric Markov switching model to track the turning points of the cycle component of selected time series. We will perform these analyses and compare their results.

2. Data

We will illustrate the Bry-Boschan algorithm and the Markov switching model with the cycle analysis of three Czech economic indicators: index of industrial production (IIP), import and composite confidence indicator (CCI). These monthly time series are available from January 2002 to August 2012 and they were seasonally adjusted by the Czech Statistical Office.

The index of industrial production usually serves as the reference time series. IIP don't respond to the cyclical movements as good as GDP, but (unlike GDP) it is available monthly. OECD had used the IIP as the reference series until March 2012 and then switched to the adjusted GDP, which was converted to the monthly estimates. However, the IIP shows strong co-movements with GDP series in the Czech Republic and doesn't need to be arbitrary changed.

The import was selected because there could be significant relationship between the business cycle and its cycle component as the Czech economy is small and open.

The composite confidence indicator (also known as economic sentiment indicator) is calculated as a weighted average of confidence indicators in industry, construction, trade, in selected services and of the consumer confidence indicator (Czech Statistical Office, 2012). Confidence indicators are very often included in the composite leading indicators.

3. Bry-Boschan algorithm

Not every peak or trough of the indicator is considered as the turning point. In 1946 Arthur Burns and Wesley Mitchell analyzed business cycles and laid the foundations of business cycle dating. The dating was executed manually and it required lots of personal judgment and therefore it wasn't quite objective.

Gerhard Bry and Charlotte Boschan introduced their algorithm for turning points detection in 1971. It was one of the first programmed approaches that were published and with the fast development of information technologies was than widely implemented. OECD and other organizations still use this algorithm with only slight changes. In the first proposal, Bry and Boschan used 12-month moving average, Spencer curve and short-term moving average of 3 to 6 month to detect the turning points. Nowadays none of these are necessary because some other techniques (like Hodrick-Prescott filter) are used to smooth the time series without shifting the turning points.

Bry-Boschan algorithm (Bry and Boschan, 1971) consists of 6 steps:

1. Identification of points higher (or lower) than 5 months on either side.

2. Enforcement of alternation of turns by selecting highest of multiple peaks (or lowest of multiple troughs).
3. Elimination of turns within 5 months of beginning and end of series.
4. Elimination of peaks (or troughs) at both ends of series which are lower (or higher) than values closer to end.
5. Enforcement of minimum cycle duration of 15 months by eliminating lower peaks and higher troughs of shorter cycles.
6. Elimination of phases whose duration is less than 5 months.

The algorithm also suggests the best practices for dealing with anomalous situations (e.g. double turns). Implementation of Bry-Boschan algorithm gave similar results as the manual analysis of the cycle and enabled to process the large datasets very quickly.

3.1 Application of Bry-Boschan algorithm

The data have to be de-trended and smoothed before the usage of Bry-Boschan algorithm. OECD (Nilsson and Gyomai, 2011) recommends to apply the Hodrick-Prescott filter twice: first to find the trend and then to smooth the cycle component.

Over the period from January 2002 to August 2012, the Bry-Boschan algorithm found three cycles measured from peak to peak in IIP and CCI time series (see figure 1 or table 2). The import cycle is missing the first peak which had to occur before January 2002. It can be assumed, that import skipped the first cycle as its other peaks and troughs usually follow the peaks and troughs of the reference time series.

For more detailed results see (Vraná, 2014).

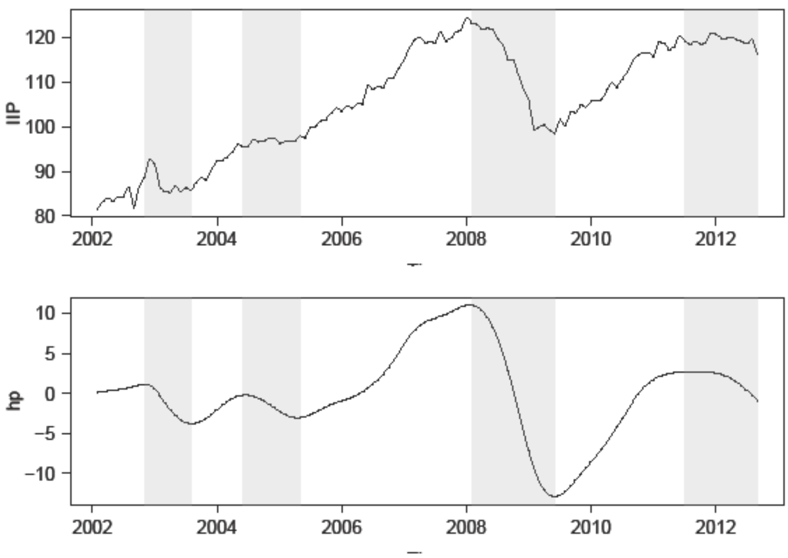

Figure 1.Index of industrial production (IIP) and its cycle component (hp) from January 2002 to August 2012 with emphasized phases of recession, which were detected by Bry-Boschan algorithm.
Source: Calculated by the author using R software.

4. Markov switching model

Several economists tried to apply the ARIMA processes on the GDP (GNP) data with an assumption that the first differences of the logged time series follow linear stationary process. Hamilton (1989) suggested that the generating process was more likely nonlinear. He pointed out that there were discrete shifts in the process that could have aligned with the phases of expansion and recession and he used Markov switching method to find and describe these regimes.

Hamilton used AR(4) model with the two-state first order Markov process, which can be written as (Goodwin, 1993)

$$y_t - \mu_{s_t} = \phi_1(y_{t-1} - \mu_{s_{t-1}}) + \phi_2(y_{t-2} - \mu_{s_{t-2}}) + \phi_3(y_{t-3} - \mu_{s_{t-3}}) + \phi_4(y_{t-4} - \mu_{s_{t-4}}) + \sigma\varepsilon_t, \quad \varepsilon_t \sim N(0,1), \tag{1}$$

$$\mu_{s_t} = \alpha_0 + \alpha_1 s_t, \tag{2}$$

where s_t = 0 or 1 denotes the low or high regime of the system. The system can switch between the regimes with the following probabilities:

$$\begin{aligned} P[S_t = 1 \mid S_{t-1} = 1] &= p, \\ P[S_t = 0 \mid S_{t-1} = 1] &= 1 - p, \\ P[S_t = 0 \mid S_{t-1} = 0] &= q, \\ P[S_t = 1 \mid S_{t-1} = 0] &= 1 - q. \end{aligned} \tag{3}$$

For this specification 9 parameters need to be estimated: α_0, α_1, p, q, ϕ_1, ϕ_2, ϕ_3, ϕ_4 and σ. However, the model doesn't require any prior information about the dates of the regimes.

The inconvenience of Markov switching model, as Levanon (2010) points out, is that the low and high regimes don't always correspond with the phases of expansion and recession. Bruno and Otranto (2004) also mention the possibility of Markov process with more than two states, which could improve the performance of the model, but worsen its interpretation.

Levanon (2010) further states that it is not necessary to apply the algorithm only to the differences of the log of the indicator, but it can be also applied to the original levels of the indicator if it is stationary.

4.1 Application of Markov switching model

We will analyze the monthly time series which have been seasonally adjusted. When Hamilton decided to use AR(4) model, he applied the model to the quarterly GNP data. Since our data contains monthly observations, the AR(12) would be more appropriate, but with regard to performed seasonal adjustments, the AR(1) model should be sufficient. Chauvet and Hamilton (2005), Diebold and Rudebusch (1996) and Levanon (2010) also tried AR(0) model, which corresponds to the white noise. The variance is usually considered constant across the regimes.

As the index of industrial production is not stationary, we transform it according to the formula

$$y_{IIP,t} = 100 \cdot \ln(IIP_t / IIP_{t-1}) \quad \textbf{(4)}$$

and we use similar transformations for all the analyzed time series. We use the Expectation-Maximization algorithm available in R package MSwM to estimate the parameters.

Table 1 shows the transition probabilities for the regimes of IIP when AR(1) model with the two-state first order Markov process has been applied. In this case, regime 1 stands for the low growth of the IIP and regime 2 stands for the high growth. When the IIP is in the low growth state this month, it will be in the high growth state next month with the probability *0.1380*. On the other hand, if it is in the high growth state this month, it will switch into the low growth state with the probability *0.0223*. These are the estimates of probabilities $(1-p)$ and $(1-q)$ from (3).

Table 1.Transition probabilities for the regimes of index of industrial production.

$S_t \backslash S_{t-1}$	Regime 1	Regime 2
Regime 1	0.8620	0.0223
Regime 2	0.1380	0.9777

Source: Calculated by the author using R software and package MSwM.

Goodwin (1993) states that when either p or q are close to *0*, it makes the model inapplicable, because the process stays in one of the regimes and generates no turning points. The p and q in the IIP model are close to *1*, which should enable us to use the model for dating the turning points in the cyclical component.

The byproduct of the Markov switching model is the filtered probabilities, which indicate the likelihood of a given regime.

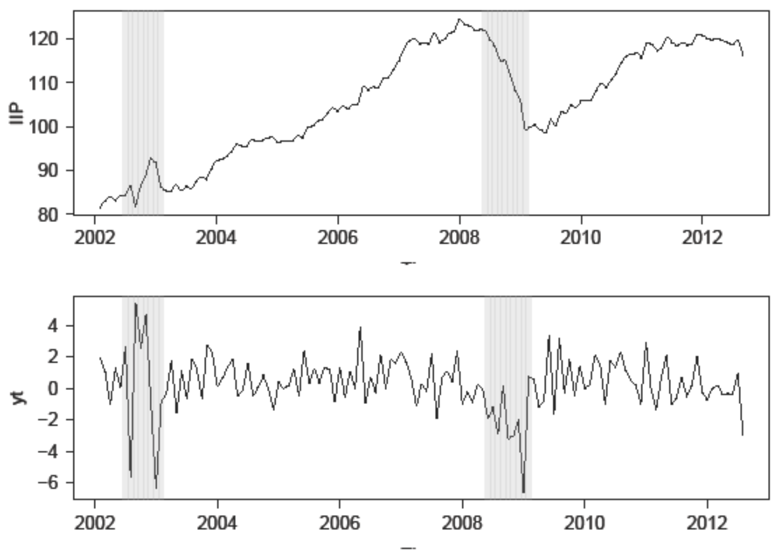

Figure 2.Index of industrial production (IIP) and the first differences of the logged IIP (yt) from January 2002 to August 2012 with emphasized phases of low growth, which were detected by Markov switching model.
Source: Calculated by the author using R software and package MSwM.

The figure 2 indicates the regimes of the Czech IIP. The Markov switching model finds 4 turning points: 3 periods of regime 2 (high growth) and 2 periods of regime 1 (low growth/decline). IIP shows rather erratic movements in the first period of low growth (between July 2002 and February 2003), but the decline in the second period (from June 2008 to February 2009) is obvious. However it is unclear whether the regimes really correspond with the phases of recession and expansion – especially the first period of regime 1 raises doubts.

Table 2 compares the dates of the turning points gathered by the Bry-Boschan algorithm and by the Markov switching model. Again, the Markov switching model finds lower number of turning points for all the analyzed time series and skips several phases that were labeled as recessions by Bry-Boschan algorithm. If we would suppose that the regimes strictly correspond with the phases of the business cycle, then the Markov switching model usually indicates the expansions sooner than the Bry-Boschan algorithm.

Table 2.Dates of the cycle turning points of index of industrial production (IIP), import and composite confidence indicator (CCI) detected by Bry-Boschan algorithm (BB) and Markov switching model (MSM).

Peak/Trough	IIP		Import		CCI	
	BB	MSM	BB	MSM	BB	MSM
P	Oct-02	Jul-02	-	-	Jun-02	-
T	Jul-03	Feb-03	Aug-03	-	Oct-03	-
P	May-04	-	Jun-04	-	Sep-04	-
T	Apr-05	-	Apr-05	-	Apr-05	-
P	Jan-08	Jun-08	Jan-08	Oct-07	Jan-08	May-08
T	May-09	Feb-09	Jul-09	Jul-09	Apr-09	Feb-09
P	Jun-11	-	Jan-12	-	Jan-11	-

Source: Calculated by the author using R software and package MSwM.

5. Conclusion

This paper compares two methods how to detect the turning points of the cycle component of economic time series, which is essential task when the composite indicators are constructed. The first of these methods is Bry-Boschan algorithm, which provides set of expert rules to select only the peaks and troughs, which could be the turning points. The other one is Markov switching method, parametric model, which is fitted to the data and produces the probabilities that the economy is in a given regime.

We analyzed three Czech economic indicators (index of industrial production, import and composite confidence indicator) and showed that the Markov switching model indicates lower number of the turning points and skips several recession phases, which were proposed by Bry-Boschan algorithm.

Whereas the Bry-Boschan algorithm is iterative and needs the time series to be de-trended and seasonally adjusted, the application of Markov switching model is more straightforward. However, there is no guarantee, that the regimes indicated by Markov switching model, truly correspond with the phases of the business cycle. That could easily be the case of the analyzed

Czech data set as the time series are rather short (from January 2002 to August 2012) and (for import and composite confidence indicator) only one low growth phase was discovered.

Therefore we recommend to continue using the Bry-Boschan algorithm which isn't so strongly affected by the length of the time series.

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