Dating the Italian Business Cycle: A Comparison of Procedures*

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Abstract

The problem of dating the business cycle has recently received many contributions, with a lot of proposed statistical methodologies, parametric and non parametric. Despite of this, only a few countries produce an official dating of the business cycle. In this work we try to apply some procedures for an automatic dating of the Italian business cycle in the last thirty years, checking differences among various methodologies and with the ISAE chronology. To this end parametric as well as non parametric methods are employed. The analysis is carried out both aggregating results from single time series and directly in a multivariate framework. The different methods are also evaluated with respect to their ability to timely track turning points.

KEYWORDS: signal extraction, turning points, parametric methods, nonparametric methods

1 Introduction

One of the key issues with which economists and researchers are often confronted to when studying and analysing the evolution of the economic activity is trying to establish the *state* of the business cycle, either because it is the main object of the analysis or because it constitutes a relevant side information for a better evaluation of other economic facts. Classical analyses of business cycle considers the existence of two possible states for an economy: expansion and recession, the latter being characterized by a long and sustained decline in economic activity. These two states are delimited by *turning points* (minima and maxima) and their list constitutes a business cycle “chronology” or “dating”.

In Italy ISAE has been establishing such a dating since it has been founded in 1999, following a long tradition set up by ISCO[1], based on the NBER methodology. Six different economic variables (see Appendix A) deemed to be important to trace the business cycle (Altissimo *et al.*, 2000) are carefully scrutinised, looking for their turning points with an automatic routine proposed by Bry and Boschan (1971). A dating for the whole economy is then proposed, resorting to a “judgemental” aggregation of the turns of single time series, obtained looking also other important variables such as GDP. A by-product of the procedure is represented by the aggregation of the six variables into a composite coincident indicator.

[1]ISCO, which stands for *Istituto nazionale per lo studio della congiuntura*, was a public institute founded in 1955 whose primary object was the study of business cycle; it merged with ISPE in 1999 to form ISAE — *Istituto di Studi ed Analisi Economica*.

In this paper we try to replicate the dating process starting from the same six variables used by ISAE and applying a number of different procedures and models in order to obtain a dating which to be compared with the official one. The aim of this exercise is too see if an automatic procedure can accurately reproduce the results of the official dating. In order to do this we resort to a number of procedures and models.

The most straightforward extension of the current practice is represented by the aggregation of the turns of the single series with an automatic procedure. Here we adopt that proposed by Harding and Pagan (2002). A variation to this scheme has also been used, namely replacing the Bry-Boschan routine with a parametric time series model. Both these approaches were termed *indirect*, as opposed to *direct* ones, where first a composite indicator is calculated, and subsequently turning points are directly calculated on the latter; thus, there is no need to aggregate the turning points of the single series. The composite indicator is obtained both with a parametric model and with a non parametric one. In the end, a simultaneous approach has been used, namely with a multivariate parametric model which allows for the production of both a chronology and a composite indicator.

In section 2 the methods used will be described more in depth, while in section 3 the empirical results are presented and some conclusions follow.

2 Methods

To establish the dates of turning points, a strong effort has been dedicated to the translation of the idea of turning points definition into appropriate algorithms. The most famous among them, proposed by Bry and Boschan (1971), is a non-parametric procedure which can be applied to a single monthly[2] time series, adjusted for seasonality. It consists of the extraction of the points identified as local maxima/minima and satisfying certain censoring rules (see subsection 2.1).

Burns and Mitchell (1946) affirmed that "a cycle consists of expansions occurring at about the same time in many economic activities", so one of the characteristics of the cycle is represented by the co-movements among variables; this implies the need of an extension of the Bry-Boschan procedure to a multivariate framework, but such an extension is not immediate (Anas and Ferrara, 2002). A possible solution relies on an *indirect* approach, in which the turning points detected on a number of single series are aggregated following some specified rules. Alternatively, we define a *direct* approach, in

[2] An extension to quarterly series is straigthforward and is proposed in Harding and Pagan (2002).

which, first, a composite indicator is obtained from the single time series; afterwards, the Bry-Boschan routine is applied to the latter.

More recently, Hamilton (1989) proposed the Markov Switching model, in which the states of recession and expansion are represented by an unobservable dichotomic variable, on which it is possible to make inference and establish what is the most probable state for each time. In this way, a parametric model allows the dating of a time series. The extension of the Markov Switching model to the multivariate case was performed by Krolzig (1997), utilizing vector autoregressive (VAR) models, and by Diebold and Rudebusch (1996), who add a Markov Switching dynamics to the coincident indicator model proposed by Stock and Watson (1991).

Finally, in order to resume and to stress the procedures we compare in this paper, we can classify the approaches in five groups. In doing this we emphasize the difference between *indirect* detection of turning points, that is turning points are detected on different time series and then aggregated, *vs.* the *direct* detection, that is, first a composite indicator is built, subsequently it is used to identify the turning points. We distinguish our methods also on the ground of parametric/non-parametric setting of the statistical methods used, respectively, to detect turning points and to aggregate them.

Needless to say, these distinctions are made purely on the ground of the need to classify the different methods used, but they should not be considered as *absolute*, in the sense that a method classified as non-parametric could well contain some parametric phases (*e.g.* seasonal adjustment). The methods we used are the following:

1. *Indirect non-parametric approach*: in this case the turning points detection on each series is performed with the Bry-Boschan procedure and the sets of turning points for each variable are aggregated with the non-parametric procedure proposed by Harding and Pagan (2002).
2. *Indirect mixed approach*: turning points are localised applying a parametric time series model to the single series, then aggregated with the non-parametric procedure proposed by Harding and Pagan (2002).
3. *Direct non-parametric approach*: turning points are detected on the aggregate composite indicator, obtained with the ISAE methodology (non-parametric smoothing by means of a band-pass filter) and the Bry-Boschan routine can then be applied directly to the latter to obtain the dating.
4. *Direct mixed approach*: an aggregate composite indicator is obtained by means of the Stock and Watson (1991) model and the dating can be derived applying the Bry-Boschan routine.
5. *Fully parametric approach*: we obtain the simultaneous construction of

a composite indicator and the detection of turning points, using the Stock and Watson model with Markov Switching dynamics.

Details on the various procedures are explained in the following subsections, whereas informations about the variables used are shown in the final Appendix.

2.1 Indirect non-parametric detection (INDNP)

In this case the detection of turning points is made on individual time series with the procedure which Bry and Boschan (1971) proposed in order to replicate in an automatic way the US business cycle turning points as established by the NBER. The original procedure consists of the following steps:

1. Determination of extreme values and their replacement;
2. determination of cycles in 12-month moving average (extremes replaced);
    (a) identification of points higher (or lower) than 5 months on either side;
    (b) enforcement of alternation of turns by selecting highest of multiple peaks (or lowest of multiple troughs);
3. determination of corresponding turns in a Spencer curve (extremes replaced);
    (a) identification of the highest (lowest) value within ±5 months of selected turns in the 12-term moving average;
    (b) enforcement of minimum cycle duration of 15 months by eliminating lower peaks and higher troughs of shorter cycles;
4. determination of corresponding turns in a short-term moving average depending on MCD (months of cyclical dominance);
    (a) identification of highest (lowest) value within ±5 months of the selected turn in the Spencer curve;
5. Determination of turning points in the original series.
    (a) Identification of the highest (lowest) value within ±4, or MCD term, whichever is larger, of the selected turn in the short-term moving average;
    (b) elimination of turning points within six months of beginning and end of series;

(c) elimination of peaks (or troughs) at both ends of series which are lower (or higher) than values closer to the end;
(d) elimination of cycles whose duration is less than 15 months;
(e) elimination of phases whose duration is less than 5 months;

6. statement of final turning points.

In this application we have used a slightly modified version, namely avoiding the replacement of extreme values.[3]

Once turning points have been obtained for each single series, their aggregation has been carried out by means of the procedure proposed by Harding and Pagan (2002). Basically, if we have a K-dimensional time series of turning points, where K is the number of variables used, the procedure consists in finding for every time point t a vector containing the K distances to the nearest peak for every time series considered. The median of this vector can then be interpreted as the mean distance to the nearest peak for the whole economy. Consider then all t points, the local minima of this series are candidate to be a peak for the whole economy. The same procedure is applied to the series of troughs.

Afterwards, censoring rules are applied so that turning points alternate and that cycles and single phases lasts not less than 15 and 5 months, respectively.[4]

2.2 Indirect mixed detection (INDMIX)

In this case the turning points of the single series are extracted by means of a parametric procedure, and they are subsequently aggregated with the aforementioned procedure proposed by Harding and Pagan (2002). The use of a parametric model to obtain a dating for a classical cycle in univariate monthly time series has been successfully implemented in García-Ferrer and Bujosa-Brun (2000) and in Bruno and Lupi (2002).

In particular, let us indicate the log of the series to be analysed with y_t and let us specify the following unobserved components model:

$$y_t = \mu_t + \gamma_t + \varepsilon_t + \delta x_t \qquad (1)$$

where the series y_t is thought of as composed by a trend component μ_t, a seasonal γ_t and an irregular ϵ_t plus a trading days component δx_t, where x_t

[3]The steps of the Bry and Boschan procedure were programmed by the authors using WinRATS-32 version 5.0, Doan (2000).

[4]A more complete description can be found on the paper by Harding and Pagan.

is the (known) number of working days in month t and δ is a coefficient to be estimated and $\varepsilon_t \sim \mathsf{NID}\,(0, \sigma^2_\varepsilon)$.

The trend component is then specified as follows:

$$\begin{aligned} \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t \\ \beta_t &= \beta_{t-1} + \zeta_t \end{aligned} \tag{2}$$

where $\eta_t \sim \mathsf{NID}\left(0, \sigma^2_\eta\right)$, $\zeta_t \sim \mathsf{NID}\left(0, \sigma^2_\zeta\right)$, and β is the *slope* of the trend.

The seasonal component is specified in trigonometric form as follows:

$$\gamma_t = \sum_{j=1}^{6} \gamma_{j,t} \tag{3}$$

where each $\gamma_{j,t}$ is generated by the following recursion:

$$\begin{bmatrix} \gamma_{j,t} \\ \gamma^*_{j,t} \end{bmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_j & \cos\lambda_j \end{bmatrix} \begin{bmatrix} \gamma_{j,t-1} \\ \gamma^*_{j,t-1} \end{bmatrix} + \begin{bmatrix} \omega_{j,t} \\ \omega^*_{j,t} \end{bmatrix}, \qquad \begin{array}{c} j = 1, \ldots, 6 \\ t = 1, \ldots, T \end{array}$$

where $\lambda_j = 2\pi j/12$ is the frequency in radians and the disturbances $\omega_{j,t}$ and $\omega^*_{j,t} \sim \mathsf{NID}\,(0, \sigma^2_\omega)$.

The model composed by equations (1), (2) and (3) constitutes the so called *Basic Structural Model* and is extensively illustrated in Harvey (1989). Here we impose the further restriction that $\sigma^2_\eta = 0$, getting a particular version of the trend, often called *smooth trend*, which is particularly suited to business cycle analysis[5].

In such a model the slope represents the *trend derivative* $\Delta\mu_t = \beta_{t-1}$. Moreover, the trend obtained is usually very smooth, thus making the dating (at least in the classical cycle) particularly easy, *i.e.* define a recession (expansion) at time t when $\Delta\mu_t = \beta_{t-1} < (\geq) 0$. Once the dating is obtained, the usual censoring rules are applied, namely that a cycle must last at least 15 months and that a phase must be at least 5 months long[6].

The aggregation of the turns of the single series is made along the lines described in the previous subsection.

2.3 Direct non-parametric approach (DIRNP)

Here the single series are first aggregated to form a composite indicator. The aggregation of the single variables is made following the current practice at

[5]The trend extracted in this way is the same as that produced by the Hodrick-Prescott filter, with the smoothing factor $\lambda = \sigma^2_\epsilon/\sigma^2_\zeta$ (Harvey and Jaeger, 1993)

[6]The series VASDV and INVIM here are considered as already free of noise, seasonality and trading days effect, so that equation 1 reduces to $y_t = \mu_t$

ISAE, as described in Altissimo *et al.* (2000). That is, the seasonally adjusted series are first smoothed with a low-pass filter built following the methodology outlined in Baxter and King (1999), in order to remove short term movements (with period less or equal than 3 months) from the original series. Afterwards, growth rates of the variables are calculated and aggregated with time varying weights inversely related to their variability. The resulting series, which represents the growth rate of the composite indicator, is transformed back, *i.e.* it is "integrated", choosing a conventional initial value.

The composite indicator is then passed trough a very simplified version of the Bry-Boschan procedure to get the turning points. The simplification lays in the fact that, being the composite indicator quite smooth, there is no need to carry out phases 1 to 4 of the procedure described in section 2.1, that is no smoothing of the series is necessary and turns can be identified directly on the original series. This point is not secondary, since early steps in the original Bry-Boschan procedure lead to a loose of data at the end-point, with a possible delay in the detection of turns.

2.4 Direct mixed (parametric and non parametric) detection (DIRMIX)

In their seminal paper, Stock and Watson (1991) (SW hereafter) proposed a parametric model to capture the comovements among selected variables, and to obtain a coincident indicator. These variables are thought as decomposable in a common unobservable factor and an idiosyncratic factor. The model can be set in state-space form, so that filtering and smoothing with the classical Kalman filter (Harvey, 1989) it is possible to estimate the common factor, which represents the coincident indicator.

For our application, a model with a very simple structure seems to adequately fit the data:

$$\begin{array}{ll} \Delta y_{it} = \gamma_i \Delta C_t + e_{it} & i = 1, \ldots, 6 \\ \psi_i\left(L\right) e_{it} = \varepsilon_{it} & \varepsilon_{it} \sim IIN(0, \sigma_i^2) \\ \Delta C_t = v_t & v_t \sim IIN(0, 1) \end{array} \tag{4}$$

with $E\left(v_t, \varepsilon_{i\tau}\right) = 0$ for each t, τ, i.

The index i refers to each of the six variables used in this work, γ_i are coefficients, $\psi_i\left(L\right)$ are polynomials in the lag operator L, Δy_{it} is the first difference of the log of the i^{th} centered indicator, C_t is the log of the common unobserved component and $\Delta C_t = C_t - C_{t-1}$. In the first equation of (4) it is clear the decomposition of each series in a common component and an idiosyncratic factor. The identified orders of the polynomials $\psi_i\left(L\right)$ are 0 for the variable VASDV, 1 for the variable MERFS and 2 for the other variables.[7] Again, turning points are identified on the composite indicator by means of the Bry and Boschan procedure.

2.5 Fully parametric approach (DIRP)

It has often been claimed that the business cycle is characterised by the presence of regimes and asymmetries; in fact the periods of high and low growth are asymmetric (in particular, Neftçi, 1982, noted that the expansion phases are seen as being longer and smoother than recessions). In order to represent these characteristics, Diebold and Rudebusch (1996) suggest to add a Markov Switching (MS hereafter) dynamics to the SW model. In this context this proposal has the further advantage of allowing the simultaneous calculation of a composite indicator and of a dating.

A SW-MS model for the representation of the Italian business cycle can be obtained by adding a switching intercept in the structure of the last equation of 4, thus getting:

$$\begin{array}{ll} \Delta y_{it} = \gamma_i \Delta C_t + e_{it} & i = 1, \ldots, 6 \\ \Delta C_t = \mu_{s_t} + v_t & v_t \sim IIN(0,1). \end{array} \tag{5}$$

In this case, we found that the presence of the autoregressive polynomial in the structure of the disturbances e_{it} implies bad inference on the regimes, so we prefer to simplify again the model, considering the e_{it}'s as white noises.

The coefficient μ_{s_t} is a switching parameter representing the mean of the coincident indicator; the subfix s_t is a binary random variable with unknown distribution, representing the state at time t (say 0 for the recession and 1 for the expansion[8]). It is supposed that s_t follows an ergodic Markov chain:

$$\Pr\left[s_t = j | s_{t-1} = i, s_{t-2} = r, \ldots\right] = \Pr\left[s_t = j | s_{t-1} = i\right] = p_{ij}, \qquad i, j, r = 0, 1$$

[7]We acknowledge the use of the GAUSS routines (slightly modified by the authors) developed by Kim, available with the book of Kim and Nelson (1999), to estimate the SW model and the successive Markov Switching model, described in the next section.

[8]One of the common criticisms to the MS model for the analysis of the business cycle is the fact that there is not a precise reason to identify a state of the model with the recession and the other state with the expansion (see, for example, Anas and Ferrara, 2002). It is worth to note that a MS model with three or more regimes could fit better and a more statistically correct approach would apply one of the existing recent procedures to identify the number of regimes (Otranto and Gallo, 2002, and Psaradakis and Spagnolo, 2003). In this paper we do not deepen this topic, assuming a priori the correspondence between the states of the economy and those of the MS model.

synthesized by the transition probabilities matrix:

$$\mathbf{P} = \begin{bmatrix} p_{00} & 1-p_{00} \\ 1-p_{11} & p_{11} \end{bmatrix}. \tag{6}$$

The algorithm to obtain the coincident indicator and the estimation of the unknown coefficients, both for models (4) and (5), is described in Kim and Nelson (1999), together with the filtering and smoothing steps to obtain the probabilities:

$$\Pr\left[s_t = i|\Psi_T\right], \qquad i = 0, 1 \tag{7}$$

where Ψ_T is the global information deriving from the observations. These results allow us to identify the turning points; in fact, when the MS model fits adequately the observations, these probabilities fall in a small interval around 0 or 1, so that (7) provides a useful inference on the regime. A common practice is to assign the observation to the regime 0 if $\Pr\left[s_t = 0|\Psi_T\right] > 0.5$, to regime 1 otherwise, detecting the periods of recession and the periods of growth (Hamilton, 1989). To compare this procedure with the other approaches, we apply the same censoring rules described in the previous subsections.

3 Empirical results

In this section we illustrate the main results of the application of the different methods. While the focus of the paper is on the problem of *dating*, which is analysed in subsection 3.1, we carried out also an analysis of the behaviour of different methods in a real time situation (subsection 3.2).

3.1 Historical results

The historical results obtained with the different methods are compared with the dating provided by ISAE. The latter has been established by Altissimo *et al.* (2000) with an approach which mixes the results from the application of the Bry and Boschan procedure, together with a judgemental assessment of whether the clustering of turning points observed at certain dates constitute a corresponding turn for the whole economy or not, and, in the affirmative case, a judgemental assessment of the location of a turning point for the whole economy.

Clearly, the choice of this chronology as a benchmark is questionable, mainly because of the use of the Bry and Boschan routine. On the other hand, the dating obtained by Altissimo *et al.* (2000) closely resembles that produced earlier by ISCO (Carnazza, 1998), which was built upon different data and methods. Moreover, such a dating is quite "official", or at least it is considered as such among practitioners, who find it as a likely picture of the business cycle evolution in Italy. Therefore, it seems a good starting point to check how the different methods here analysed perform.

The procedures proposed all agree in identifying the two recessions of the seventies', the first due to the oil shock in 1973-4 and the second, short but deep, in 1977. All the methods agree, moreover, in finding a downturn in the early months of 1980, due to the second oil shock. Official ISAE dating records a strong and long recession, ending only in march 1983. Also the other methods give a similar picture, with the exception of DIRNP, which records a short recovery (an extra-cycle) in the second half of 1981.

Starting from 1983 a long expansion took place, following the official ISAE dating, until March 1992, when a recession started which lasted until July 1993. The other procedures often do not match this dating. In particular, INDNP, DIRNP and DIRMIX find a short extra-recession in 1990, mainly due to a contraction observed in the industrial sector, while DIRP sets directly as a recession the entire period from March 1990 to August 1993. Moreover, INDMIX, DIRMIX and DIRP find a short contraction during the period 1984-85.

During the rest of the nineties' all the procedures examined agree on the recession of 1995-96, as well as in finding a peak at the end of 2000. The "direct" methods identify a recession phase also in 1998-99, during the far-east countries crisis. Undoubtedly some variables, mainly industrial production, showed a downward trend during that period, but ISAE judged this movement as too partial[9], so that it could not be considered as a recession in the classical cycle, and the indirect procedures INDNP e INDMIX seems to agree on that. In the end, many of the procedures proposed find a trough at the end of 2001.

The results obtained show a tendency of the direct methods to find out more cycles than those detected by ISAE (three more for DIRNP and DIRMIX, two more for DIRP), while the indirect methods are more reliable with respect to this point, having detected only one extra-cycle each. A similar behaviour was found also by Artis *et al.* (1995) with reference to the Bry and Boschan procedure; to solve that problem they put a further constraint to the phase amplitude, which was required to be at least as large as one standard error of the monthly growth rate of the series. Actually, direct methods which build a composite indicator upon which the dating is carried out (DIRNP and DIRMIX) can suffer from the fact that even if a recession (expansion) characterises just one variable, if it is very pronounced the

[9]See ISAE, (2000), Rapporto trimestrale, luglio.

Table 1: Turning points identified with the different methods[a]

Turning points	ISAE	INDNP	INDMIX	DIRNP	DIRMIX	DIRP
Peak	mar-74	dec-73	feb-74	feb-74	jan-74	jan-74
Trough	may-75	aug-75	may-75	aug-75	aug-75	may-75
Peak	feb-77	dec-76	dec-76	jan-77	dec-76	nov-76
Trough	dec-77	jan-78	jan-78	dec-77	dec-77	sep-77
Peak	mar-80	jan-80	feb-80	jan-80	mar-80	nov-79
Trough				jun-81		
Peak				feb-82		
Trough	mar-83	mar-83	feb-83	feb-83	may-83	may-83
Peak			aug-85		aug-84	aug-85
Trough			jan-86		jan-85	jan-86
Peak		aug-89		apr-90	nov-89	feb-90
Trough		jun-90		dec-90	mar-91	
Peak	mar-92	feb-92	dec-91	jan-92	feb-92	
Trough	jul-93	jul-93	jul-93	aug-93	aug-93	aug-93
Peak	nov-95	oct-95	aug-95	dec-95	aug-95	dec-95
Trough	nov-96	aug-96	sep-96	jun-96	dec-96	dec-96
Peak				jul-98	dec-97	dec-97
Trough				jan-99	dec-98	apr-99
Peak	dec-00	oct-00	oct-00	nov-00	dec-00	nov-00
Trough		dec-01	dec-01	mar-02		

[a] The names of the different methods are as follows:
ISAE: official dating provided by ISAE;
INDNP: Indirect non-parametric detection;
INDMIX: Indirect mixed detection;
DIRNP: Direct non-parametric detection;
DIRMIX: Direct mixed detection;
DIRP: Direct fully parametric detection.

composite indicator itself can experience a downturn (upturn). To correct for such a behaviour it would be necessary to consider the *diffusion* of the recession (expansion) among the different variables considered, which is something that in the official dating is pursued, although not in a formal way (ISAE, 2000). DIRP should be, in principle, less affected by this problem because the dating it produces does not depend directly on the calculation of the composite indicator.

Indeed, the methods described in section 2 can be easily complemented with a diffusion index:

$$D_t = \frac{\sum_{i=1}^{6} I_{i,t}}{6} \tag{8}$$

where $I_{i,t}$ is an indicator variable which takes the value 0 if variable $y_{i,t}$ is in recession, otherwise it takes the value 1. The diffusion index D_t is bounded between 0 and 1 and a period is considered as a recession if it is strictly less than 0.5, *i.e.*, if al least four out of the six variables considered are in recession. Here we calculate two different sets of the variables $I_{i,t}$, one based on the dating obtained with the Bry and Boschan procedure (diff. index BB), the other with the dating procedure based on the parametric model given by equations (1), (2) and (3) (diff. index P).

The results of table 2 point out that taking into account the diffusion of cyclical phases does matter in replicating the ISAE chronology, in the sense that cyclical phases are exactly the same as those detected by ISAE, although the single turns can be somewhat shifted in time. Moreover, this result does not depend on the way $I_{i,t}$ is calculated.

Table 2: Turning points and diffusion indexes

Turning points	ISAE	diff. index BB	diff. index P
Peak	mar-74	jan-74	mar-74
Trough	may-75	may-75	may-75
Peak	feb-77	jan-77	jan-77
Trough	dec-77	nov-77	nov-77
Peak	mar-80	mar-80	mar-80
Trough	mar-83	oct-82	nov-82
Peak	mar-92	feb-92	dec-91
Trough	jul-93	may-93	jun-93
Peak	nov-95	nov-95	oct-95
Trough	nov-96	aug-96	aug-96
Peak	dec-00	aug-00	oct-00
Trough		mar-02	feb-01

3.2 Real-time results

A historical simulation has been carried out in order to detect how sensitive the different procedures are in order to early detect the turning points. The simulation is an almost "real-time" one, in the sense that the last available vintage of the raw series has been considered (except for quarterly national accounts variables, which are seasonally adjusted) and seasonal adjustment has been carried out for each period, as such taking into accounts revisions implied by the seasonal adjustment itself [10]. The simulation has been carried out from December 1985 to September 2002, each time increasing the time span by 3 months.

The main results are shown in table 3, where the delay of different methods in the detection of the last five turning points[11] are showed. Overall the method DIRNP seems to perform better than the others on average; moreover, considering the single points it always outperforms the other procedures, except in last turning point. All the methods seem to be quite robust with reference to the stability of the outcome, in the sense that detection of a false turns (with respect to the final outcome of each method) rarely occurs.

Table 3: Delay of different methods in the detection of turning points (in months)

Turning points	INDNP	INDMIX	DIRNP	DIRMIX	DIRP
mar-92	3	6	3	6	7[(a)]
jul-93	8	5	5	5	8
nov-95	7	7	4	7	7
nov-96	7	7	1	7	7
dec-00	6	3	9	6	6
Average delay	6.2	5.6	4.4	6.2	7.0

[a] This refers to the delay in the detection of the peak of February 1990

[10]Seasonal adjustment has been carried out using STAMP (Koopman *et al.*, 2000), with the model described in equations (1), (2) and (3). In this case σ^2_η was not restricted to be zero. The seasonally adjusted series is obtained subtracting from the original one the seasonal component γ_t, as well as the trading days effect δx_t.

[11]The comparison has been carried out just on the last five turning points, because during the nineties the different methods give more results which are more similar than during the eighties.

4 Conclusions

In this paper we compare different procedures for dating the business cycle of the Italian economy. The benchmark is represented by the chronology proposed by ISAE. For this reason the variables used in the experiment are the six series selected by Altissimo et al. (2000), on which the ISAE dating is currently based.

The approaches selected cover on one hand the possible methodologies in terms of parametric and nonparametric models and, on the other hand, in terms of direct and indirect detection of turning points; the procedures adopted are the most frequently used for each identified category of approaches.

The results obtained can be read subdividing the time span in three intervals. Until 1983 the different methods provide similar results; particularly they capture the two oil shocks of 1973-74 and 1980-81. The 1983-1992 period is characterised by several extra-cycles detected by the various approaches, in contrast with the ISAE dating, particularly with the methods we call *direct* ones. During the nineties' the results are more consistent with the ISAE official chronology. Moreover, if we complement the previous methods with a diffusion index, using it to "confirm" a recession, all the extra-cycles are eliminated.

Although the choice of ISAE dating as a benchmark is questionable, mainly because it partly uses some of the methods compared here, nevertheless it uses also a lot of judgement in establishing the turns, so that the exercise undertaken here should make sense. The results demonstrate that the differences in dating among the various procedures are not dramatic, provided we complement the methods with the diffusion index, so the choice of the procedure could depend on the experience and interests of the researcher. The ISAE dating contains a certain degree of subjectivity, being based on a "judgemental" aggregation of the turning points of the six series analysed, whereas the other procedures are automatic; so, the application of the Altissimo *et al.* (2000) method can be utilized only by experienced business cycle analysts. The DIRP methods extract a common component from various time series, so they are necessarily based on statistical models using a multiple equations system; they are appealing from a statistical point of view, providing a probabilistic measure of the cyclical status for each time and a cyclical indicator, but the correct specification of the model is a crucial step of the procedure; in fact we have noted in our experiments that different ARMA specifications for SW and SW-MS models imply different results in terms of dating. In addition, these models depend on the time interval adopted, obtaining possible different inferences on the state of the economy (as in Otranto, 2001, analysing the Italian business cycle with quarterly data). Methods based on indirect and nonparametric methodologies would be preferable for non-expert users because they could be applied in a totally automatic way with some more confidence in the results.

Finally, concerning the timeliness in the detection of turning points, the approach of building a composite indicator non-parametrically (DIRNP) seems to be a good choice in this context. The flexibility implied in such an indicator, *e.g.* the use of time-varying aggregation weights, is difficult to realize in a parametric framework and could explain some of the success of such an indicator.

A Data

The variables used in this paper are the same as those utilized in the paper of Altissimo *et al.* (2000). In particular they are:

PROIS : Index of industrial production: total industry excluding construction;
MERFS : Quantity of goods (tons) transported on railways;
STRGI : Percentage of overtime hours worked over ordinary ones in large industrial firms;
IMPD1 : Imports of investment goods (quantity);
INVIM : Investment in machinery and equipment at constant prices;
VASDV : Value added of service sectors, excluding mainly non-market sectors (education, health services, public administration).

The rationale behind the selection of these variables goes beyond the aim of this paper and is widely described in the cited article of Altissimo *et al.*. Here we underline that the first four variables are raw (not seasonally adjusted) and recorded at monthly frequency, while the last two (INVIM and VASDV) are quarterly and seasonally adjusted.

In order for the latter to be used in our comparison, they have been transformed to monthly frequency by means of the routine `DISTRIB.SRC` coming with the software Winrats 32 v. 5.0 (Doan, 2000).

This procedure assumes that the monthly data are generated by the process:

$$y_t = y_{t-1} + u_t$$

where $u_t \sim \mathsf{NID}(0, \sigma^2)$. The quarterly data Y are assumed to be observed without error. Moreover, the higher frequency data sums to the lower frequency values across every quarter. The procedure `DISTRIB.SRC` then estimates maximum likelihood y's which produce the correct Y's.

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