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Characterising the Business Cycle for Accession Countries

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Abstract

We analyse the evolution of the business cycle in the accession countries, after a careful examination of the seasonal properties of the available series and the required modification of the cycle dating procedures. We then focus on the degree of cyclical concordance within the group of accession countries, which turns out to be in general lower than that between the existing EU countries (the Baltic countries constitute an exception). With respect to the Eurozone, the indications of synchronization are also generally low and lower relative to the position obtaining for countries taking part in previous enlargements (with the exceptions of Poland, Slovenia and Hungary). In the light of the optimal currency area literature, these results cast doubts on the usefulness of adopting the euro in the near future for most accession countries, though other criteria such as the extent of trade and the gains in credibility may point in a different direction.

JEL Classification: C19, C40, E32, E39

Keywords: Business cycles, dating algorithms, cycle synchronization, EU enlargement, seasonal adjustment.

1 Introduction

This paper focuses on the business cycle experience of the accession countries. Aside from its intrinsic interest, a natural motivation for such an investigation can be derived from the prospect that these countries, shortly after acceding to EU, will be encouraged to qualify for participation in EMU. Actually, in joining the EU these countries acquire the "acquis communautaire" which, *inter alia*, obliges them to attempt to qualify for EMU participation. The formal criteria under which such participation will be enjoined are those provided by the Treaty of European Union (the Treaty of Maastricht). No accession country has been allowed an "opt-out" from the obligation to join if it meets the criteria, such as was negotiated by the UK, and by Denmark.

Optimal Currency Area (OCA) theory provides an alternative set of criteria which countries might do well to consider to obtain advice on the advisability and best timing of such a passage. According to the traditional statement of OCA (following the seminal paper of Mundell, 1961), the dominant criteria are the extent of trade with the potential partner countries (trade is a positive indication for union) and the extent to which the experience of shocks is common (symmetric) or asymmetric (an asymmetry of shocks being a negative indication). A widely-used device for measuring the symmetry or asymmetry of shocks is a measure of the synchronicity of business cycle experience – hence the relevance of this paper to this decision. It is also in this light that the paper makes a comparison between the relative business cycle experience of the current enlargement countries and that in some of the late joiners in previous periods.

The analysis of the business cycle of the Accession countries is rendered difficult by the structural break that marks the transition from the centrally planned to a market economy regime, and by the fact that following recovery from the "transition recession" the accession countries followed a path of more or less uninterrupted and speedy economic development and growth. In the post-transition period locating the classical cycle, with its reference to an upper turning-point characterization defined in terms of an *absolute* subsequent decline in activity is thus not very rewarding, producing in general at most one cycle.

Because of the pervasive growth in the post-transition period, the deviation cycle (where the turning points are characterized by *changes relative to trend*) represents a more promising and appropriate version of the business cycle. We detect this cycle by applying a band-pass filter based on two low-pass Hodrick-Prescott filters, and then apply dating rules (which incorporate minimum phase and cycle duration restrictions) to the data series so isolated, along the lines of Artis, Marcellino and Proietti (2002, AMP henceforth).

More cycles are revealed by the application of this method and we proceed to examine their synchronization by calculating cross-correlations and measures of concordance. We find that the degree of concordance *within* the group of accession countries is not as large as that in general between the existing EU countries (the Baltic countries constitute an exception). Between them and the Eurozone the indications of synchronization are generally low when GDP data are used. Interestingly, when industrial production data are used, these conclusions are slightly modified. Where the Baltic countries continue to form a within-group bloc of highly related economies (but now also involving the Czech Republic), when cross-correlation measures are used, it is evident that Hungary also has a high degree of synchronicity in its cyclical movements with the Eurozone and individual member countries. The concordance measure offers a more generous view of cyclical sympathy between a number of accession countries (all except Latvia and Lithuania) and the Eurozone, however - and the cyclical sympathy between some of these countries (Poland, Slovenia, Estonia, Hungary, the Czech Republic) and Germany is especially marked.

On the other hand, relative to the position obtaining for countries taking part in previous enlargements, the accession countries appear less convergent in (industrial production) business cycle terms with their prospective partners, with the exceptions of Poland, Slovenia and Hungary. Moreover, evaluating the dynamic behaviour of the correlation of industrial production between accession countries and the euro area, a downward trend is evident in the recent period for all countries except Poland and Hungary.

The structure of the paper is as follows. In Section 2 we discuss the available information set, which is quite limited temporally and of rather poor statistical quality. We use industrial production series rather than GDP, the former being available for longer time periods and at a higher (monthly) frequency, but with a marked (and changing) seasonal pattern, that requires a careful treatment before the cycle can be revealed. In Section 3 we review the business cycle dating algorithm proposed by AMP and discuss how to modify it to deal with the seasonal adjustment. In Section 4 we present the results for the classical and deviation cycle. In Section 5 we focus on the previous recent accession episodes, i.e., Greece, Spain and Portugal in the ‘80s and Austria, Finland and Sweden in the ‘90s. In Section 6 we summarize the established relevant features of business cycle experience in the Accession countries, and to conclude we revert to some of the Optimal Currency Area considerations in order to put our findings in perspective. The Appendix provides additional details on the dating algorithm.

2 The seasonal adjustment of the industrial production series

The accession countries have recently made a substantial step towards statistical harmonisation with the EU.[1]. The quarterly national accounts macro aggregates are produced at a very high level of compliance with the European System of Accounts (ESA95) methodology. However, they are available for a very short time span, and display surprisingly little cyclical variation. In particular, the amplitude of the output gap, as a percent of total

[1]See the reports prepared by the European Commission, available at the website http://europa.eu.int/comm/enlargement/report2002/index.htm, and, in particular, Chapter 12 of the individual country documents reports.

GDP, is comparable to, or smaller than, that of other European Union countries and the Euro area as a whole, which is puzzling.

Therefore, we prefer to base our analysis on industrial production index (total industry) series. The latter are available for a longer time span than GDP, compare table 1, are disaggregated at the monthly frequency and display more cyclical sensitivity than GDP estimates, in this respect proving more informative for monitoring business cycle fluctuations. We will concentrate on eight of the 10 enlargement countries, excluding Cyprus and Malta, and on a set of EU countries used as a benchmark. On average, according to disaggregation of GDP estimates by economic activity, the share of output that is absorbed by industry is roughly 1/3.

For the analysis of business cycles it is important to eliminate the seasonal component from the industrial production (IP henceforth) series and other sources of high frequency movements, since they could interfere with the dating of the overall peaks and troughs. Seasonally adjusted IP series are available for most of the countries under analysis, whose statistical agencies make widespread use of the Tramo-Seats seasonal adjustment procedures (Gómez and Maravall, 1996). However, for some of the countries (Slovakia, Estonia and Lithuania), a relevant calendar component is still present and has to be adjusted before proceeding to the dating. More generally, the application of standard seasonal adjustment procedures could prove rather problematic for most series because of the changes in seasonal pattern due to reporting habits and data collection strategies during the transition period, as documented in OECD (1997). Therefore, we prefer to analyze the raw IP series, plotted in figure 1, and develop in this section a proper seasonal adjustment methodology.

2.1 The seasonal adjustment methodology

We propose to seasonal adjust the monthly series of industrial production for all the 10 accession countries in the panel and for the selected EU series and Russia using variants of the basic unobserved components time series model (Harvey, 1989). The series, possibly after a transformation, are additively decomposed as follows:

$$y_t = \mu_t + \gamma_t + \delta' x_t + \epsilon_t, \quad t = 1, \dots, T,$$

where μ_t is the trend component, γ_t is the seasonal component, the x_t's are appropriate regressors that account for calendar effects, namely working days[2], moving festivals (Easter) and the length of the month, and $\epsilon_t \sim \text{NID}(0, \sigma^2_\epsilon)$ is the irregular component. The decision whether to take logarithms was based on the overall performance of the model and on diagnostics based on the standardised innovations.

The trend component is assumed to evolve according to the *local linear trend model*:

$$\begin{array}{rcccccl} \mu_{t+1} & = & \mu_t & + & \beta_t & + & \eta_t, \qquad \eta_t \sim \text{NID}(0, \sigma^2_\eta), \\ \beta_{t+1} & = & & & \beta_t & + & \zeta_t, \qquad \zeta_t \sim \text{NID}(0, \sigma^2_\zeta), \end{array} \tag{1}$$

where β_t is the stochastic slope, that in turn evolves as a random walk; the disturbances η_t, ζ_t, are independent of each other and of any remaining disturbance in the model.

The seasonal component has a trigonometric representation, such that the seasonal effect at time t arises from the combination of six stochastic cycles:

$$\gamma_t = \sum_{j=1}^{6} \gamma_{jt},$$

where, for $j = 1, \dots, 5$,

$$\begin{array}{rcl} \gamma_{j,t+1} & = & \cos\lambda_j \gamma_{j,t} + \sin\lambda_j \gamma^*_{j,t} + \omega_{j,t} \quad \omega_{j,t} \sim \text{NID}(0, \sigma^2_{\omega_j}) \\ \gamma^*_{j,t+1} & = & -\sin\lambda_j \gamma_{j,t} + \cos\lambda_j \gamma^*_{j,t} + \omega^*_{j,t} \quad \omega^*_{j,t} \sim \text{NID}(0, \sigma^2_{\omega_j}) \end{array}$$

and $\gamma_{6,t+1} = -\gamma_{6,t} + \omega_{6,t}$. Above, $\lambda_j = \frac{2\pi}{12} j$ denotes the frequency at which each seasonal cycle is defined; thus, $\gamma_{1,t}$ defines a nonstationary (first-order integrated) stochastic cycle

[2]We experienced using 6 regressors, each measuring the number of weekdays in excess of the number of Sundays, but eventually model selection criteria suggested the more parsimonious single regressors contrasting the number of working days in the week (Monday to Friday) with the number of Saturdays and Sundays, multiplied by 5/2.

at the frequency $\pi/6$, also known as the fundamental frequency, corresponding to a period of 12 months; the second, $\gamma_{2,t}$, defines a biannual cycle, that is a cycle with period equal to six months, and so forth; finally, $\gamma_{6,t}$ is a stochastic cycle defined at the frequency π, corresponding to a period of two observations. The disturbances ω_{jt} and ω^*_{jt} are assumed to be normally and independently distributed with common variance $\sigma^2_{\omega_j}$, that may vary with j; they are also independent of the other disturbances in the model. See Harvey (1989) and Proietti (2000) for further details on the properties of this seasonal model.

This basic representation needs to be modified to allow for the presence of structural breaks, due to the transition to a market economy. Preliminary investigation suggests that the structural change is not peculiar to a single component, but affects all of them, and can be seen as a change in the prediction error variance of the series. The latter may be abrupt or take place smoothly over time. Moreover, according to the length of the series, there may be two or multiple regimes; for instance, for Latvia, Hungary and Slovenia, whose series start in 1980, and Poland, a three regimes model, characterising respectively the pre-transition, the transition and the post-transition dynamics, is highly plausible.

If σ^2_{kt} denotes any of the time-varying disturbances in the model ($k = \eta, \zeta, \epsilon, \omega_j, , j = 1, \dots, 6$), we adopt a multiple regime model, with smooth transition across the various regimes, see van Dijk, Teräsvirta and Franses (2002), such that

$$\sigma^2_{kt} = c^2_k \sigma^2_t,$$

where c^2_k is a time-invariant positive constant and

$$\ln \sigma^2_t = \sum_{l=1}^{m} \frac{\varsigma_l}{1 + \exp[-\kappa_l(t - \tau_l)]}, \quad \tau_1 < \cdots < \tau_l < \tau_m;$$

$\exp(\sum_{j=1}^{l} \varsigma_j)$ are the variance inflation (reduction) factors for regime l, τ_l is the time around which the regime change is located, and $\kappa_l > 0$ is the smoothness parameter that determines the speed of the transition. Hence, $m + 1$ denotes the number of regimes.

The model is estimated by maximum likelihood using the support of the Kalman filter[3].

[3]Estimation and signal extraction were performed in Ox 3.3 using the Ssfpack library, version beta 3.0;

The seasonally adjusted series is the minimum mean square error estimate of $y_t^* = \mu_t + \epsilon_t$, that is $\mathsf{E}(y_t^* | \mathcal{F}_T)$, where $\mathcal{F}_T$ is the complete information set. This is computed by the Kalman filter and smoother, conditionally on the ML parameters estimates.

2.2 Overview of estimation results

The two regime model $(m = 1)$ was fitted to the monthly indexes of the Czech Republic and Slovakia, which are available starting from January 1990 and 1989, respectively, i.e. close to the beginning of the transition. The likelihood test of the restriction that the variance of the seasonal cycles is invariant ($\sigma^2_{\omega_j} = \sigma^2_\omega$) was accepted, which led to a more parsimonious parameterisation. The model fits a drop in the variance of the series occurring in January 1992: the estimated τ_1 is in fact located at January 1992 for both series; the transition to the new regime is very fast and the variance reduction factors are 0.06 and 0.02 respectively for the two series. The overall impression is that the model with a regime change performs very satisfactorily; this is corroborated by the residual autocorrelation and normality test statistics, that are not significant. The calendar component is highly significant and has larger amplitude in the Czech case.

For a second group of countries, composed of Poland, Hungary, Latvia and Slovenia, for which pre-transition data are available, a three regime model was adopted. The logarithmic transformation is supported for Hungary (from figure 1 it is clearly seen that at least in the post-transition period, the variance increases with the trend); moreover, for this country the transition is well accommodated by the variation in the slope parameter, β_t: the variance inflation factors are $\exp \hat{\varsigma}_1 = 1.40$ and $\exp(\hat{\varsigma}_1 + \hat{\varsigma}_2) = 1.19$ with τ_1 and τ_2 roughly corresponding to January 1985 and January 1997. Fundamentally, it appears that the downward trend in output that marked the transition to a market economy is smoother than the other countries; the dating exercise also highlights that that downward movement is more prolonged and less steep. Given that the linear specification provided an excellent

see Koopman, Doornik and Shephard (2001) fit and did not highlight any departure from the stated assumptions, we decided to adopt it.

The parameter estimates for Slovenia, $\exp \hat{\varsigma}_1 = 4.87$ and $\exp(\hat{\varsigma}_1 + \hat{\varsigma}_2) = 2.02$, with $\hat{\tau}_1$ and $\hat{\tau}_2$ corresponding respectively to the end of 1988 and of 1992, and the high κ_l values, underlie a quick transition to a regime characterised by increased volatility, that eventually settles down to a less variable regime. Similar results are obtained for Latvia; the middle regime covers the three full years, from 1990 to 1992 included. The third regime is characterised by a variance inflation factor close to one, perhaps suggesting that one may adopt an exponential transition model rather than one with multiple regimes (see Lundbergh and Teräsvirta, 2002). The transition to a new regime is fast, but in the logarithmic specification, the location parameters are the same, but the other estimates $\hat{\kappa}_1 = 475.72, \hat{\kappa}_2 = 0.04$, $\exp \hat{\varsigma}_1 = 19.50$ and $\exp(\hat{\varsigma}_1 + \hat{\varsigma}_2) = 0.51$, underlie a smooth transition from the second regime to the third, and a variance that is slowly declining over time. This is not necessarily contrasting with the model for the original scale of observations, and in fact the components are very similar.

The Polish case is peculiar in that the series seems to be subject to a recent change in variability (see figure 1) that it is not accommodated by the logarithmic transformation. The model that provides a satisfactory fit features four regimes ($m = 3$) for the prediction error variance: the pre-transition variance regime ended in December 1988; the next regime, between 1989.1 and 1992.12, is characterised by a variance inflation factor of about 4.5; in the post-transition regime we assist to a relevant drop of volatility (v.i.f.: 0.8); at the beginning of 1998 the series undergoes an increase of variability (v.i.f: 1.1). The auxiliary residuals (Harvey and Koopman, 1992) further suggested the presence of a level shift, taking place in December 1989.

Estonian and Lithuanian IP series do not pose a change-point problem; nevertheless, their seasonal adjustment provides two interesting case studies in the differential role of seasonal cycles. As a matter of fact, the null that the disturbance variances $\sigma^2_{\omega_j}$ are constant across j is strongly rejected. In particular, for Lithuania $\sigma^2_{\omega_j} = 0$ for $j = 1, 5, 6$, whereas $\sigma^2_{\omega_1} = 1.51$, $\sigma^2_{\omega_2} = 0.02$, $\sigma^2_{\omega_3} = 0.09$, $\sigma^2_{\eta} = 6.47$, $\sigma^2_{\epsilon} = 15.39$. Hence, only the first, second and third harmonics, corresponding to seasonal cycles with periods 6, 4, and 3 months, have nonzero disturbance variances. For Estonia, instead, the estimated $\sigma^2_{\omega_j}$s are larger for the fundamental frequency and the first harmonic. Finally, in both cases the seasonal pattern is fairly evolutive: for instance, in the case of Estonia, January increases its role over time as a period of seasonal trough in production.

The seasonally adjusted series are displayed in the figures 2-6, along with their classical turning points that are defined in the next section.

3 The business cycle dating algorithms

Our investigation focuses on two popular notions of economic cycles: the first is the classical business cycle definition, according to which the business cycle is a sequence of alternating expansions and recessions in the level of aggregate economic activity; according to the second, the fluctuations are relative to a trend or potential value. This is often referred to as a growth, or deviation, cycle (Mintz, 1969).

The cycle characteristics are the same under the two definitions - they are often summarised with the three *D*s': *depth, duration* and *diffusion* - and the dating methods are similar, although the latter requires the separation of the cycle from the trend, which proves rather controversial.

A dating algorithm operationalises the notion of business cycle and aims at estimating the position of turning points; in particular, it should enforce the following: i. alternation of peaks and troughs; ii. minimum duration ties for the phases (typically 6 months, 2 quarters) and a full cycle (15 months, 5 quarters); iii. depth restrictions; iv. assessment of uncertainty (probabilistic vs deterministic dating).

The Bry and Boschan (BB, 1971) monthly dating algorithm addresses explicitly points i. and ii. Depth restrictions, motivated by the fact that only major fluctuations qualify for the phases, are not explicitly considered, but are achieved via the successive dating of three filtered series with decreasing degree of smoothness, such that at each stage a neighbourhood of the turning points identified at the previous stage is explored.

The dating strategy adopted in this paper, developed in Artis, Marcellino and Proietti (2003, AMP), is made up of three main steps: pre-filtering, which aims at isolating the fluctuations in the series with period greater than the minimum cycle duration; preliminary identification of turning points via a suitably defined Markov chain that enforces alternation of turning points and minimum duration constraints; final identification of turning points on the original series.

The strategy shares the spirit of the BB routine but it deviates from it in several respects. In the first place, for the classical cycle the BB moving averages are replaced by low-pass signal extraction filters belonging to the Butterworth family. The Hodrick and Prescott (HP, 1999) filter with smoothness parameter identified according to a specific cut-off frequency arises as a special case; see Pollock (1999) and Gómez (2001) for further details on Butterworth filters. As far as the deviation cycle is concerned, we concentrate on the band-pass version of the so called HP cycle extraction filter that aims at extracting all the fluctuations with periodicity in the range between 1 year and a quarter and 8 years, more details are provided in section 4.2.

Secondly, the identification of turning points is made according to the Markov chain algorithm documented in AMP and summarised in the Appendix, that generalizes the method suggested by Harding and Pagan (2001); this simplifies significantly the dating process and opens the way both to assessing the uncertainty associated with the dates and to the multivariate assessment of the business cycle. The Markov chain dating algorithm automatically enforces the alternation of peaks and troughs, and the minimum phase and full cycle duration restrictions. Depth restrictions are easily enforced either directly or indirectly, by enhancing the smoothness properties of the signal extraction filter.

While the deviation cycle is scored directly on the HP band-pass component, for classical dating the final turning points are identified in two steps: in the first, provisional peaks and troughs are identified on the low-pass component; the second step determines the turning points in the original series, identifying the highest (peaks) and smallest (trough) value in an neighbourhood of size ± 5 months around the tentative turning points identified in the previous step. Turning points within the minimum phase at both ends of the series are eliminated, and phases and full cycles whose duration is less than the prescribed minimum are also eliminated.

The Markov chain dating algorithm is applied to the IP series resulting from the analysis of the previous section, namely, to seasonally adjusted series that have also been linearised by the identification of outliers and structural breaks. These operations are far from neutral and indeed are the source of rather controversial points: for instance, a sharp turning point may be flagged as an additive outlier by the model that is at the basis of our seasonal adjustment methodology. On the other hand, it is clear that additive outliers and level shifts can have a dramatic impact on turning points identification.

A more important issue is the evaluation of the effects of this pre-filtering of the series, possibly followed by the application of low-pass or band-pass filters, on the uncertainty associated with the identified business cycle turning points and phases. The main tool we use is the simulation smoother. This is an algorithm that allows us to draw simulated samples from the posterior distribution of a signal conditional on the available data; see de Jong and Shephard (1995) and Durbin and Koopman (2002) for details.

In our case, the interest lies in generating repeated draws $\tilde{y}_t^{(i)*} \sim y_t^*|\mathcal{F}_T, i = 1, \ldots, M$, where $y_t^* = \mu_t + \epsilon_t$ is the seasonally adjusted series; abstracting from calendar and regression effects, this is achieved by drawing samples from the joint distribution of the seasonal disturbances $\{\omega_{jt}, \omega_{jt}^*, j = 1, \ldots, 6, t = 1, \ldots, T\}$ conditional on the full observation set and the estimated model parameters, using the seasonal dynamic model to construct draws $\tilde{\gamma}_t^{(i)} \sim \gamma_t|\mathcal{F}_T$, and subtracting them from the original series.[4]

[4]A similar procedure is used to deal with the effects of the band-pass filters, see AMP for details. The dating algorithms are coded in Ox 3.3 by Doornik (2000).

Once the peaks and troughs are identified, the chronology can be recoded into a 0-1 series, where 1 indicates that the observation belongs to a recessionary period and 0 otherwise. It is then possible to compare different countries on the basis of their cyclical concordance. For that, we compute the standardised concordance index, proposed in AMP (2002) and defined below. With respect to standard correlation analysis, the concordance statistic provides a more direct measure of the similarity of the cyclical pattern of two countries.

From the panel of binary indicators of the state of the economy, $S_{it}, t = 1, \ldots, T, i = 1, \ldots, N$, with $S_{it} = 1$ if country i is in recession at time t and zero otherwise, the simple matching similarity coefficient between any pair of countries i and j is defined as:

$$I_{ij} = \frac{1}{T} \sum_{t=1}^{T} \left[S_{it} S_{jt} + (1 - S_{it})(1 - S_{jt}) \right].$$

The latter is affected by the proportion of time spent in recession and is mean-corrected as in Harding and Pagan (2001):

$$I_{ij}^{*} = 2 \frac{1}{T} \sum_{t=1}^{T} (S_{it} - \bar{S}_i)(S_{jt} - \bar{S}_j).$$

Finally, this index can be divided by a consistent estimate of its standard error under the null of independence (see AMP), which is the square root of

$$\hat{\sigma}_{ij}^{2} = \hat{\gamma}_i(0)\hat{\gamma}_j(0) + 2 \sum_{\tau=1}^{l} \left(1 - \frac{\tau}{T}\right) \hat{\gamma}_i(\tau)\hat{\gamma}_j(\tau),$$

where l is the truncation parameter (here $l = 15$), and $\hat{\gamma}_i(\tau)$ is the lag τ sample autocovariance of S_{it}. This yields a test statistic with standard normal asymptotic distribution.

4 Business cycles in accession countries

In this section we apply the dating algorithm to the IP series for the accession countries, focusing first on the classical definition of business cycle and then on the deviation cycle notion.

4.1 Classical Business Cycles

The seasonally adjusted IP series and their turning points determined by the above procedure are plotted in figures 2-5. Peaks and troughs are flagged by a vertical line and the corresponding date is reported. In figure 6 we also propose a chronology of the IP classical cycle for Germany, Austria, Italy and the Euro area as a whole; the seasonally adjusted figures were again obtained from the raw series using the unobserved component model (see section 2).

Our dating exercise considers the full sample available; thus, the proposed chronology is such that for some countries the major downturn is associated with the fall in output due to the economic transition, which represents a genuinely structural, rather than cyclical phenomenon. Nevertheless, the dating exercise enables us to locate this relevant phenomenon over time and to highlight the differences in duration and speed of recovery among the accession countries.

The following table reports some summary statistics concerning the classical business cycle in the eight enlargement countries, calculated starting from 1993. Conditional on the peak-trough dates we have computed the proportion of time that is spent in expansion (second column), the average duration of recessions, the average output loss in index points (original scale) in the downturns; steepness, reported in column 5, is the ratio of the output loss and the average duration: it measures the amount of output that is lost on average in each month spent in recession, and thus it tends to be large if a large portion of output is lost in a short period. The output loss and steepness are also expressed as a percentage of total output in the last two columns.

Series	Prop. Time in Expansion	Ave. duration of recessions	Output loss (original scale)	Steepness of recession	Output loss %	Steepness (%)
Czech Rep.	0.78	9.0	5.56	0.62	5.35	0.59
Slovakia	0.86	8.5	7.41	0.87	6.86	0.81
Poland	0.80	12.0	6.80	0.57	5.09	0.42
Hungary	0.88	7.0	7.59	1.08	5.39	0.77
Slovenia	0.81	11.5	9.45	0.82	9.28	0.81
Latvia	0.59	16.3	21.51	1.32	20.10	1.23
Estonia	0.71	14.0	9.42	0.67	8.03	0.57
Lithuania	0.72	11.5	15.69	1.36	14.51	1.26
Average	0.77	11.2	10.43	0.91	7.01	0.62
Germany	0.78	9.0	4.27	0.47	4.02	0.45
Austria	0.89	12.0	9.34	0.78	6.89	0.57
Italy	0.62	11.5	4.90	0.43	4.76	0.41
Eurozone	0.82	7.3	3.07	0.42	2.76	0.38

Some of the post-transition business cycle characteristics are not dissimilar from those of the the EU benchmarks and the Eurozone; namely, the proportion of time spent in expansion is around 0.75, a shade less than the the value for the Eurozone, which amounts 0.81; it is noteworthy that the country more prone to recession is actually Italy, for which this proportion is 0.62. The (unweighted) average duration of the downturns is slightly less than one year, which is longer than the Eurozone (7.3 months), but is comparable to Italy (11.2); the dispersion around the average is not negligible, however, and it must be stressed that duration is larger for the Baltic series.

The difference lies with the amplitude of the downturns, as it emerges from the comparison of the percentage of output lost on average in recession: this fact is only in part compensated by the average duration of the recession so that recession tends to be steeper than in the EU countries considered.

In order to investigate the synchronisation of the classical business cycles within the enlargement countries and between them and the EU we have computed, using the available data starting from January 1993, the pairwise correlation coefficients of the annual growth rates, $\Delta_{12} \ln y_t$, that are reported in table 2. Correlated growth is necessary but not sufficient for synchronisation: as a matter of fact, a classical recession loosely speaking corresponds to a period when a measure of growth *over a particular horizon* is below zero. Let us call the measure *underlying growth*. The required measure is not immediately available since it needs to embody phase and cycle duration constraints, but if it were available and stationary, then the recession probability would depend on the expected value of underlying growth and on its autocovariance function. Thus, two countries with perfectly correlated underlying growth need not be synchronous, unless average growth is also coincident; see Harding and Pagan (2001).

With the above interpretative caveats in mind, the values reported in the table highlight that the average correlation within the enlargement countries is smaller than that of the EU selected countries, the largest correlations being found between the Czech Republic, Latvia and Estonia. Moreover, Poland and Hungary show the largest correlations with the EU.

The values for the cyclical concordance statistics, reported in table 3, show that only Poland and Hungary have significant concordance with one or more of the selected EU countries and the Eurozone, which confirms the previous finding.

Focusing, to save space, on these two countries, Poland and Hungary, to evaluate the uncertainty surrounding the proposed business cycle dating we apply the simulation smoother and in figure 7 we report the proportion of times each observation is flagged as a peak, a trough (reverse scale) or belongs to a recessionary phase. The plots illustrate quite effectively the greater uncertainty surrounding the turning points at the end of the sample for Hungary, which shows up in the spread of the frequency distribution of a turning point along the time axis. For instance, there are three candidate points for the last peak, whereas the May 1995 peak is much sharper. Also, the beginning of the transition period for Poland (1989.1) is marked quite clearly, while for Hungary it is rather blurred.

4.2 Deviation Cycles

The deviation cycle has been extracted using the band-pass version of the so-called Hodrick and Prescott filter, which attempts to isolate the fluctuations with a periodicity between 1.25 and 8 years. The filter is easily obtained from the difference of two low-pass filters, the first being the HP trend filter with smoothness parameter, λ_1, corresponding to the cut-off frequency, $\omega_l = 2\pi/(1.25s)$, where s is the number of observations in a year; this reduces the amplitude of high-frequency components, with period less than $1.25s$ years, e.g. 5 quarters or 15 months. The second is the HP filter for trend extraction with smoothness parameter λ_2 corresponding to $\omega_u = 2\pi/(8s)$ (period of 8 years), which aims at retaining the components with period greater than 8 years. The smoothness parameter is related to the cut-off frequency via the equation: $\lambda = [2(1 - \cos\omega)]^{-2}$. See Pollock (1999) and Gomez (2000) for further details. Hence, for quarterly data ($s = 4$), $\lambda_1 = 0.52$ and $\lambda_2 = 667$ (notice that the latter is smaller than the value suggested by Hodrick and Prescott for quarterly data, which is 1600), whereas in the monthly case ($s = 12$), $\lambda_1 = 33.45$ and $\lambda_2 = 54535$.

The choice of the second cut-off frequency is arbitrary[5], but we follow the convention used by Baxter and King (1999). As a matter of fact, the HP band-pass filter could be viewed as a finite sample implementation of the Baxter and King ideal filter. With respect to the approximation proposed by these authors, it provides estimates for the first and final three years, that obviously rely on asymmetric filters, and it does not suffer from the Gibbs phenomenon.

It is a matter of debate whether we should concentrate our analysis and dating efforts on the band-pass component rather than the high pass one (that is, in our case, the HP cycle corresponding to λ_2); the latter is affected by high frequency variation, which greatly interferes with the dating process, so that the dating procedure would nevertheless need

[5]According to the Burns and Mitchell definition, "…in duration business cycles vary from more than one year to ten or twelve years; …"

to go through a preliminary stage where turning points are identified on the band-pass series. Then, a local search on the high-pass series around the provisional turning points would be required. However, we have decided to adopt the first solution.

The dating is carried out as in AMP, namely, we cumulate the HP band-pass component and apply the Markov chain dating algorithm to identify the points at which the deviation cycle crosses zero (the duration restrictions are enforced at this stage); subsequently, the maximum (peak) or the minimum (trough) are located between two crossings.

The deviation cycles extracted from the monthly indices of industrial production available from 1993.1 onwards are plotted in fig. 8. The most relevant cyclical characteristics are reproduced in the following table:

Series	Prop. Time in Expansion	Ave. Duration Recession	Output loss (%)	Steepness
Czech Republic	0.42	31.3	3.36	0.11
Slovakia	0.43	17.0	5.11	0.30
Poland	0.43	17.3	3.88	0.22
Hungary	0.52	29.0	11.03	0.38
Slovenia	0.53	19.0	4.63	0.24
Latvia	0.50	20.0	8.00	0.40
Estonia	0.44	27.0	12.65	0.47
Lithuania	0.54	19.0	11.98	0.63
Average	0.45	22.4	7.58	0.34
Germany	0.50	20.0	4.80	0.24
Austria	0.41	16.8	4.39	0.26
Italy	0.48	15.8	3.86	0.24
Eurozone	0.43	22.7	4.52	0.20

The average proportion of time spent in expansion hovers around the theoretical benchmark 0.5. The most relevant fact is that the amplitude is generally greater than in the EU benchmark countries and the Eurozone, as the output loss statistic highlights; provided that the average duration of recession does not differ much, the steepness of recessions is also greater.

The correlation coefficients reported in table 4 are high within the three European countries, the Baltic states, and between Hungary, Poland, Slovenia and the Euro area. On the other hand, the standardised concordance index (table 5) indicates that lack of cyclical concordance can be rejected for most accession countries, with the exception of Latvia and Lithuania.

These results are more encouraging in terms of cyclical concordance with European countries than what we have obtained with classical cycles, but they should be interpreted with care. Actually, the role of the concordance statistic is diminished, since the deviation cycle is measured on a interval scale, so that the nominal characterisation, using the recession indicators S_{it}, is poorer than in the original scale. The correlation coefficients are also problematic because the danger of spurious associations is boosted by the adoption of a band-pass filter, see King and Rebelo (1993), Harvey and Jäger (1993) and Cogley and Nason (1995).

5 The lesson drawn from previous accession episodes

The previous analyses were essentially static, the concordance statistics aiming at assessing the global concordance with a reference cycle (e.g. the German cycle or the Eurozone one), over the post-transition period. We now turn our attention to local measures of cyclical synchronisation that seek to answer a slightly different question: is concordance with the Eurozone cycle increasing over time, and at the end of the sample, roughly coincident with the time of enlargement, is it comparable in size to that witnessed in previous accession episodes?

There are essentially two strategies to address these issues, from the descriptive standpoint: the first is to compare the correlation or concordance statistics over non-overlapping subsamples computing the correlations for non-overlapping subperiods, as in Artis and

Zhang (1999); the second is to compute moving measures over rolling windows with the same width. We adopt the second here, concentrating on local correlation estimates, but we deviate from the usual practice of using a rectangular window of a fixed size, and use instead more localised estimates of the correlation coefficient that can be computed also at the end of the sample.

In particular, if x_t and y_t are a pair of zero mean variables, we adopt the measure:

$$r_{ij,t} = \frac{\sum_j K(j) x_{t-j} y_{t-j}}{\left[\sum_j K(j) x_{t-j}^2 \cdot \sum_j K(j) y_{t-j}^2\right]^{1/2}},$$

where $K(j)$ is the Epanechnikov Kernel with bandwidth h:

$$K(j) = \frac{3}{4}\left[1 - \left(\frac{j}{h+1}\right)^2\right].$$

This replaces the uniform kernel $K(j) = 1$ for $|j| \leq h+1$ that is customarily employed in analyses of this type and provides weights that decline quadratically with the distance from time t. The bandwidth is a crucial parameter; in the monthly application we consider $h = 18$, corresponding to a 3 years rolling window. The estimates at the beginning and at the end of the sample are based on an asymmetric window.

Figure 9 plots the unweighted average of the pairwise moving correlations between the monthly and annual growth rates of the accession countries (excluding Estonia and Lithuania, that have shorter series) and 10 EU countries (Germany, Austria, Italy, France, Spain, Portugal, Ireland, Belgium). At the end of the sample both series are close to zero and are at an historical low, but the monthly growth rate estimates suggest that the downward tendency has been reversed.

As far as the deviation cycle is concerned, for each of the enlargement country industrial production HP band-pass series we computed the local correlations with Germany, Austria, Italy, the Eurozone and Russia. Despite the many caveats in the interpretation of these measures, their pattern over time, reproduced in figure 10, is highly informative; in particular, it reveals that at the end of 2002 Poland, Hungary and Slovenia show high concordance (and divergence from Russia); the Czech Republic and Slovakia tend to move away from the Euro area and its benchmark countries in the year 2002; the Baltic countries share similar tendencies, but they have been in the past less correlated (as is clearly visible for Latvia and Estonia) with the Euro area, and more correlated with Russia.

The process of European integration has experienced already four waves of accessions, the first occurring in 1973 (Denmark, Ireland and the United Kingdom), the second in 1981 (Greece), the third in 1986 (Spain and Portugal); finally, at the beginning of 1995 Austria, Finland and Sweden joined the European Union. The issue that emerges quite naturally is whether the degree of business cycle synchronisation was similar at the time of these earlier accession as it is now for the current enlargement. To investigate this question we perform a similar exercise using IP data up to accession time (end of year previous to accession), that is we extract the deviation cycle using the same methods and we compute its moving correlation with a set of member countries (Germany, Italy and France). The the analysis does not take into account the problem of data revision, that is however minor with respect to industrial production.

From figure 11 it emerges that the business cycle correlation was generally higher in those previous episodes, and that only Poland, Hungary and Slovenia comply with the same level of cyclical synchronisation.

6 Conclusions

In this paper we have analysed the evolution of the business cycle in the accession countries. In a first step we have addressed two problems related with the available data, namely, the development of a proper seasonal adjustment procedure and the modification of the dating algorithm to take into account the seasonal adjustment when computing the peak-trough probabilities. Then we have applied the dating algorithm to the resulting seasonally adjusted IP series, and computed correlation and concordance measures to evaluate the similarities of the cyclical experience across accession countries and with respect to European countries and the euro area as a whole.

We find that the degree of concordance *within* the group of accession countries is not in general as large as that between the existing EU countries (the Baltic countries constitute an exception). Between them and the euro area the indications of synchronization are generally rather low, with the exception of Poland and Hungary, and lower relative to the position obtaining for countries taking part in previous enlargements (again with the exceptions of Poland, Hungary and this time Slovenia).

How do these results relate to the motivation that we mentioned in the introduction, namely the purpose of providing some information relevant to the assessment of the value and timing of entry into the EMU? For a positive indication one might like to have a verdict of "sustainable convergence": from this point of view the results might be said to have a negative quality. The degree of synchronisation is low both in comparison to the general run of intra-EMU measures and in comparison with the position for earlier enlargement occasions, although there is considerable variation within the group as a whole and for some countries – principally those formerly classified in "Group 1", the indications are much more favourable. However, there are a number of caveats that must be borne in mind.

The first is apparent in the review of the statistical record. The available data series is not a long one and the time since the regime change of transition from centrally planned to market economy remains, still, comparatively short – hardly enough to accommodate two cycles. The second is that these countries are in a state of fast development, which promises to change much in the structure of their economies, possibly including the character of their cyclical behaviour. Other investigators have of course emphasised these caveats in their work – and at least in terms of sample size this study, being the most recent, has the longest series available to it. This is certainly quite an advantage.

Indeed lack of usable data has often obliged investigators to take roundabout routes to reach an assessment of the shock-symmetry criterion. Buiter and Grafe (2001), use the correlation of the annual change in inventories of Group 1 Accession countries with the change in inventories in France and Germany as a measure of cyclical synchronisation (basing themselves on the idea that stock cycle is a driver for the business cycle). Their data show (for the period 1994-98) that the (unweighted) average of inventory change correlations of EU countries with France is positive whereas that of Group 1 Accession countries is negative; on the other hand, the average correlation of the Group 1 countries with Germany is positive and higher than the average for EU countries. Buiter and Grafe also show summary data on the structure of industry and employment by sector for the Group 1 countries in comparison to the average for the EU in 1985 and in 1995 and averages for the EU "late joiners" (Greece, Ireland, Spain and Portugal). The idea is that structural dissimilarity would conduce to asymmetric shocks. The difference between the Group I countries and the EU in 1994/95 does not seem to be much bigger than the difference between the group of late joiners and the EU in 1985, though the oversize agricultural sector in Poland stands out, along with its low productivity. On the other hand, to the extent that Central Bank interest rates register a shock stabilisation objective, the strong negative correlations these authors find for Hungary, Czech Republic, Estonia and Poland relative to Germany or the ECB (period: January 1998 – September 2000) suggests an asymmetry in their stochastic experience.

Fidrmuc (2001) draws attention to other recent work in this area (especially that by Boone and Maurel (1998, 1999) which exploits unemployment data) and supplies some observations of his own. In particular *(ibid*, Table 4), correlations of industrial production and GDP growth in the period 1993-99 between the Group 1 countries and Germany are presented. These are not in every case less than the corresponding correlations for EU countries; there is slender evidence, though (based on only two Group 1 countries' experience) that the correlations rose between 1991-99 and 1993-99. A well-known suggestion is that trade intensity and business cycle synchronicity are positively associated phenomena (e.g. Frankel and Rose, 1997 and 1998); Fidrmuc exploits this idea in an interesting way by first re-estimating the Frankel-Rose relationship (using a measure of intra-trade rather than total trade) in a sample of OECD countries and then using the relationship to project the business cycle synchronicity between a sample of Accession countries and Germany. The very high levels of trade performed by these countries with Germany ensures the prediction of a high value for synchronicity also. Korhonen (2001, 2003) also provides a review of previous work and supplies some fresh estimates of business cycle synchronicity based on industrial production data, the conclusions of which are much in line with our own.

This brings us to the final point to be made here. Business cycle synchronicity, however adequately it may be measured, is only one criterion in the OCA literature favouring a currency union. Two others – one traditional, the other a product of recent experience - must be mentioned in the current context. The traditional criterion is that of a high level of trade: in and of itself this is a positive indication for monetary union and the fact is that the Accession countries uniformly demonstrate very high levels of trade with EU countries (see Buiter and Grafe (2001) for a recent compilation of the evidence). The "new" criterion, still controversial in this particular application, relates to the acquisition of policy credibility and hence stability in the currency and related features, that membership of a monetary union may afford to a country which has an uncertain policy history, and perhaps lacks extensive capital markets denominated in its own currency and has little reputation.[6] A number of the accession countries have shown an interest, guided by this criterion, in "joining EMU early" – e.g., by establishing a Euro Currency Board or Euroizing (See Nuti (2002) for a discussion of these options).

Of course, it is not the purpose of this paper to review the case for monetary union for the countries in question. We have endeavoured to establish "the facts of the matter" only for the business cycle experience of these countries.

[6] Such a criterion has been formalised recently in Alesina and Barro (2002). The reference to domestic capital market size follows the suggestion that the "fear of floating" for a small economy may be rationally associated with an overexposure to exchange rate devaluation when debt is predominantly denominated in foreign currency (see., e.g. Calvo and Reinhart (2002)). Hence a monetary union option is more attractive.

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Appendix: the algorithm for dating the business cycle

The dating algorithm proposed by AMP enforces the alternation of turning points and minimum duration restrictions. It is based on a Markov chain (MC), whose order is determined by the minimum full cycle duration; the MC is converted into a first order MC with a sparse transition matrix that can be scored according to specific data patterns.

At time t the series can be in either of two mutually exclusive states or *phases*: expansion (E_t) or recession (R_t). The expansion ends with a peak, whereas a trough terminates the recession. For the enforcement of the alternation of peaks and troughs and minimum duration ties, it is useful to isolate the turning points within the two basic states. This is done by partitioning the basic states as follows:

$$\mathsf{E}_t \equiv \begin{cases} \mathsf{EC}_t & \text{(Expansion Continuation)} \\ \mathsf{P}_t & \text{(Peak)} \end{cases} ; \quad \mathsf{R}_t \equiv \begin{cases} \mathsf{RC}_t & \text{(Recession Continuation)} \\ \mathsf{T}_t & \text{(Trough)} \end{cases}$$

Letting $p_{EP} = P(\mathsf{P}_{t+1}|\mathsf{EC}_t)$ denote the probability of making a transition to a peak within an expansionary pattern, $p_{EE} = P(\mathsf{EC}_{t+1}|\mathsf{EC}_t) = 1 - p_{EP}$, and analogously $p_{RT} = P(\mathsf{T}_{t+1}|\mathsf{RC}_t)$, $p_{RR} = P(\mathsf{RC}_{t+1}|\mathsf{RC}_t) = 1 - p_{RT}$, we define a first order Markov chain (MC) with four states, denoted S_t, and transition matrix:

	EC_{t+1}	P_{t+1}	RC_{t+1}	T_{t+1}
EC_t	p_{EE}	p_{EP}	0	0
P_t	0	0	1	0
RC_t	0	0	p_{RR}	p_{RT}
T_t	1	0	0	0

We now introduce *minumum duration constraints*, that are important for the characterisation of the chain, as they increase its memory and serial dependence. Let D and N denote the minimum full cycle and phase durations, with $D \geq 2N$. The former (e.g. D=15 months is adopted by Bry and Boschan, 1971, and in the paper) determines the *order* of the MC, whereas both determine the *number of admissible states* when the chain is converted into a first order chain.

This is so since we need knowledge of the past D states to forecast the current state, and once a transition to a turning point is made, that is $S_t = \mathsf{P}_t$ or $S_t = \mathsf{T}_t$, then $S_{t+j} = \mathsf{RC}_{t+j}$ or $S_{t+j} = \mathsf{EC}_{t+j}$, respectively, for $j = 1, \ldots, N-1$, since the next $N-1$ states can only be of the same continuation type to enforce the phase duration.

The D-th order Markov chain is then converted into a first order one by combining D consecutive elements of the original chain, S_t. The states of the derived MC are thus defined by the collection:

$$S_t^* = \{S_t, S_{t-1}, \ldots, S_{t-D+1}\}.$$

As a result of duration ties, the total number of states is $M = 2N+(D-N+1)(D-N+2)$.

The transition matrix for S_t^* is very sparse and easily derived: states ending with a peak (trough) at t move with probability one to one and only one state ending with recession (expansion) continuation at time $t+1$. Expansion (recession) continuation states can make a transition to states of the same type with probability $p_{_{EE}}$ ($p_{_{RR}}$) or move to a peak (trough) with probability $p_{_{EP}}$ ($p_{_{RT}}$), if the previous trough (peak) occurred at least $N-1$ periods apart, otherwise they move with probability 1 to a continuation state of the same type.

Next, for the purpose of scoring the transition probabilities it is helpful to classify the states S_t^* into the following groups:

$\mathcal{S}_{_{EP}}$, which defines the set of states featuring an expansionary state at time t ($S_t = \mathsf{EC}_t$) and that are available for a transition to a peak.

$\mathcal{S}_{_{EE}}$, which defines the set of states featuring an expansionary state at time t ($S_t = \mathsf{EC}_t$) that can only make a transition to an expansion continuation state.

$\mathcal{S}_{_{P}}$, which defines the set of states featuring a peak at time t ($S_t = \mathsf{P}_t$).

$\mathcal{S}_{_{RT}}$, which defines the set of states featuring a recessionary state at time t ($S_t = \mathsf{RC}_t$) and that are available for a transition to a trough.

$\mathcal{S}_{RR}$, which defines the set of states featuring a recessionary state at time t ($S_t = \mathsf{RC}_t$) that can only make a transition to a recession continuation state.

$\mathcal{S}_{T}$, which defines the set of states featuring a trough at time t ($S_t = \mathsf{T}_t$).

Finally, $\mathcal{S}_E = \mathcal{S}_{EP} \cup \mathcal{S}_{EE} \cup \mathcal{S}_P$ is the set of expansionary states, and $\mathcal{S}_R = \mathcal{S}_{RT} \cup \mathcal{S}_{RR} \cup \mathcal{S}_T$ that of recessionary states.

The transition probabilities p_{RT} and p_{EP} uniquely characterise the MC. Our approach is to score them according to patterns in the data, as in Harding and Pagan (2002, 2003). In particular, let us define expansion and recession terminating sequences, ETS_t and RTS_t, respectively, as:

$$\begin{aligned}
\mathsf{ETS}_t &= \{(\Delta y_{t+1} < 0) \cap (\Delta_2 y_{t+2} < 0) \cap \cdots \cap (\Delta_N y_{t+N} < 0)\} \\
&= \{y_t > (y_{t+1}, \ldots, y_{t+N})\} \\
\mathsf{RTS}_t &= \{(\Delta y_{t+1} > 0) \cap (\Delta_2 y_{t+2} > 0) \cap \cdots \cap (\Delta_N y_{t+N} > 0)\} \\
&= \{y_t < (y_{t+1}, \ldots, y_{t+N})\}
\end{aligned} \tag{2}$$

where $\Delta_j = 1 - L^j$. The former defines a candidate point for a peak, which terminates the expansion, whereas the latter defines a candidate for a trough.

For a given definition of the terminating sequence, the rules for scoring the transition probabilities of the chain are set out as follows:

If $\{S_t^* = s_{EP}, s_{EP} \in \mathcal{S}_{EP}\}$ *and* ETS_{t+1} *is true, then* $\{S_{t+1}^* = s_P, s_P \in \mathcal{S}_P\}$. *Hence, the transition probability* p_{EP} *is computed as:*

$$\begin{aligned}
p_{EP} &= P\left(\{S_t^* = s_{EP}, s_{EP} \in \mathcal{S}_{EP}\} \cap \mathsf{ETS}_{t+1}\right) \\
&= \mathrm{I}(\mathsf{ETS}_{t+1}) \sum_{s_{EP} \in \mathcal{S}_{EP}} P\left(S_t^* = s_{EP}\right),
\end{aligned} \tag{3}$$

where $\mathrm{I}(\cdot)$ *is the indicator function. Else, if* ETS_{t+1} *is false then the expansion is continued, that is* $S_{t+1}^* = s_{EP}, s_{EP} \in \mathcal{S}_{EP}$*; the associated transition probability is* $p_{EE} = 1 - p_{EP}$.

Else, if $\{S_t^* = s_{RT}, s_{RT} \in \mathcal{S}_{RT}\}$ *and* RTS_{t+1} *is* true, *then* $\{S_{t+1}^* = s_T, s_T \in \mathcal{S}_T\}$. *Hence, the transition probability* p_{RT} *is computed as:*

$$\begin{aligned}
p_{RT} &= P\left(\{S_t^* = s_{RT}, s_{RT} \in \mathcal{S}_{RT}\} \cap \mathsf{RTS}_{t+1}\right) \\
&= \mathrm{I}(\mathsf{RTS}_{t+1}) \sum_{s_{RT} \in \mathcal{S}_{RT}} P\left(S_t^* = s_{RT}\right),
\end{aligned} \tag{4}$$

Else, if RTS_{t+1} *is false, then the recession is continued, that is* $S^*_{t+1} = s_{_{RT}}, s_{_{RT}} \in \mathcal{S}_{RT}$*; the associated transition probability is* $p_{_{RR}} = 1 - p_{_{RT}}$.

For instance, if at time t the chain S^*_t is in any of the states belonging to the class $(S)_{_{EP}}$, and ETS_{t+1} is true, i.e. an expansion terminating sequence occurs at time $t+1$, the chain moves to a new state S^*_{t+1} featuring a peak at time $t+1$, ($S_{t+1} = \mathsf{P}_{t+1}$).

Probabilistic dating replaces the indicator function, $\mathrm{I}(\cdot)$, with the probability of the terminating sequences, $\mathcal{P}^{(ETS)}_{t+1}, \mathcal{P}^{(RTS)}_{t+1}$.

If $\mathcal{F}_t$ denotes the collection of $\mathrm{I}(\mathsf{ETS}_j), \mathrm{I}(\mathsf{RTS}_j), j = 1, 2, \ldots, t$, and $P(S^*_t|\mathcal{F}_t)$ denotes the probability of being in any particular state at time t conditional on this information set, the algorithm recursively produces $P(S^*_t|\mathcal{F}_t)$, for all $t = 1, \ldots, T$, and hence, marginalising previous states $S_{t-j}, j = 1, \ldots, D$, the probabilities of each elementary event, $P(S_t|\mathcal{F}_t)$, and $P(\mathsf{E}_t|\mathcal{F}_t) = P(\mathsf{EC}_t|\mathcal{F}_t) + P(\mathsf{P}_t|\mathcal{F}_t)$, $P(\mathsf{R}_t|\mathcal{F}_t) = P(\mathsf{RC}_t|\mathcal{F}_t) + P(\mathsf{T}_t|\mathcal{F}_t)$, can be obtained. For instance,

$$P(\mathsf{E}_t|\mathcal{F}_t) = \sum_{s_{_E} \in \mathcal{S}_E} P\left(S^*_t = s_{_E}\right).$$

Table 1: Data availability for accession countries

Country	GDP (quarterly)		IPI (monthly)	
	Start	End	Start	End
Czech Republic (CZE)	1994.q1	2002.q4	1990.m01	2002.m12
Slovak Republic (SVK)	1993.q1	2002.q1	1989.m01	2002.m12
Poland (POL)	1995.q1	2002.q2	1985.m01	2002.m12
Hungary (HUN)	2001.q1	2002.q2	1980.m01	2002.m12
Slovenia (SVN)	1992.q1	2002.q1	1980.m01	2002.m12
Estonia (EST)	1993.q1	2002.q1	1995.m01	2002.m12
Latvia (LVA)	1995.q1	2002.q1	1980.m01	2002.m12
Lithuania (LTU)	1995.q1	2002.q1	1996.m01	2002.m11

Table 2: Industrial Production - Correlation of yearly growth rates, $\Delta_{12} \ln y_t$ (computed on available data points from 1993 to 2002). Values greater than 0.7 in bold.

	CZE	SVK	POL	HUN	SVN	EST	LVA	LIT	D	A	I	EURO
CZE	1.00	0.54	0.09	0.09	0.35	**0.75**	**0.77**	0.55	0.20	-0.01	0.18	0.15
SVK	0.54	1.00	0.15	0.09	0.36	0.52	0.43	0.61	0.31	0.28	0.38	0.35
POL	0.09	0.15	1.00	0.40	0.34	0.53	-0.04	-0.12	0.51	0.47	**0.70**	0.63
HUN	0.09	0.09	0.40	1.00	0.37	0.34	0.03	-0.11	**0.83**	0.68	0.49	**0.77**
SVN	0.35	0.36	0.34	0.37	1.00	0.51	0.05	0.35	0.50	0.27	0.38	0.45
EST	**0.75**	0.52	0.53	0.34	0.51	1.00	0.68	0.40	0.47	0.31	0.48	0.46
LVA	**0.77**	0.43	-0.04	0.03	0.05	0.68	1.00	0.62	0.12	-0.06	0.02	0.04
LIT	0.55	0.61	-0.12	-0.11	0.35	0.40	0.62	1.00	0.02	-0.24	0.05	-0.01
D	0.20	0.31	0.51	**0.83**	0.50	0.47	0.12	0.02	1.00	0.67	0.58	**0.92**
A	-0.01	0.28	0.47	0.68	0.27	0.31	-0.06	-0.24	0.67	1.00	0.61	**0.77**
I	0.18	0.38	**0.70**	0.49	0.38	0.48	0.02	0.05	0.58	0.61	1.00	**0.80**
EURO	0.15	0.35	0.63	**0.77**	0.45	0.46	0.04	-0.01	**0.92**	**0.77**	**0.80**	1.00

Table 3: Industrial Production - Classical Business Cycle - Standardised Concordance Index (computed on available data points from 1993 to 2002). Values greater than 2.33 (99-th percentile of a standard normal variate) in bold.

	CZE	SVK	POL	HUN	SVN	EST	LVA	LIT	D	A	I	EURO
CZE	-	1.53	0.40	-0.39	**3.24**	**3.26**	1.99	1.38	1.94	-0.92	1.18	1.67
SVK	1.53	-	1.09	0.41	**2.36**	**2.44**	0.74	1.76	-0.54	-0.70	1.13	0.62
POL	0.40	1.09	-	1.79	0.60	0.00	-0.55	-0.40	0.90	**2.62**	**2.96**	**3.26**
HUN	-0.39	0.41	1.79	-	0.81	0.59	-1.58	-0.85	**2.96**	**2.91**	0.75	2.03
SVN	**3.24**	**2.36**	0.60	0.81	-	**3.58**	0.72	1.39	0.96	-0.78	-0.18	0.22
EST	**3.26**	**2.44**	0.00	0.59	**3.58**	-	1.55	1.47	1.08	-1.03	-0.52	0.09
LVA	1.99	0.74	-0.55	-1.58	0.72	1.55	-	1.93	-0.01	-1.32	1.58	0.45
LIT	1.38	1.76	-0.40	-0.85	1.39	1.47	1.93	-	-0.88	-1.04	0.01	0.17
D	1.94	-0.54	0.90	**2.96**	0.96	1.08	-0.01	-0.88	-	1.99	1.18	**2.76**
A	-0.92	-0.70	**2.62**	**2.91**	-0.78	-1.03	-1.32	-1.04	1.99	-	1.70	**3.15**
I	1.18	1.13	**2.96**	0.75	-0.18	-0.52	1.58	0.01	1.18	1.70	-	**3.18**
EURO	1.67	0.62	**3.26**	2.03	0.22	0.09	0.45	0.17	**2.76**	**3.15**	**3.18**	-

Table 4: Industrial Production - Correlation of HP bandpass deviation cycles (computed on available data points from 1993 to 2002).

	CZE	SVK	POL	HUN	SVN	EST	LVA	LIT	D	A	I	EURO
CZE	1.00	0.62	0.40	-0.08	0.37	**0.84**	**0.81**	**0.74**	0.17	-0.09	0.27	0.16
SVK	0.62	1.00	0.33	0.00	0.31	0.52	0.42	**0.71**	0.23	0.28	0.48	0.32
POL	0.40	0.33	1.00	0.55	0.48	0.68	0.23	-0.13	0.66	0.57	0.66	0.67
HUN	-0.08	0.00	0.55	1.00	0.59	0.23	-0.18	-0.28	**0.92**	**0.82**	**0.70**	**0.91**
SVN	0.37	0.31	0.48	0.59	1.00	0.67	-0.04	0.34	0.67	0.34	0.57	0.65
EST	**0.84**	0.52	0.68	0.23	0.67	1.00	**0.72**	0.54	0.45	0.12	0.41	0.40
LVA	**0.81**	0.42	0.23	-0.18	-0.04	**0.72**	1.00	**0.79**	0.03	-0.18	0.00	-0.02
LIT	**0.74**	**0.71**	-0.13	-0.28	0.34	0.54	**0.79**	1.00	-0.04	-0.39	0.05	-0.04
D	0.17	0.23	0.66	**0.92**	0.67	0.45	0.03	-0.04	1.00	**0.75**	**0.72**	**0.95**
A	-0.09	0.28	0.57	**0.82**	0.34	0.12	-0.18	-0.39	**0.75**	1.00	**0.75**	**0.84**
I	0.27	0.48	0.66	**0.70**	0.57	0.41	0.00	0.05	**0.72**	**0.75**	1.00	**0.88**
EURO	0.16	0.32	0.67	**0.91**	0.65	0.40	-0.02	-0.04	**0.95**	**0.84**	**0.88**	1.00

Table 5: Industrial Production - HP bandpass deviation cycles - Standardised Concordance Index (computed on available data points from 1993 to 2002). Values greater than 2.33 (99-th percentile of a standard normal variate) in bold.

	CZE	SVK	POL	HUN	SVN	EST	LVA	LIT	D	A	I	EURO
CZE	-	1.47	**2.65**	2.31	2.15	1.63	0.54	1.60	**2.45**	0.84	2.00	**2.61**
SVK	1.47	-	1.83	1.68	1.51	1.61	0.89	1.88	2.14	**2.50**	**3.11**	**2.84**
POL	**2.65**	1.83	-	**2.97**	**2.97**	**2.86**	1.27	1.19	**3.43**	2.38	**3.16**	**3.50**
HUN	2.31	1.68	**2.97**	-	2.93	2.50	0.56	1.73	**3.14**	2.34	2.18	**3.18**
SVN	2.15	1.51	**2.97**	**2.93**	-	**2.80**	1.40	1.12	**3.45**	1.68	1.85	**2.89**
EST	1.63	1.61	**2.86**	**2.50**	**2.80**	-	**2.56**	1.58	**3.20**	1.65	**2.47**	**2.83**
LVA	0.54	0.89	1.27	0.56	1.40	**2.56**	-	1.88	1.92	0.83	1.26	1.34
LIT	1.60	1.88	1.19	1.73	1.12	1.58	1.88	-	1.49	0.98	1.21	1.55
D	**2.45**	2.14	**3.43**	**3.14**	**3.45**	**3.20**	1.92	1.49	-	2.11	**2.65**	**3.65**
A	0.84	**2.50**	**2.38**	**2.34**	1.68	1.65	0.83	0.98	2.11	-	**2.78**	**2.95**
I	2.00	**3.11**	**3.16**	2.18	1.85	**2.47**	1.26	1.21	**2.65**	**2.78**	-	**3.54**
EURO	**2.61**	**2.84**	**3.50**	**3.18**	**2.89**	**2.83**	1.34	1.55	**3.65**	**2.95**	**3.54**	-

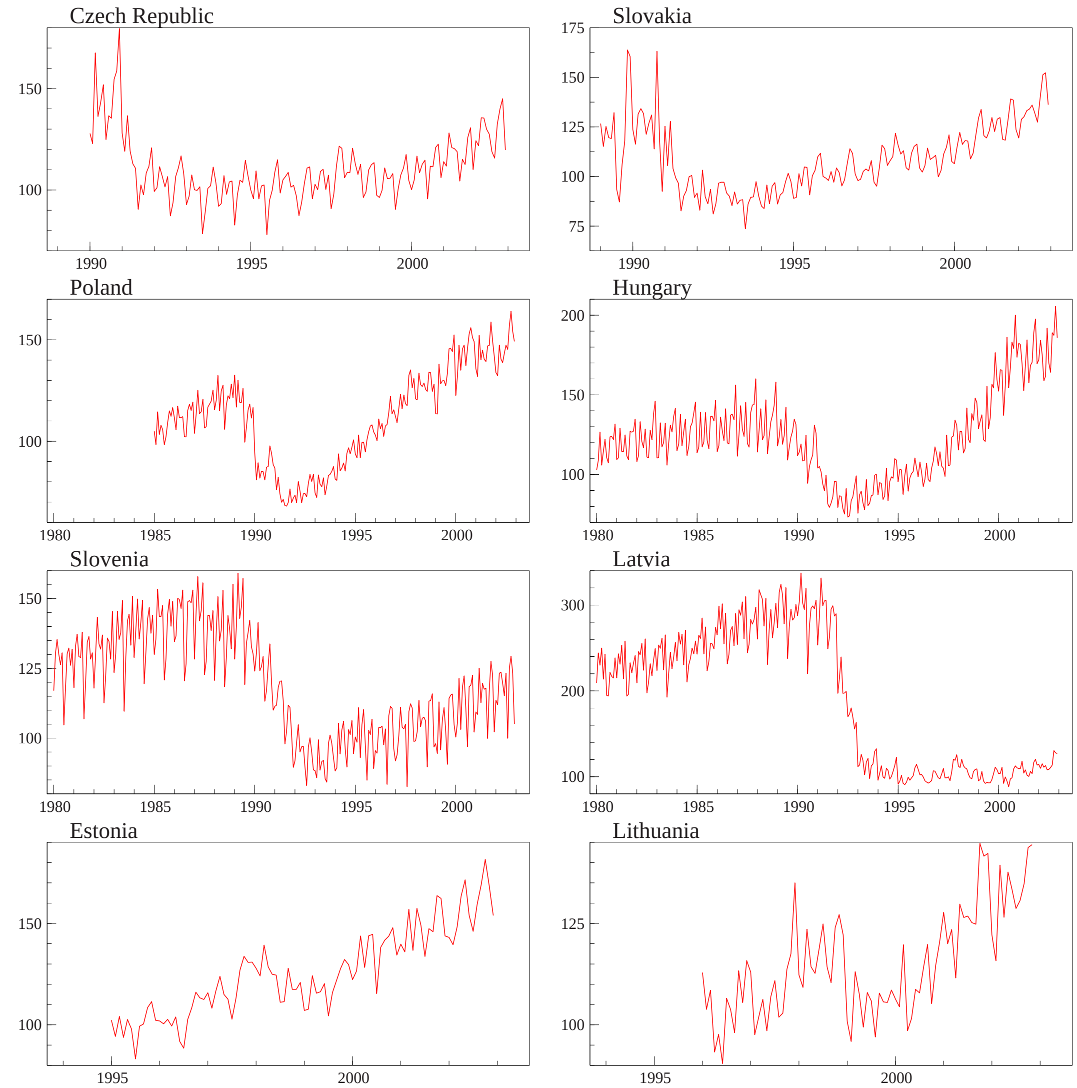

Figure 1: Index of industrial production: Original series.

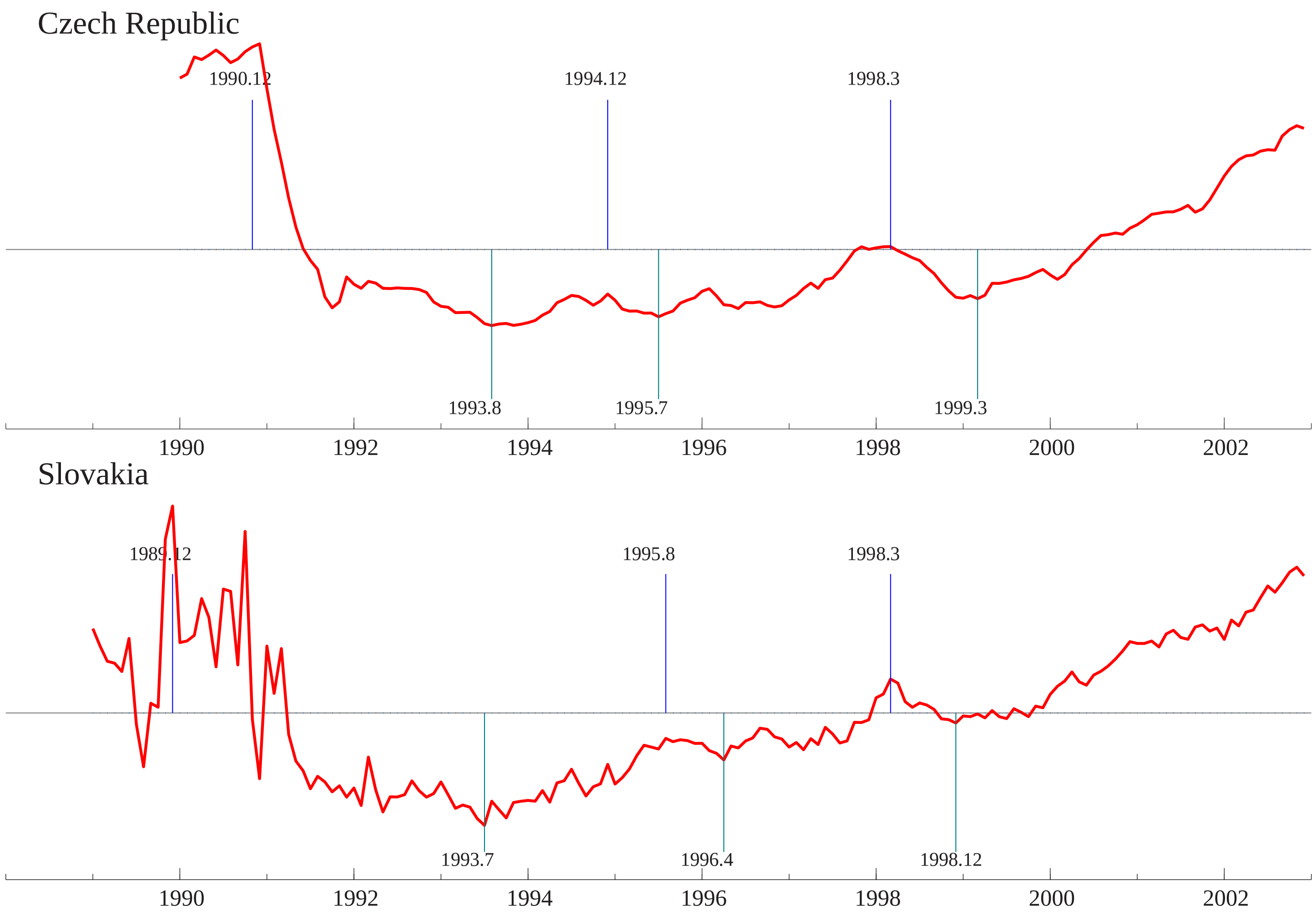

Figure 2: Czech Republic and Slovakia: Industrial Production classical cycle turning points.

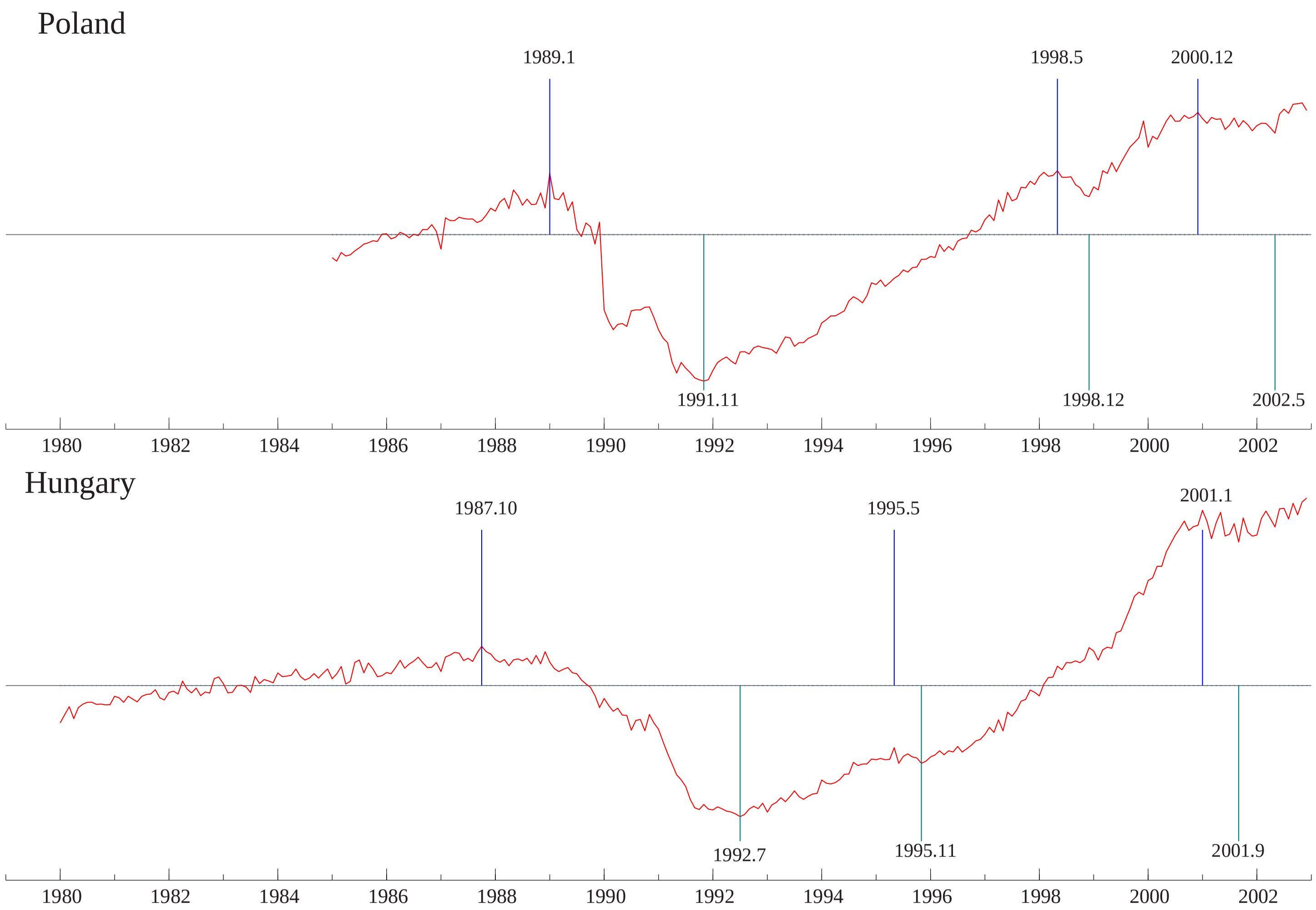

Figure 3: Poland and Hungary: Industrial Production classical cycle turning points.

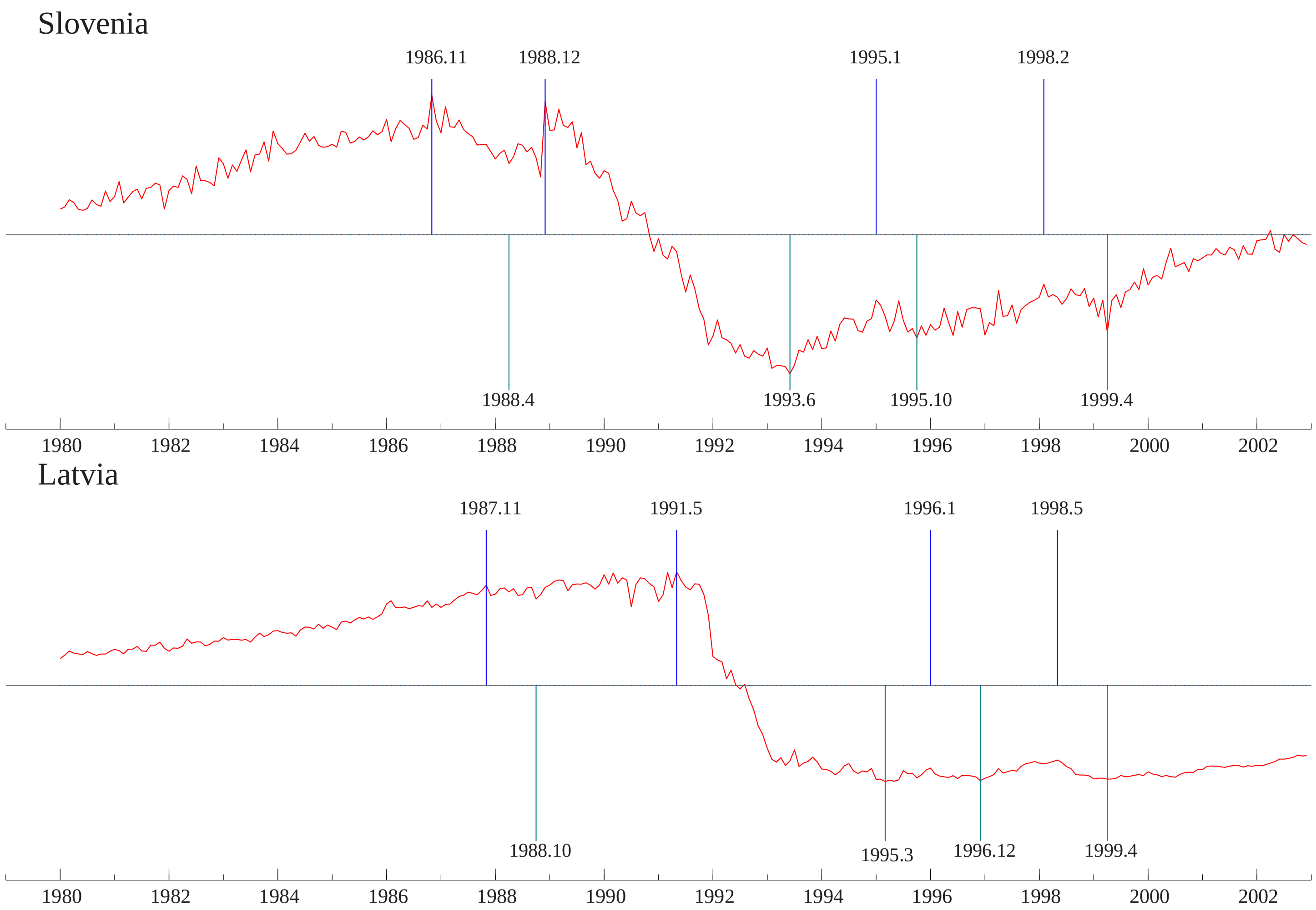

Figure 4: Slovenia and Latvia: Industrial Production classical cycle turning points.

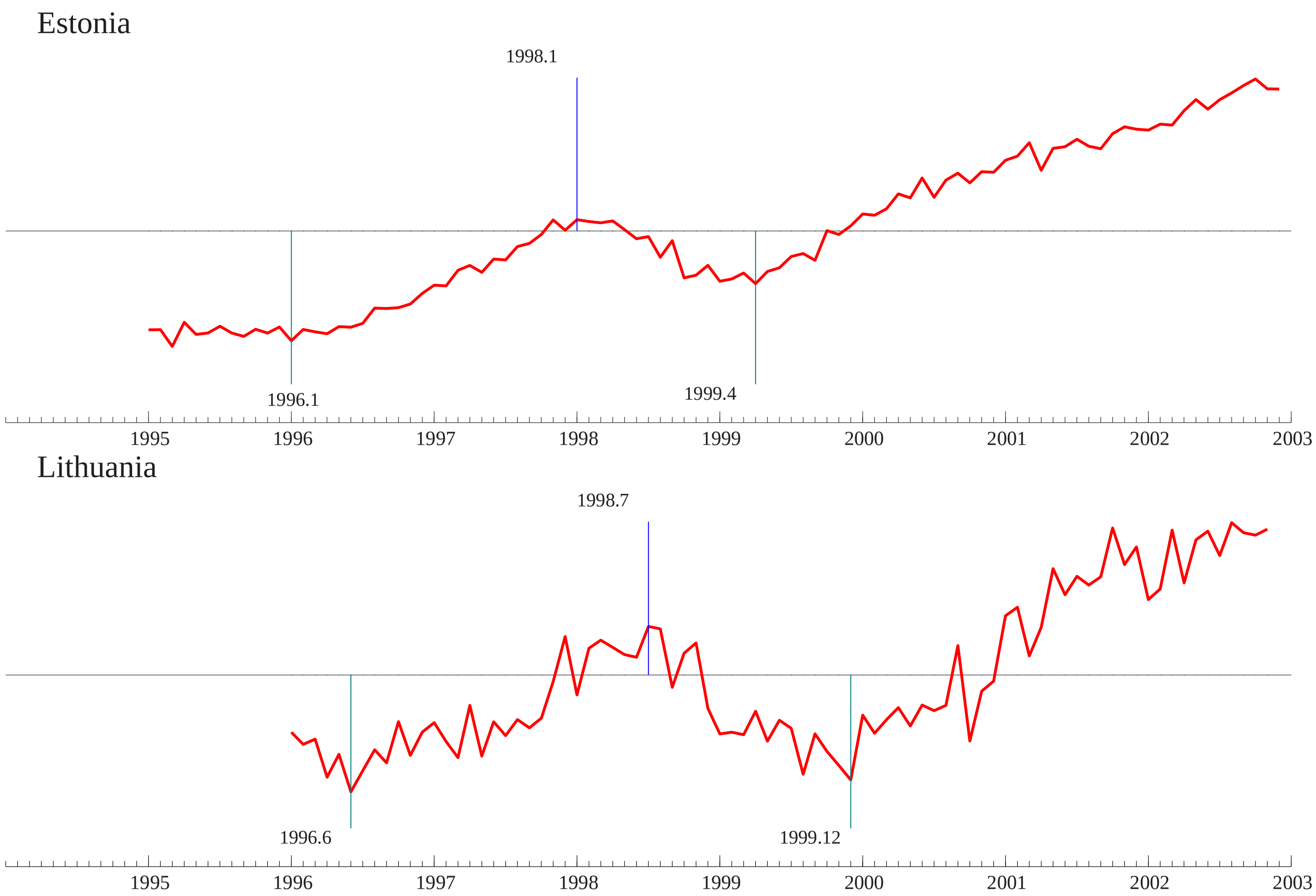

Figure 5: Estonia and Lithuania: Industrial Production classical cycle turning points.

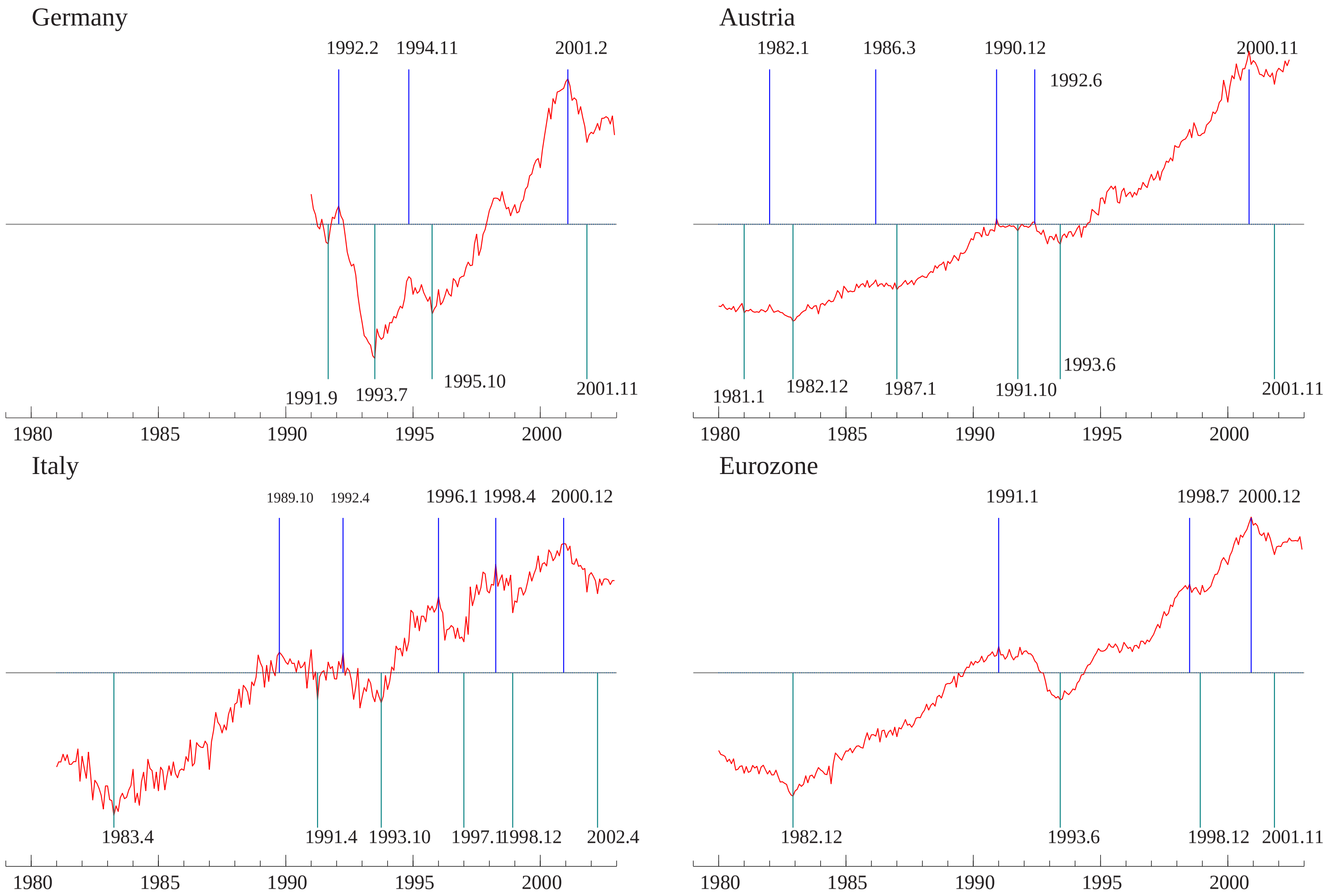

Figure 6: Euro Area: Industrial Production classical cycle turning points.

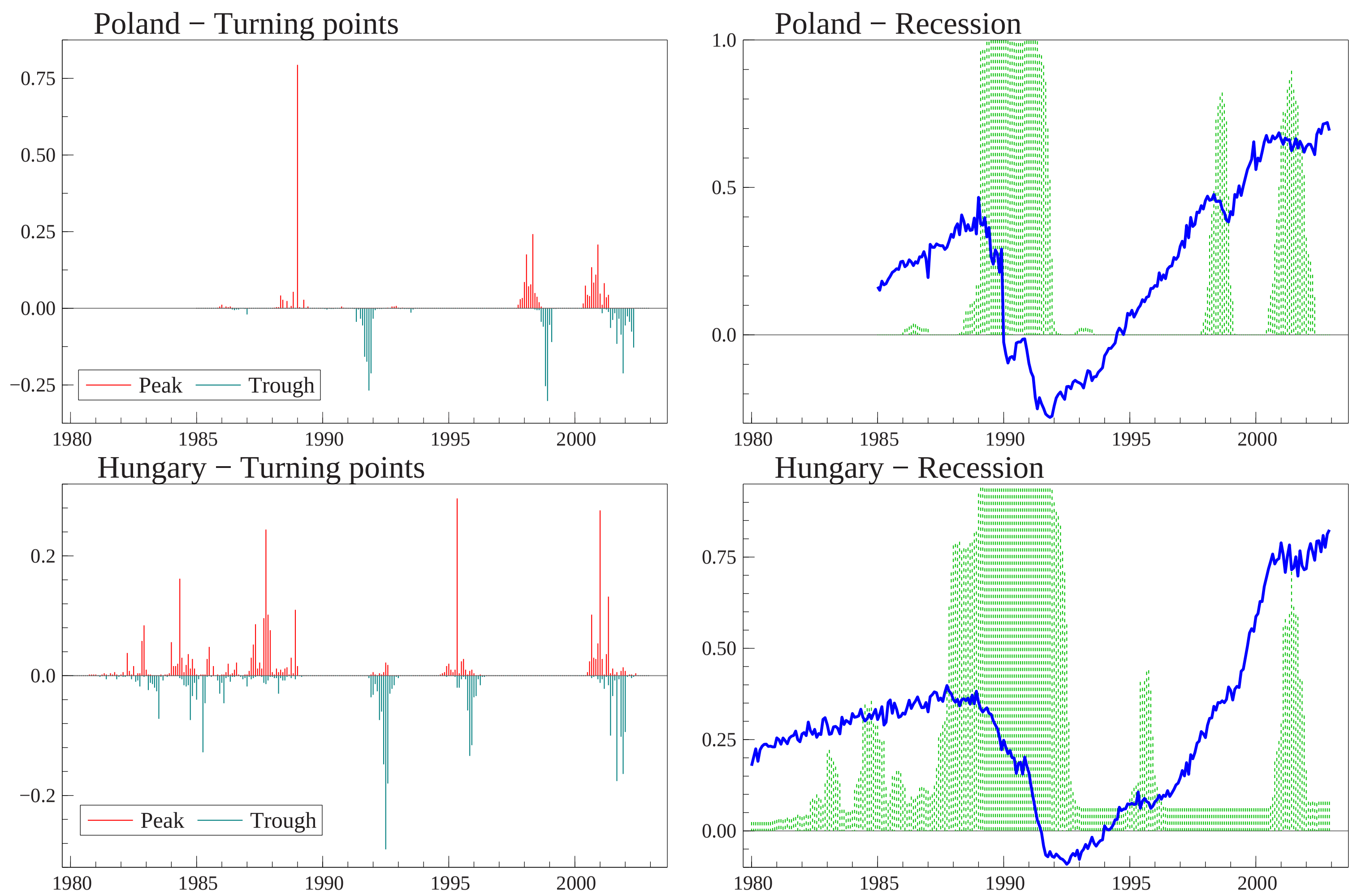

Figure 7: Poland and Hungary: Index of Industrial Production. The left panels display the relative frequency with which each observation is identified as a peak or a trough (inverted scale); in the right panels the frequency with which each observation is in recession is displayed. The relative frequencies were evaluated using $M = 1000$ draws from the posterior distribution of the seasonally adjusted series.

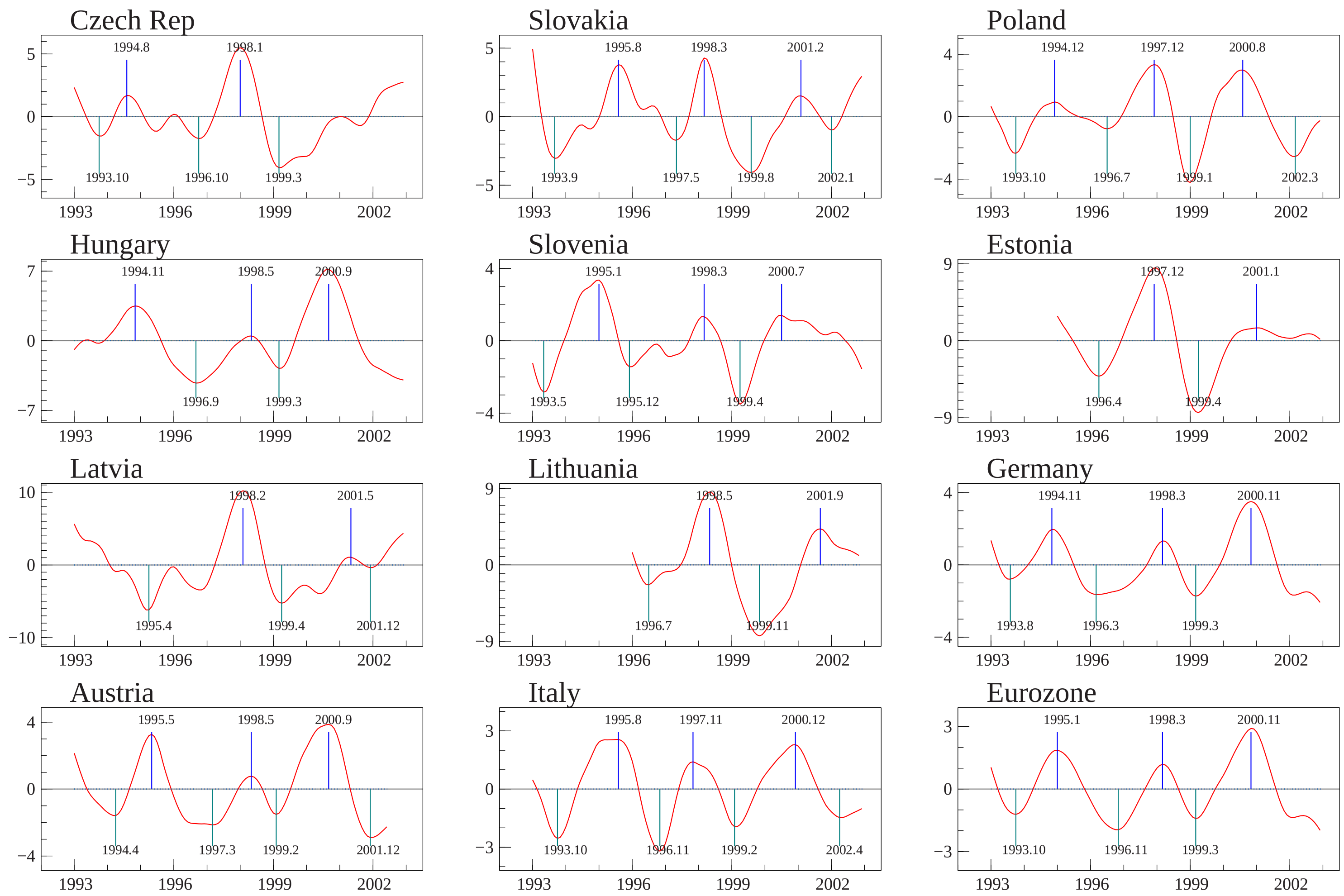

Figure 8: Industrial Production: Deviation cycles (HP-Bandpass) and turning points (1993-2002).

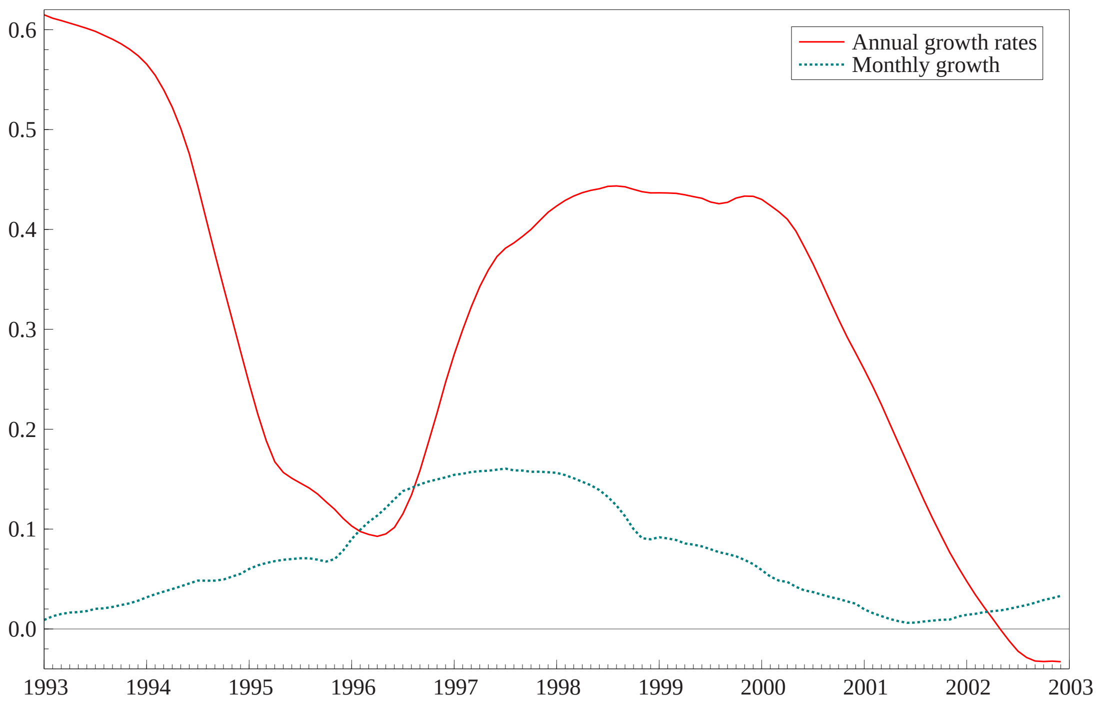

Figure 9: Industrial production monthly and yearly growth rates: average of moving correlations between enlargement countries and EU countries.

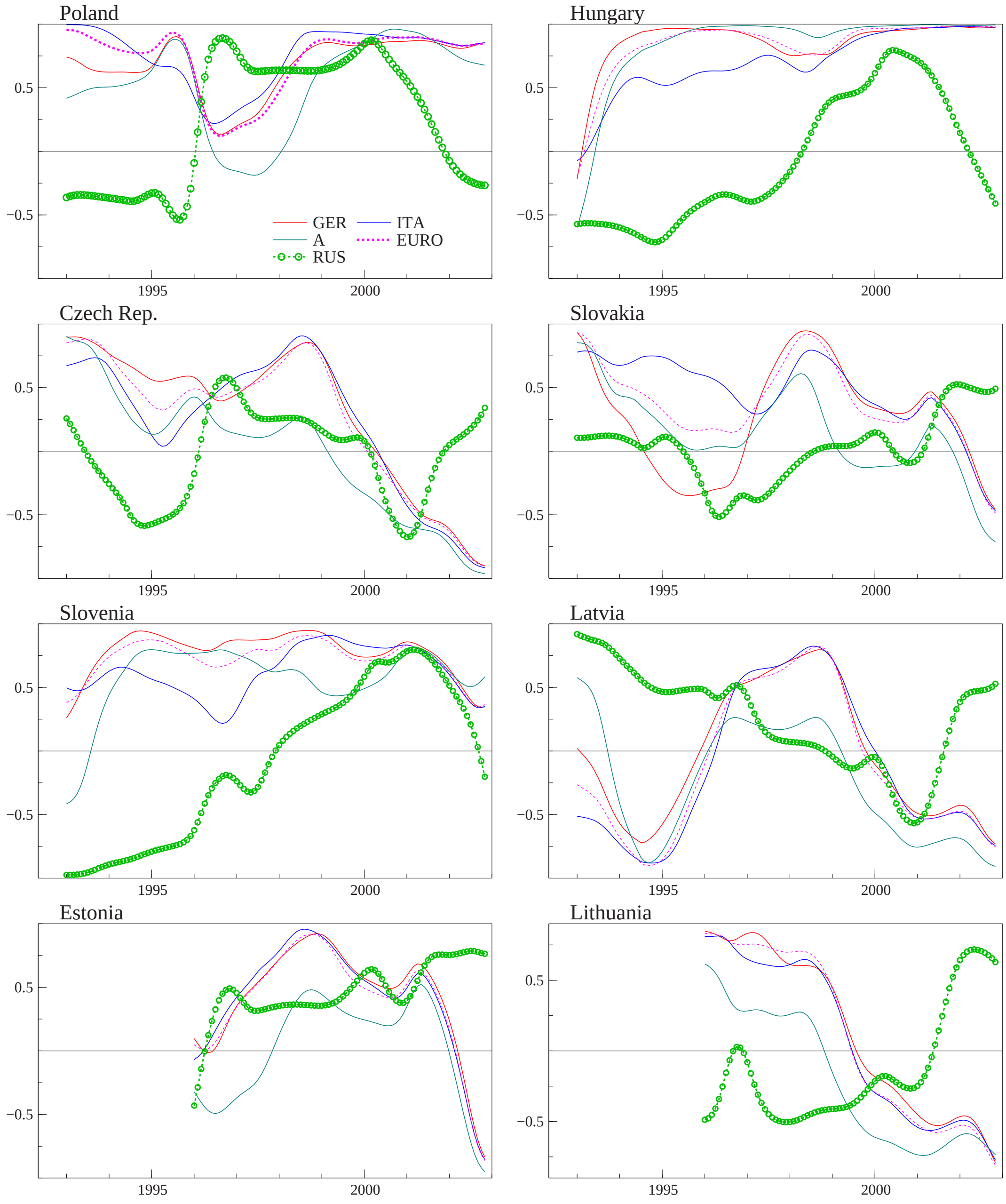

Figure 10: Industrial production deviation cycles of accession countries: moving correlations with Germany, Italy, Austria, Eurozone and Russia.

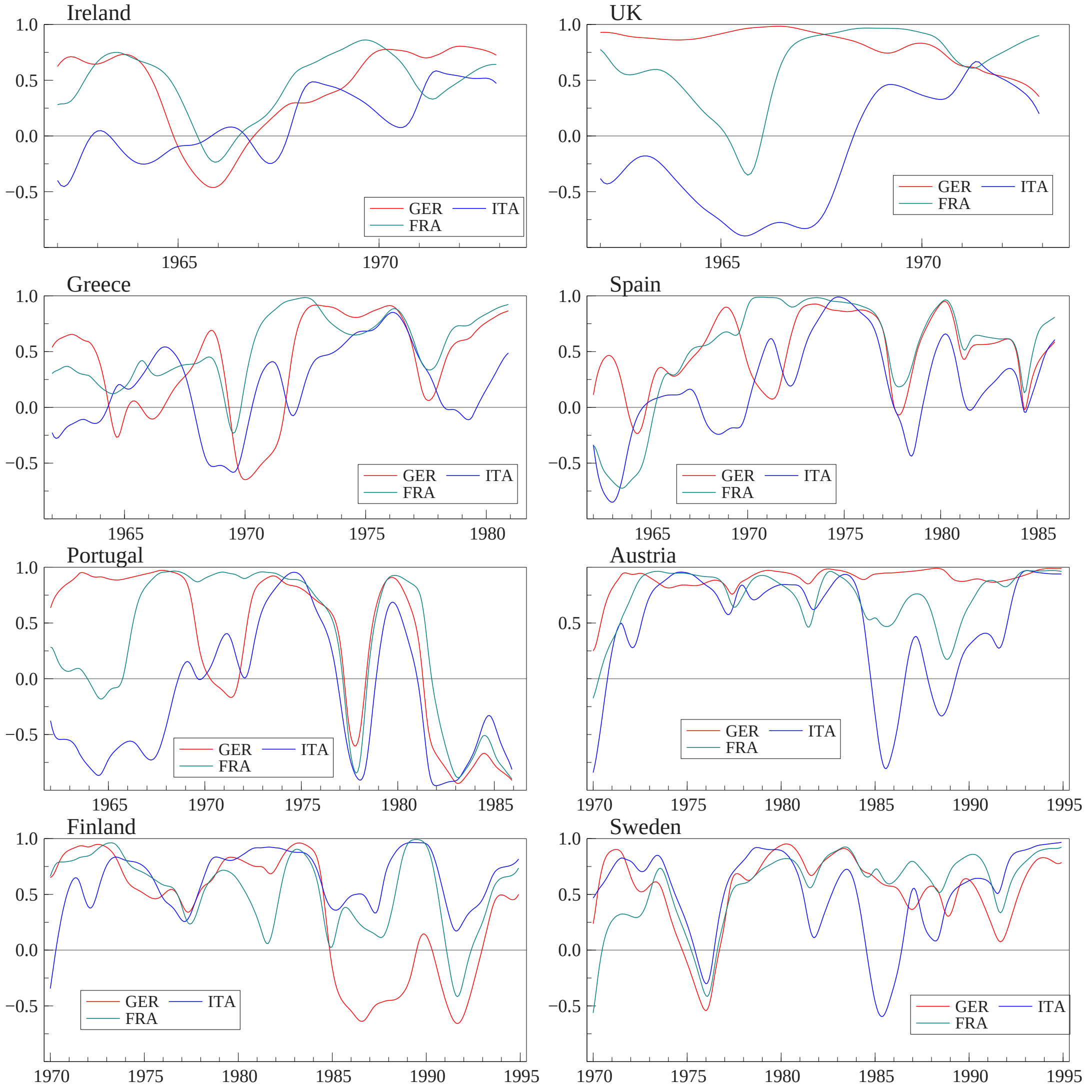

Figure 11: Moving correlation estimates for earlier accession countries.