Dating the Euro Area Business Cycle

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Sommario

In this paper we compare alternative approaches for dating the Euro area business cycle and analyzing its characteristics. First, we review a dating procedure that allows us to impose length, size and amplitude restrictions, and to compute the probability of a phase change. Second, we apply the procedure for dating both the classical Euro area cycle and the deviation cycle, where the latter is obtained by a variety of methods, including a modified HP filter that reproduces the features of the BK filter but avoids end-point problems, and a production function based approach. Third, we repeat the dating exercise for the main Euro area countries, evaluate the degree of synchronization, and compare the results with the UK and the US. Finally, we construct indices of business cycle diffusion, and assess how widespread are cyclical movements throughout the economy.

JEL Classification: E32, E39

Keywords: Business cycle, Euro area, cycle dating, cycle synchronization

1 Introduction

The business cycle can be broadly defined as a pervasive oscillatory movement in economic activity. The term 'cycle' is a misnomer to the extent to which it suggests a regular periodicity; one of its features is that the length and depth (duration and amplitude) of the cycle seems to vary. Indeed one of the current preoccupations of US business cycle experts (e.g., Stock and Watson, 2002) is to explain the apparent lengthening of the cycle there in recent history.

This seems a good time to begin the compilation of stylized facts about the Euro Area business cycle as the commitment to a single European monetary policy gives new life to the concept of a European economy. The recent setting-up, by the CEPR, of a Euro Area business cycle dating committee, analogous to the NBER's dating committee for the US economy, reflects this sentiment (see *www.cepr.org* for details). The pervasive character of a business cycle extends, in the European context, beyond the requirement that the leading sectors of the economy should be moving in sympathy with each other, to the complementary requirement that the economies of the member states, too, should display a degree of concordance with each other. Whilst the main emphasis of this paper falls on the analysis of univariate series (principally GDP), we also devote a substantial portion of the paper to the elaboration and measurement of the concepts of concordance and diffusion.

At the simplest level, the two broad definitions of the cycle recognized in the literature, the so-called classical cycle and the growth or deviation cycle, can be easily conveyed. The difference between the two is straightforward: in the case of the deviation cycle, turning points are defined with respect to deviations of the rate of growth of GDP from an appropriately defined trend rate of growth whilst the classical cycle, by contrast, selects its turning points on the basis of an absolute decline (or rise) in the value of GDP. There is a large technical literature which is concerned with the best method of extracting a trend from the data, and it turns out that the method adopted may carry quite important implications for the subsequent dating of the turning points.

In early post-war decades, especially in Western Europe, growth was relatively persistent and absolute declines in output were comparatively rare; the growth cycle then seemed to be the concept of greater analytical interest, especially as inflexions in the rate of growth of output could reasonably be related to fluctuations in the levels of employment and unemployment. In more recent decades, however, there have been a number of instances of absolute decline in output, and popular description at any rate has focussed more on the classical cycle (for example there is a widespread impression that a recession defines itself as two consecutive quarters of absolute decline). It can certainly be queried why it should be so important whether economic activity declines absolutely - a classical recession - or simply grows at a dismal rate (the current European experience). In both cases unemployment is likely to be rising. The answer is probably simply that absolute declines are relatively rare and surely signal a relatively dramatic condition. Certainly, the classical cycle definition affords shelter from the concern mentioned above that de-trending methods can affect the information content of the series in unwonted ways.

In this paper we analyze the business cycle in the Euro Area and in its main constituent economies, comparing both concepts of the cycle. Previous formal work documenting the cyclical experience of the Euro Area economy is quite sparse, being limited essentially to the paper by Agresti and Mojon (2001), which applies the notion of a growth or deviation cycle based on the use of the bandpass filter, and work by Harding and Pagan (Harding and Pagan, 2001, Pagan, 2002) which focuses principally on the notion of the classical cycle. We adopt Harding and Pagan's dating methodology, whilst setting it in the context of the Markov Chain approach of Artis, Marcellino and Proietti (2002, AMP henceforth), which gives it added flexibility, e.g., in introducing depth or amplitude restrictions, and dating monthly series. Our results on dating the cycle largely confirm the findings in these previous studies.

We employ GDP as a basic broad-based measure of economic activity, but also study the cyclical evolution of other variables, such as employment, investment, consumption and net exports to examine their possible role in relation to the cycle, rather than as giving indications for a different dating of the cycle itself.

Any study of the Eurozone economy faces a problem of data availability. The Eurozone only came into being on the 1st January 1999, and the study of business cycles needs a larger sample than three-and-a-half years. To extend the data back in time encounters the problem of aggregation when exchange rates are prone to change: in these circumstances there is no "perfect" method of aggregation. We have employed, for the most part, an updated version of the data that have been constructed for the ECB's Area-wide model (see, in the first instance, Fagan, Henry and Mestre, 2001), conducting a check against the main alternatively-generated series, that produced by Beyer, Doornik and Hendry (2001). The comparison allows us to conclude that our results are rather robust to the method of aggregation.

The paper is organized as follows. In section 2 we discuss in more detail the definition of classical and deviation cycles. In Section 3 we review a set of tools to analyse business cycles, including the basic dating algorithm and several extensions, different filters to generate the deviation cycle and their properties and relationships, measures of business cycle characteristics, and concordance statistics. In Section 4 we comment on a few basic facts underlying the dating of different definitions of the cycle. In Section 5 we present our analysis of the Euro Area broad aggregates. In Section 6 we turn our attention to country-specific cycles. In Section 7 we consider diffusion index and multivariate business cycle assessment. In Section 8 we summarise and conclude.

2 Business Cycle Definitions

In this paper we focus on two essential notions of the business cycle: classical cycles and growth (or deviation) cycles. The classical business cycle is a sequence of expansions and contractions in the absolute level of economic activity. Its definition is effectively condensed in this widely quoted excerpt from Burns and Mitchell (1946, p. 3):

> ”Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organise their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own.”

In the U.S., the National Bureau of Economic Research (http://www.nber.org) provides a chronology of the classical business cycle, based on the consensus of a set of coincident indicators concerning production, employment, real income and real sales, that is widely accepted among economists and policy makers. The main business cycle features are defined by the well-known three D's: *depth*, *diffusion* and *duration*; according to the latter the period of a complete cycle, albeit not necessarily constant, ought to be longer than a year.

The growth cycle is defined in terms of the deviation from trend or potential output, and thus within an additive or multiplicative trend-cycle decomposition; accordingly, it is already measured on a quantitative scale, but it can be dated using similar methods. Moreover, in practical applications the diffusion requirement is enforced by concentrating the analysis on a single measure of aggregate economic activity, such as gross domestic product (GDP).

Historically, the rationale for investigating the deviation cycle is that "...Absolute prolonged declines in the level of economic activity tend to be rare events when the economy grows at a sustained and stable rate, so that in practice many economies have not exhibited recessions in classical terms for many years, so other approaches to produce information on economic fluctuations have been proposed." (Minz, 1969). This is nevertheless a minor argument nowadays, as the notion of the cycle as the deviation of current output from its potential has become increasingly relevant for the conduct of monetary policy and for the cyclical adjustment of budget deficits.

A third notion, that of a growth rate cycle, refers to cyclical upswings and downswings in the growth rate of economic activity *at a given horizon*. Hence, a recession is defined as a prolonged and sustained decline in underlying growth. Growth rate chronologies are produced by ECRI (the Economic Cycle Research Institute: http://www.businesscycle.com); they adopt a measure of underlying growth with an annual horizon that is constructed as follows (Layton and Moore, 1989):

$$\left[\frac{y_t}{\sum_{j=0}^{s-1} y_{t-j}/s}\right]^{2s/(s+1)},$$

where s is the number of observations in a year; for instance, when $s = 12$ the formula above yields the so-called "six-month smoothed growth rate", based on the ratio of the latest month's figure to its average over the preceding twelve months, raised to the power $12/6.5$ to express it as an annual rate.

The relationships among the three types of cycle are analysed in more detail in Section 4, after defining the dating algorithm and other tools for business cycle analysis in the next Section.

3 Business Cycle Measurement

Dating the business cycle is a particular kind of measurement; it is quintessential to the classical business cycle, for which it amounts to establishing a set of reference dates that mark the phases or states of the economy. Usually two phases, recessions and expansions, are considered, that are delimited by peaks and troughs in economic activity. However, multiphase characterisations are not lacking in the literature: the popular definition due to Burns and Mitchell (1946) postulated four states: expansion, recessions, contractions, recovery; see also Sichel (1994) for an ex-ante three phases characterisation of the business cycle, and Artis, Krolzig and Toro (2001) for an ex-post three-phases one based on a model with Markov switching. We stick to the two phases characterisation and review the Markov chain based dating algorithm developed in AMP in subsection 3.1. In subsection 3.2 we indicate the required changes for dating a pre-filtered series, e.g. a seasonally adjusted or band-filtered series. In subsections 3.3-3.5 we consider other modifications of the algorithm to deal with, respectively, deviation cycles, monthly time series, and depth restrictions. In subsections 3.6-3.8 we review some of the most commonly used filters for the construction of deviation cycles, namely, band-pass filters, Hodrick and Prescott filters, and model based filters. The information conveyed by the identified peaks and troughs has to be complemented by other measures, which aim at assessing the depth or amplitude and steepness of economic fluctuations. These are discussed in subsection 3.9. Finally, in subsection 3.10 we review a concordance statistic that was proposed by AMP to compare the cyclical experiences of different countries.

3.1 Dating Algorithm

For exposition's sake we illustrate the dating algorithm with reference to the quarterly case. A few details concerning the monthly case are deferred to subsection 3.4. Additional details can be found in AMP.

At any time t the economy can be in either of two mutually exclusive states or *phases*: expansion, denoted E_t, or recession, denoted R_t. We adopt the convention that a peak terminates an expansion, whereas a trough terminates a recession. For the imposition of a minimum duration constraint and to enforce the alternation of peaks and troughs, it is useful to distinguish turning points within these basic states, by posing:

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

From EC_t we can make a transition to P_{t+1} or continue the expansion, $(\mathsf{EC}_t \rightarrow \mathsf{EC}_{t+1})$, but not viceversa, since only $\mathsf{P}_t \rightarrow \mathsf{RC}_{t+1}$ is admissible. Analogously, from RC_t we can visit either RC_{t+1} or T_{t+1}, but from T_t we move to EC_{t+1} with probability 1.

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

The dating rules impose ties on the minimum duration of a phase, which amounts to two quarters, and on the minimum duration of a full cycle. The latter is defined in terms of peak-to-peak or trough-to-trough patterns and amounts to five quarters, as a direct transposition of the original (monthly) Bry and Boschan (1971) rule to the quarterly case. In imposing this rule, it must be remembered that T (or P) cannot be counted both as the end of recession (expansion) and as the beginning of expansion (recession): thus, for instance, the pattern $\{\mathsf{T}_{t-4}, \mathsf{EC}_{t-3}, \mathsf{P}_{t-2}, \mathsf{RC}_{t-1}, \mathsf{T}_t\}$ is not admissible as a full cycle. The minimum duration constraints are important for the characterisation of the chain, determining the order of the MC and the number of admissible states.

The tie on the full cycle duration yields a 5th order MC that can be converted to a first order one by combining elements of the original chain, S_t. The states of the derived MC are defined by the collection:

$$S_t^* = \{S_{t-4}, S_{t-3}, S_{t-2}, S_{t-1}, S_t\}.$$

The ties however reduce the number of states to 24. The transition matrix is rather sparse and depends uniquely on the two parameters p_{EP} and p_{RT}. We adopt the strategy of scoring them according to patterns in the series, y_t, thereby following Harding and Pagan's non-parametric approach. In particular, we will concentrate on the BBQ rule by Harding and Pagan (2001), according to which an expansion termination sequence, ETS_t, and a recession terminating sequence, RTS_t, are defined respectively as follows:

$$\begin{aligned} \mathsf{ETS}_t &= \{(\Delta y_{t+1} < 0) \cap (\Delta_2 y_{t+2} < 0)\} \\ \mathsf{RTS}_t &= \{(\Delta y_{t+1} > 0) \cap (\Delta_2 y_{t+2} > 0)\} \end{aligned} \quad (1)$$

The former defines a candidate point for a peak, which terminates the expansion, whereas the latter defines a candidate for a trough. Here Δ is the backward difference operator, $\Delta y_t = y_t - y_{t-1}$.

If at time t the chain S_t^* is in any of the expansionary states for which a transition to a peak is possible and an expansion terminating sequence occurs at time $t+1$, i.e ETS_{t+1} is true, then we move to a new state S_{t+1}^*, such that $S_{t+1} = \mathsf{P}_{t+1}$ and the previous four elementary states are common to the last four in S_t^*.

It is useful at this point to classify the states of S_t^* by defining the sets:

$\mathcal{S}_{EP}$ 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.

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

$\mathcal{S}_{RT}$ 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.

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

The set of expansionary states, $\mathcal{S}_E$, which contains $\mathcal{S}_{EP}$, $\mathcal{S}_P$, and all states S_t^* in expansion at time t ($S_t = \mathsf{EC}_t$) that, due to duration ties, can only continue the expansion.

The set of recessionary states, $\mathcal{S}_R$, which contains $\mathcal{S}_{RT}$ and $\mathcal{S}_T$, and all states S_t^* in recession at time t ($S_t = \mathsf{RT}_t$) that, due to duration ties, can only continue the recession.

The scoring rules are then formalised in the following algorithm:

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:*

$$\begin{aligned} p_{EP} &= P\left(\{S_t^* = s_{EP}, s_{EP} \in \mathcal{S}_{EP}\} \cap \mathsf{ETS}_{t+1}\right) \\ &= \mathrm{I}(\mathsf{ETS}_{t+1}) \sum_{s_{EP} \in \mathcal{S}_{EP}} P\left(S_t^* = s_{EP}\right), \end{aligned} \tag{2}$$

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:*

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

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* $p_{RR} = 1 - p_{RT}$ ■

The case when ETS_{t+1} and RTS_{t+1} are both false is implicitly covered by the above dating rule. Probabilistic dating based on a maintained stochastic process replaces the indicator function, $\mathrm{I}(\cdot)$, with the probability of the terminating sequences, $\mathcal{P}_{t+1}^{(ETS)}, \mathcal{P}_{t+1}^{(RTS)}$.

Let $\mathcal{F}_t$ denote the collection of $\mathrm{I}(\mathsf{ETS}_j), \mathrm{I}(\mathsf{RTS}_j), j = 1, 2, \ldots, t$, and let $P(S_t^*|\mathcal{F}_t)$ denote the probability of being in any particular state at time t conditional on this information set. Assuming that this probability is known we can compute recursively the probability of the chain at subsequent times using the probability filter described in AMP.

The algorithm recursively produces $P(S_t^*|\mathcal{F}_t)$, for all $t = 1, \ldots, T$, and hence, marginalising previous states $S_{t-j}, j = 1, 2, 3, 4$, 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,

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

3.2 Dating unobserved components

In real applications it is usually the case that we date the business cycle on a signal extracted from a time series, rather then on the original series itself. For instance, all the series considered in this paper are seasonally adjusted. For deviation cycles, that are dealt with in the next section, this is usually the only available option. Therefore, we entertain unobserved components more often than we are actually aware of.

If the unobserved component, here denoted by ς_t, arises from model based signal-extraction techniques (for instance we aim at dating the business cycle on the seasonally adjusted series obtained from the combination of a trend-cycle component and an irregular component of known parametric form), then, apart from the obvious option of dating the sequence $\tilde{\varsigma}_{t|T}$, which denotes some inference (usually the expectation) on the signal conditional on the full available sample, we can score the transition probabilities using the probability of the terminating sequences, referred to the ς_t, $\mathcal{P}_{t+1}^{(ETS)}$, $\mathcal{P}_{t+1}^{(RTS)}$, rather than the indicator function. The virtue of this option is that we are more aware of the uncertainty surrounding e.g. turning point estimation. These probabilities can be estimated via the simulation smoother of de Jong and Shephard (1995) implemented in SsfPack. This algorithm repeatedly draws simulated samples from the posterior distribution $\tilde{\varsigma}_t^{(i)} \sim \varsigma_t|Y_T$, so that repeating the draws a sufficient number of times we can get Monte Carlo estimates of different aspects of the marginal and joint distribution of the terminating sequences. An example is provided in Artis, Marcellino and Proietti (2003) who characterise the business cycle for accession countries using model-based seasonally adjusted industrial production series.

Other plausible reasons for considering unobserved components are to make our dating procedure more resistant to outlier contamination and to censor variability that is not relevant to the analysis of business cycle fluctuations, such as high frequency noise. The need for the latter often arises with reference to monthly industrial production, that even after a working days adjustment commonly displays relevant high frequency components. This motivates us to employ a low pass filter, dealt with in the subsequent sections, that dampens all the fluctuations with a periodicity less than the minimum cycle duration, i.e. five quarters or 15 months.

3.3 Dating the deviation cycle

The dating algorithm is tailored for dating classical business cycles. When we are dealing with deviation cycles (also known as growth cycles), we want to avoid a peak being located where output is below trend levels. In effect we want to insist that an expansion phase, to qualify as such, must have brought output above trend. Therefore, for a zero mean deviation cycle, we may want to amend the BBQ rule (and call it BBQDC) by redefining the terminating sequences as follows:

$$\begin{aligned} \mathsf{ETS}_t &= \{(y_t > 0) \cap (\Delta y_{t+1} < 0) \cap (\Delta_2 y_{t+2} < 0)\} \\ \mathsf{RTS}_t &= \{(y_t < 0) \cap (\Delta y_{t+1} > 0) \cap (\Delta_2 y_{t+2} > 0)\} \end{aligned} \quad (4)$$

The algorithm scores the cycle in real time; thus, nothing prevents that, within a period in which $y_t < 0$, the first local minimum is flagged as a trough and that this is above the global minimum. A solution would be to run the algorithm on the reversed series, but this strategy is effective only if just two minima occur within that period. Our experience is that multiple minima are likely to occur, and thus our preferred alternative strategy works out as follows:

- Run the usual BBQ algorithm on the *cumulated* y_t series, $c(y)_t$. The turning points detected by this procedure correspond to the crossing of the zero line. For instance a peak in $c(y)_t$ coincides with the latest $y_t > 0$; all subsequent values will be below zero until a trough is found, which is the last point such that $y_t < 0$. Minimum duration constraints continue to operate, but are no longer defined in terms of P-T or P-P on y_t; they relate to successive crossing of zero.

- Between two adjacent T-P turning points find the maximum of y_t so as to locate the global peak of y_t; Between two adjacent P-T turning points find the minimum of y_t so as to locate the global trough of y_t.

This strategy works effectively in sorting out the local minima problem and will be labelled BBQDC2.

3.4 Dating monthly time series

For monthly time series the nature of the proposed algorithms is the same. Following Bry and Boschan (1971) the minimum durations are respectively 5 months for each phase and 15 months for full cycles. This yields a 15th order MC that can be represented as a first order MC with $m = 122$ states.

The terminating sequences are defined as follows:

$$\begin{aligned} \mathsf{ETS}_t &= \{\textstyle\bigcap_{j=1}^{5}(\Delta_j y_{t+j} < 0)\} \\ \mathsf{RTS}_t &= \{\textstyle\bigcap_{j=1}^{5}(\Delta_j y_{t+j} > 0)\} \end{aligned}$$

where $\Delta_j = 1 - L^j$.

The most commonly dated monthly time series is industrial production, see e.g. AMP for the Euro area and Artis *et al.* (2003) for the accession countries.

3.5 Depth (amplitude) restrictions

The algorithms presented above can be readily modified to enhance depth or amplitude restrictions on the definition of expansion- and recession- terminating sequences. These aim at isolating major fluctuations thereby robustifying the dating process.

Given a threshold value $c > 0$, in the quarterly case we can define

$$\begin{aligned} \mathsf{ETS}_t &= \{(\Delta y_{t+1} < -c) \cap (\Delta_2 y_{t+2} < -2c)\} \\ \mathsf{RTS}_t &= \{(\Delta y_{t+1} > c) \cap (\Delta_2 y_{t+2} > 2c)\} \end{aligned}$$

For instance, if the series we are entertaining is in logarithms $c = 0.005$ could be a candidate value.

Imposing amplitude constraints in dating the classical business cycle is complicated by the fact that the two phases typically differ in their amplitude: expansions are longer but characterised by a lower average drift rate. This suggests that c might be made to vary according to the phase.

An alternative strategy uses signal extraction techniques, e.g. low-pass filters in the classical case, to isolate the most ample fluctuations. This is of course at odds with sharp turning points identification, since the probability of peaks and troughs is smeared onto adjacent sample points, but certainly offers a robustification of the algorithm with respect to outliers and high frequency components.

3.6 Band-Pass filters

Baxter and King (1999) argue that the ideal filter for measuring the deviation cycle should retain unaltered the fluctuations with periodicity ranging from one and a half to eight years, while removing high and low frequency components. This is known as a *band-pass* filter (see, e.g. Priestley, 1981), and its theoretical frequency response function takes the rectangular form: $w(\omega) = \mathrm{I}(2\pi/(8s) \leq \omega \leq 2\pi/(1.5s))$, where $\mathrm{I}(\cdot)$ is the indicator function, and s is the number of observations per year. Moreover, the phase displacement of the filter should always be zero, if it is to preserve the timing of peaks and troughs; the latter requirement is satisfied by a symmetric filter.

A band-pass filter is easily constructed by contrasting two *low-pass* filters; a low-pass filter retains the low frequencies up to a cutoff ω_0. Its ideal frequency response function has the form:

$$w_{lp}(\omega) = \begin{cases} 1 & \text{if } |\omega| \leq \omega_c \\ 0 & \text{if } \omega_c < |\omega| \leq \pi \end{cases}$$

The coefficients of the filter are then given by the inverse Fourier transform of $w_{lp}(\omega)$:

$$w_{lp}(L) = \frac{\omega_c}{\pi} + \sum_j \frac{\sin(\omega_c j)}{\pi j}(L^j + L^{-j}).$$

Now, given the two business cycle frequencies, $\omega_{c1} = 2\pi/(8s)$ and $\omega_{c2} = 2\pi/(1.5s)$, the band-pass filter is

$$w_{bp}(L) = \frac{\omega_{c2} - \omega_{c1}}{\pi} + \sum_{j=1}^{\infty} \frac{\sin(\omega_{c2} j) - \sin(\omega_{c1} j)}{\pi j}(L^j + L^{-j}). \quad (5)$$

Thus, the ideal band-pass filter exists and is unique, but entails an infinite number of leads and lags, so in practice an approximation is required.

Baxter and King (1999) show that the K-terms approximation to the ideal filter (5) that is optimal in the sense of minimising the integrated squared approximation error is simply (5) truncated at lag K. They propose using a three years window, i.e. $K = 3s$, as a valid rule of thumb for macroeconomic time series. They also constrain the weights to sum up to zero, so that the resulting approximation is a detrending filter: denoting the truncated filter $w_{bp,K}(L) = w_0 + \sum_1^K w_j(L^j + L^{-j})$, the weights of the adjusted filter are $w_j - w_{bp,K}(1)/(2K+1)$.

3.7 The Hodrick-Prescott Filter

Hodrick and Prescott (1997) define the estimator of the trend, μ_t, as the minimiser of the penalised least square criterion:

$$PLS = \sum_{t=1}^{T}(y_t - \mu_t)^2 + \lambda \sum_{t=3}^{T}(\Delta^2 \mu_t)^2, \tag{6}$$

where the first summand measures fidelity and the second roughness; λ is the *smoothness parameter* governing the trade-off between them.

The HP filter coincides with the smoothed estimator of the trend component of the local linear trend model:

$$\begin{array}{lllllllll} y_t & = & \mu_t & + & \epsilon_t, & & & \epsilon_t \sim \text{NID}(0, \sigma^2_\epsilon), & t = 1, 2, \dots, T, \\ \mu_t & = & \mu_{t-1} & + & \beta_{t-1} & + & \eta_t, & \eta_t \sim \text{NID}(0, \sigma^2_\eta), & \\ \beta_t & = & & & \beta_{t-1} & + & \zeta_t, & \zeta_t \sim \text{NID}(0, \sigma^2_\zeta), & \end{array} \tag{7}$$

with the restrictions $\sigma^2_\eta = 0$ and $\sigma^2_\epsilon / \sigma^2_\zeta = \lambda$. The connection with the signal-noise ratio makes clear that the Lagrange multiplier, λ, measures the variability of the (noise) cyclical component relative to that of the trend, and regulates the smoothness of the long-term component. As σ^2_η approaches zero, λ tends to infinity, and the limiting representation of the trend is a straight line. HP purposively select the value $\lambda = 1600$ for quarterly time series.

The HP detrended or cyclical component is the smoothed estimate of the irregular component in (7) and, although the maintained representation for the deviations from the trend is a purely irregular component, the filter has been one of the most widely employed tools in macroeconomics to extract measures of the business cycle.

Assuming the availability of a doubly infinite sample, $y_{t+j}, j = -\infty, \dots, \infty$, the Wiener-Kolmogorov filter (see Whittle, 1963) provides the minimum mean square linear estimator (MMSLE) of the trend:

$$\tilde{\mu}_{t|\infty} = w_{HP}(L) y_t,$$

where

$$w_{HP}(L) = \frac{\sigma_\zeta^2}{\sigma_\zeta^2 + |1-L|^2\sigma_\epsilon^2} = \frac{1}{1+\lambda|1-L|^4} \tag{8}$$

and we have written $|1-L|^2 = (1-L)(1-L^{-1})$. Replacing $L = 1$ in the above expression, it can be seen that the weights sum up to one.

The frequency response function of the filter is:

$$w_{HP}(e^{-\imath\omega}) = \frac{1}{1+4\lambda(1-\cos\omega)^2};$$

notice that this is 1 at the zero frequency and decreases monotonically to zero as ω approaches π. Its behaviour enforces the interpretation of (8) as a low-pass filter, and the corresponding detrending filter, $1 - w_{HP}(L)$, is the high-pass filter derived from it.

The implicit cut-off frequency is the value ω_c corresponding to a gain $|w_{HP}(e^{-\imath\omega})| = 1/2$. This satisfies the equation

$$\lambda = [4(1-\cos\omega_c)^2]^{-1}; \tag{9}$$

for a given smoothness parameter (9) can be solved with respect to the cut-off frequency ω_c, giving $\omega_c = \arccos(1 - 0.5\lambda^{-1/2})$. See Gómez (2002) and Kaiser and Maravall (2001). For instance, setting $\lambda = 1600$ we get that the HP filter for quarterly data is a low-pass filter with $\omega_c = 0.158$ corresponding to a period of 39.69 quarters, about 10 years, which is strictly outside the range proposed by Baxter and King (1999). If we let s denote the number of observations in a year, in the sequel we shall write HP(p/s) to denote a low-pass filter that retains to a large extent those components with period greater than p/s years. For instance, HP(1.25) aims at dampening all the fluctuations with a periodicity less than the minimum cycle duration, i.e. five quarters or 15 months.

Similarly, it is possible to design a band-pass filter for business cycle extraction as the difference of two HP detrending filters, the first for $\omega_c = 2\pi/(1.25s)$ and the second for $\omega_c = 2\pi/(8s)$: for quarterly data it is easy to show that the cycle will result from the difference of two trend estimates, the first with $\lambda = 0.52$ and the second with $\lambda = 677.13$. The former defines a low-pass filter dampening the fluctuations with a period smaller than 5 quarters (1.25 years), whereas the latter defines a low-pass filter cutting off the fluctuations with a period smaller than 8 years. The resulting component retains to a given extent the fluctuations with a period between 5 quarters and

8 years, and in this respect produces estimates of the cycle that are comparable to the BK cycle, although slightly noisier, without suffering from unavailability of the end of sample estimates.

3.8 Model-based filters

In a recent paper, Harvey and Trimbur (2003) have proposed a general class of model-based filters for extracting trend and cycles in macroeconomic time series, showing that the design of low-pass and band-pass filters can be considered as a signal extraction problem in an unobserved components framework.

They consider the class of m-th order stochastic trend:

$$\begin{array}{rcllll} \mu_{1t} & = & \mu_{1,t-1} & + & \zeta_t & \\ \mu_{it} & = & \mu_{i,t-1} & + & \mu_{i-1,t}, & i = 2, \dots, m \end{array} \tag{10}$$

This is the recursive definition of an m-fold integrated random walk, such that $\Delta^m \mu_{mt} = \zeta_t$. When the observational model is $y_t = \mu_{mt} + \varepsilon_t$, the Wiener-Kolmogorov trend extraction filter is a low-pass filter with impulse response:

$$w_{\mu,m}(L) = \frac{1}{1 + q^{-1}|1 - L|^{2m}}, \quad q = \sigma^2_\zeta / \sigma^2_\epsilon$$

Notice that $m = 2$ gives exactly the HP filter; $m = 1$ produces two-sided exponential smoothing. As m increases, the filter is a close approximation to the ideal low-pass filter.

Similarly, an n-th order stochastic cycle is defined as:

$$\left[\begin{array}{c} \psi_{1t} \\ \psi^*_{1t} \end{array} \right] = \rho \left[\begin{array}{cc} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{array} \right] \left[\begin{array}{c} \psi_{1,t-1} \\ \psi^*_{1,t-1} \end{array} \right] + \left[\begin{array}{c} \kappa_t \\ 0 \end{array} \right],$$

$$\left[\begin{array}{c} \psi_{it} \\ \psi^*_{it} \end{array} \right] = \rho \left[\begin{array}{cc} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{array} \right] \left[\begin{array}{c} \psi_{i,t-1} \\ \psi^*_{i,t-1} \end{array} \right] + \left[\begin{array}{c} \psi_{i-1,t} \\ 0 \end{array} \right], \tag{11}$$

The univariate representation for such a process is:

$$\psi_{nt} = \left[\frac{1 - \rho\cos\lambda_c L}{1 - 2\rho\cos\lambda_c L + \rho^2 L^2} \right]^n \kappa_t;$$

Harvey and Trimbur show that if the model is

$$y_t = \mu_{mt} + \psi_{nt} + \epsilon_t,$$

where ϵ_t is white noise, the optimal estimators of the trend and the cycle, produced by the Kalman filter and smoother, are respectively low-pass and band-pass model-based filters.

3.9 The Analysis of Business Cycle Information

Harding and Pagan (2001) have stressed that, aside from the dating of their turning points, business cycles can be analysed for other information concerning their duration, amplitude and "shape". They suggest a number of measures of which we retain the three mentioned, accompanied by an expression of the probability of being in one of the two phases. The basic concept is that of the phase, of which we distinguish two - an expansion phase which lasts from the quarter following the identified trough to (and including) the peak; and a recession, which lasts from the quarter following the peak until (and including) the trough. Average phase duration is simply the number of periods (here, quarters) which an expansion, on average, contains. Amplitude is a measure of the depth of a cycle, that is the cumulative increase, during the expansion phase, of the measure of economic activity in question, whilst average amplitude is simply the average value over all expansion phases of this quantity. Dividing amplitude by duration gives a measure of steepness. Harding and Pagan (2001) suggest a "triangle analogy", for thinking about these measures, in which the upright is the amplitude, the length the duration and the hypotenuse is the expansion or recession phase. There is quite a large literature devoted to examining the exact shape of the expansion phase, in particular investigating whether the early part of the expansion of the expansion is steeper than the later part. We do not have a sufficiently large sample of cycles to make this an interesting exercise here. We do, however, also measure the probabilities (frequencies) of expansion and recession phase experience. Thus for a sample of complete cycles the probability of being in expansion is simply the ratio of average expansion duration to the sum of average expansion and recession durations.

3.10 Concordance statistic

Given a panel of binary indicators of the state of the economy, $S_{it}, t = 1, \dots, T, i = 1, \dots, N$, available for N countries, a measure of business cycle concordance between the pair of countries

i and j is the simple matching similarity coefficient:

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

Let $\bar{S}_i = T^{-1}\sum_t S_{it}$ denote the estimated probability of being in state 1 (e.g. recession); then, under the assumption that S_{it} and S_{jt} are independent the estimate of the expected value of the concordance index is $2\bar{S}_i\bar{S}_j = 1 - \bar{S}_i - \bar{S}_j$. Subtracting this from I_{ij} gives the mean-corrected concordance index (Harding and Pagan, 2001, 2002):

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

The asymptotic test proposed by AMP is based on a standardised concordance index. For this purpose we need to divide I^*_{ij} by a consistent estimate of the standard error of I^*_{ij} under the null of independence. Now, under the null

$$\begin{aligned}\text{Var}(I_{ij}) &= \tfrac{4}{T^2}\mathsf{E}\left[\textstyle\sum_{t=1}^{T}(S_{it} - E(S_{it})(S_{jt} - E(S_{jt}))\right]^2 \\ &= \tfrac{4}{T}\left[\gamma_i(0)\gamma_j(0) + 2\textstyle\sum_{\tau=1}^{T-1}\tfrac{T-\tau}{T}\gamma_i(\tau)\gamma_j(\tau)\right]\end{aligned}$$

where $\gamma_i(0) = \mathsf{E}[(S_{it} - E(S_{it}))(S_{i,t-\tau} - E(S_{it}))]$.

Hence,

$$T^{1/2}I^*_{ij} \rightarrow \text{N}(0, 4\sigma^2), \quad \sigma^2 = \gamma_i(0)\gamma_j(0) + 2\sum_{\tau=1}^{\infty}\gamma_i(\tau)\gamma_j(\tau),$$

and a consistent estimate of σ^2 is

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

where l is the truncation parameter.

4 Classical cycles, deviation cycles and growth

It is perhaps useful to recall a few basic facts underlying the dating of the classical and deviation cycle, and illustrate them:

- Neglecting duration ties, classical recessions (i.e. P-T dynamics in the log-level y_t), correspond to periods of prevailing negative growth, $\Delta y_t < 0$. In effect, negative growth is sufficient, but not necessary under Bry and Boschan dating rules. Periods of positive growth can be observed during a recession, provided that they are so short lived that they do not determine an exit from the recessionary state.

- As a matter of fact, it is immediately established that turning points in y_t correspond to Δy_t crossing zero (from above zero if the turning point is a peak, from below in the presence of a trough in y_t). This is strictly true under the calculus rule, according to which $\Delta y_t < 0$ terminates the expansion.

- If y_t is I(1) with constant drift μ, turning points in the linearly detrended series,

$$y_t - \mu_0 - \mu t,$$

  correspond to Δy_t crossing the mean. As a consequence, recessions correspond to periods of below average growth, $\Delta y_t < \mu$.

- If y_t admits the log-additive decomposition, $y_t = \mu_t + \psi_t$, where ψ_t denotes the deviation cycle, then growth is in turn decomposed into trend and cyclical changes:

$$\Delta y_t = \Delta \mu_t + \Delta \psi_t.$$

  Hence, deviation cycle recessions correspond to periods of growth below potential growth, that is $\Delta y_t < \Delta \mu_t$. This is so since, prolonged declines in ψ_t, i.e. $\Delta \psi_t < 0$ (a deviation cycle recession), imply $\Delta y_t - \Delta \mu_t < 0$. Using the same arguments, turning points correspond to Δy_t crossing $\Delta \mu_t$. A classical recession requires that the *sum* of potential growth and cyclical growth is below zero, that is $\Delta \mu_t + \Delta \psi_t < 0$.

- Drawing from the previous facts, classical recessions are always a subset of deviation cycle recessions, and there may be multiple classical recession episodes within a period of deviation cycle recessions.

- Beaudry and Koop (1993) proposed a measure of the depth of recession, *current depth of recession*, based on the deviation of current output from its historical maximum:

$$CRD_t = y_t - \max_{j \leq t} y_j$$

This measure is in the spirit of classical business cycle analysis since it is valid for series displaying systematic upward trends and takes (negative) non-zero values when an absolute decline in output occurs. However, it is a much more extreme view, as the end of the recession takes place when output catches up its historical maximum value. On the positive side it provides a measure of the amplitude of the recessionary movements. With respect to the classical definition implemented in this paper, peaks will be coincident, although CRD_t does not impose duration ties, but a trough in our dating algorithm will tend to correspond to a trough in CRD_t, which starts moving towards zero, but will continue to be negative, signalling a recession. More local definitions. e.g. $CRD_t = y_t - \max_{k=0,1,\dots,m} y_{t-k}$, are possible and the resulting chronology will get closer to the classical one.

- Growth rate cycle: turning points in growth rates delimit patterns of positive and negative acceleration ($\Delta^2 y_t$). ECRI produces such chronologies; according to their definition, "Growth rate cycle downturns are pronounced, pervasive and persistent declines in the growth rate of aggregate economic activity. The procedures used to identify peaks and troughs in the growth rate cycle are entirely analogous to those used to identify business cycle turning points, except that they are applied to the growth rates of the same time series, rather than their levels". We shall return shortly to growth rate cycles when discussing the chronology arising from the EuroCoin index.

Figure 1 illustrates all these facts with respect to the Euro area GDP series; this was first smoothed by HP(1.25), although we will continue to refer to it as the series, y_t, and then decomposed into a trend component and a cyclical, one using respectively HP(8) and the residuals from it (which amounts to the HP bandpass filter HP(1.25)-HP(8)). The first two plots present the turning points of the classical and deviation cycle. We draw attention on the fact that the classical recessionary episode is strictly contained in the deviation one, and that the troughs are located at the same data point; although this is fortuitous, the trough in y_t occur later than that in ψ_t. The third plot reproduces Δy_t and potential growth, $\Delta \mu_t$, highlighting that deviation cycle peaks correspond to the last period of a sequence of growth above potential growth. Similarly, the deviation cycle trough corresponds to the last period of actual below potential growth. Coincidentally, this also corresponds to the last period of growth below the zero threshold. A classical peak, instead, corresponds to the last period of a sequence of positive growth rates, $\Delta y_t > 0$.

EuroCoin, built by Altissimo et al. (2001) using dynamic factor analysis, is a composite coincident index of the Euro area *growth rate* cycle. As a matter of fact, it extracts the common dynamics from a large set of indicators that are made stationary by differencing.

Figure 2 presents and compares the growth rate cycle chronologies for the index and for GDP growth, using the Eurostat series from 1991.1 onwards. The turning point for the former were determined on the original monthly series and then, for comparison purposes, we aggregate the series and the dates at the quarterly frequency of observation. For GDP growth we also plot, in the third panel, the filtered series HP(1.25), removing high frequency variation, and the corresponding chronology.

ECRI states that dating the growth rate cycle requires the same rules as the classical cycle, in which case a recession implies an absolute decline in growth; when growth is stationary there is some scope also for scoring growth rate cycle as a deviation cycle, where the deviation is intended from the average growth rate: in such circumstances, a recession still implies a deceleration of growth, but it can be terminated only if growth is below its mean (a trough cannot be found if $\Delta y_t > \mu$.

Two features stand out in the Figure. The first pertains to the different chronology of GDP growth arising from filtering; the second is that the EuroCOIN phases agree more closely with those determined on the HP(1.25) filtered growth rates. The concordance index I_{ij} between the EuroCOIN and HP(1.25) filtered GDP growth amounts to 0.8 (its expected value under the independence assumption is 0.5) and the concordance test statistic is 3.12. There is not much evidence for significant concordance with the raw GDP chronology ($I_{ij} = 0.65$ and the concordance statistic is 1.51, which is not significant). The closer agreement with the HP(1.25) should be expected, since dynamic factor techniques smooth away high frequency movements.

5 The aggregate cycle

This section analyses aggregate time series data available for the Euro Area both from the classical and deviation cycle perspective. The emphasis is on Euro Area GDP, but we also consider its decomposition into expenditure components and the labour market. The national accounts aggregates are measured at constant prices.[1]

5.1 The classical business cycle

Our classical business cycle chronology is presented compactly in Figure 3. Two alternative measures of Euro Area GDP are employed: the "AWM series" (this comes from an updated version of the data set underlying the application of the "Area-wide model", see Fagan, Henry and Mestre, 2001) and the "BDH" series, constructed by Beyer, Dornik and Hendry (2001). The former has a longer sample period (1970-2002) than the latter (1980-2001) and thus reveals one more cycle. The three cycles identified in the shorter data period overlap almost exactly, with exception of a shorter recession in the early '80s using AWM, 2 quarters versus 4 quarters with BDH, and of the last trough which is anticipated by one quarter if one takes the BDH measure. The different length of the recession in the early '80s is likely due to a revision in GDP data for this period, since AMP, using the original AWM data set, found exactly the same dating for this period as BDH. In this case, the chronology of turning points, not surprisingly, is also exactly as in Harding and Pagan (2001).

It should also be noticed that the two quarters recession in 1982 is a minor event and could be censored if the dating algorithm were tailored to impose ties on the depth of recessions and expansions. In this case, the peak would be in 80:1 and the trough in 82:4. With this modification the dating becomes very similar to that achieved by the CEPR dating commettee (see www.cepr.org). The peak dates are exactly the same, while two trough dates differ by one quarter (82:4 for us versus 82:3 for CEPR and 93:2 for us versus 93:3 for CEPR).

Figure 3 also presents the expansion/recession classification based on GDP growth rates, which basically confirms the previous findings.

Table 1 displays some descriptive statistics. For the moment we concentrate on those pertaining to GDP (denoted YER in the table). These reflect a notable asymmetry between the average length of expansions and recessions, the former much longer (30 quarters) than the latter (3 quarters), which is to be expected of classical cycles in a growing economy. The probabilities of being in

[1]All the computations in the paper were performed using the object oriented matrix programming language Ox 3.0 by Doornik (2001), and the library of state space function SsfPack 2.3 by Koopman et al. (1999).

one or other phase reflect the relative values of these phase lengths (about 90% versus 10%). The amplitudes of the expansion periods are also much bigger than those of the recession periods. ”Steepness”, following the suggestion of Harding and Pagan (2001), is measured as the quotient of the amplitude and the duration of the phase. Expansions last longer, and are steeper than recessions, which are quite brief and yet more gently sloped. All figures are rather similar to what AMP found with the original AWM data set.

Table 1 also displays comparable information for a number of other series - notably the national accounts categories pertaining to private and government consumption (PCR and GCR), fixed capital formation (ITR), imports and exports of goods and srvices, and net exports (MTR, XTR, Net Imp) and inventory change (SCR), together with employment (LNN), productivity (LPROD), unemployment (URX) and unit labour costs (ULC). Standard theory would suggest that investment and inventories are likely to be the most cyclical components of GDP, and this expectation is borne out in the data: more cycles are identified, the recession and expansion probabilities are more nearly equal and the steepness of the phases is more nearly equal. It is not surprising perhaps to find, on the other hand, that the cyclical behaviour of private consumption is much in line with that of GDP as a whole, whilst government consumption is the smoothest component of all. Exports and imports of goods and services, and even more, the net of the two, seem to be highly cylical in their behaviour. Employment and unemployment exhibit more cycles than GDP, which might seem surprising, but this feature disappears when deviation cycles are considered, as we will see in the next Section.

5.2 Deviation Cycles

Figure 4 presents several measures of the deviation cycle in Euro Area GDP, with the associated turning points detected by the dating algorithm BBQDC2 of Section 3.3, with restrictions on the size of the fluctuations that will be discussed shortly. The first measure is the Baxter and King cycle. Because of the moving average estimation that forms part of the Baxter-King procedure, this is only available for the central part of the sample excluding the first and last 12 quarters. The second measure, displayed on the upper right panel, is the HP bandpass filtered cycle, which results from subtracting the HP(1.25) trend with smoothing parameter $\lambda = 0.52$, which defines a low-pass filter dampening the fluctuations with a period smaller than 4 quarters (1.25 years, e.g. high frequency noise) from the HP(8) trend with smoothing parameter $\lambda = 677$, which in turn defines a low-pass filter cutting off the fluctuations with a period smaller than 8 years.

For many purposes, the deviation cycle can be identified with the output gap. Thus a comparison may be interesting. The bottom panels display measures of the output gap derived respectively from a bivariate model of GDP and CPI inflation and a multivariate model based on total factor productivity, labour force participation rates, the unemployment rate, capacity utilisation and CPI inflation, implementing the production function approach (PFA), see Proietti, Musso and Westermann (2002) for details.[2] The first equation of the bivariate model decomposes output into potential, μ_t, represented as a local linear trend, and the output gap, ψ_t, a stationary ARMA(2,1) process:

$$y_t = \mu_t + \psi_t,$$

$$\begin{aligned}
\mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t, & \eta_t &\sim \text{NID}(0, \sigma^2_\eta) \\
\beta_t &= \beta_{t-1} + \zeta_t, & \zeta_t &\sim \text{NID}(0, \sigma^2_\zeta) \\
\psi_t &= \rho \cos \lambda_c \psi_{t-1} + \rho \sin \lambda_c \psi^*_{t-1} + \kappa_t, & \kappa_t &\sim \text{NID}(0, \sigma^2_\kappa) \\
\psi^*_t &= -\rho \sin \lambda_c \psi_{t-1} + \rho \cos \lambda_c \psi^*_{t-1} + \kappa^*_t, & \kappa^*_t &\sim \text{NID}(0, \sigma^2_\kappa)
\end{aligned}$$

where η_t, ζ_t, κ_t, and κ^*_t are mutually independent. The price equation is a version of Gordon's triangle model of inflation, specified as follows:

$$p_t = \tau_t + \textstyle\sum_k \delta_k(L) x_{kt}$$

$$\begin{aligned}
\tau_t &= \tau_{t-1} + \pi^*_{t-1} + \eta_{\pi t} & \eta_{\pi t} &\sim \text{NID}(0, \sigma^2_{\eta\pi}), \\
\pi^*_t &= \pi^*_{t-1} + \theta_\pi(L)\psi_t + \zeta_{\pi t} & \zeta_{\pi t} &\sim \text{NID}(0, \sigma^2_{\zeta\pi}).
\end{aligned}$$

where the regressors are commodity prices x_{kt} and the nominal effective exchange rate of the Euro. The only link between the prices and output equations is the presence of ψ_t as a determinant

[2]The PFA model considered here is the one featuring pseudo-integrated cycles. The paper highlights the uncertainty issue arising from model-based univariate estimation of the output gap, and performs a rolling forecast exercise whose outcome is that the bivariate model produces the best forecasting performance in the test period considered.

of underlying inflation, π_t^*. The reduced form is

$$\Delta^2 p_t = \theta_\pi(L)\psi_{t-1} + \sum_k \delta_k(L)\Delta^2 x_{kt} + (1+\vartheta L)\epsilon_t,$$

so that $\theta_\pi(1) = 0$ (the level effect is zero) the output gap has only transitory (change) effects on inflation.

The notion of an output gap is more specialised than the deviation cycle in output, since it provides a measure of inflationary pressures. This poses a new issue to the dating of the gaps: if the interest lies in dating periods in which the inflationary pressures are positive or negative, then the system would feature two states according to whether $\psi_t > 0$ or $\psi_t < 0$. However, as the evidence reported in Proietti, Musso and Westermann (2002) clearly points out, it is the change effect associated with $\Delta\psi_t$ that is more relevant than the level effect exerted by the output gap, which brings us back to the problem of dating expansions and recessions in the level of ψ_t. We also notice in passing that the scoring of the gap according to whether it is positive or negative is a by-product of BBQDC2.

Figure 4 shows a broad agreement in the identified turning points: the 74.1 and 80.1 peaks are common to the four representations. The location of the start of the 90s recession is more uncertain since there are two neighbouring local maxima at the beginning of 1990 and 1992, which is featured by the expenditure components and the GDP of individual countries. Also the beginning of the 80s expansion is scored differently by the different methods.

As stated above, the BBQDC2 dating algorithm featured restrictions on the amplitude of the fluctuations: in its first stage, by which change of signs in ψ_t are identified by using the usual BBQ dating rules on the cumulated cycle, we censored fluctuations around zero with amplitude less than 0.5% of total GDP. Amplitude restrictions are perfectly sensible, although they inevitably underlie some degree of arbitrariness, as the amplitude of the deviation cycle differs according to the signal extraction model or technique being used (see eg. figure 4), the maximum amplitude usually being achieved by linear detrending of the series.

Table 2 presents some characteristics of the deviation cycles extracted by the HP quarterly bandpass filter not using any censoring rule on the amplitude of the fluctuations. This results in a relatively large number of turning points, compare e.g. the YER series with figure 4, and affects the duration and the amplitude statistics. The stylised fact that is however robust to the choice of censoring rules is that the average amplitude of recessions and expansions is about the same, as implied by the symmetry of the cyclical model or signal extraction filter. It is important to stress that this is an implication of the representation of the cycle that is chosen, although a model based framework allows us to test for business cycle nonlinearity and asymmetry (see, e.g.. Proietti, 1998). Table 2 confirms that investment (ITR) is one of the most cyclically variable expenditure component of GDP, featuring an average amplitude of 5% for both phases. Employment and unemployment are now less cyclical than GDP.

The Harvey and Trimbur (2003) cycles, see section 3.8, estimated by the Kalman filter and smoother using a second order representation for the trend and the cycle, are reported in figure 5 for a few selected series, along with recession probabilities and the probabilities of peaks and troughs (on a reverse scale). The estimated parameters imply a smooth representation for the cycle, $(1 - \phi L)^2 \psi_t = \kappa_t$, i.e. a second order autoregressive representation with two common real roots at the zero frequency. As a result the estimated component is relatively smooth and this has a bearing on turning points characterisation which need not to be sharp (the ITR series being an exception). The chronology for GDP arising from this representation is slightly different from that obtained from the other approaches that we considered. Fundamentally, the depth of the downturn at the beginning of the 80's and the subsequent recovery are emphasised; this is a consequence of the smoothness prior imposed on the cyclical dynamics, which makes the extracted component much more stable and less responsive to the kind of shorter run fluctuations that occurred in the mid seventies and at the end of the nineties. For instance, the estimated cycle for ITR does not fall below zero in 1975 and no trough is detected. We also notice that the recession probabilities are never sharp, which is again an expression of the fundamental trade-off between smoothness in the signal evolution and the resolution, or sharpness, in detecting cyclical changes.

6 Country-specific cycles

Our analysis of country-specific cycles focuses on two data sets, the first relating to the GDP at constant prices for five countries, Germany, France, Italy, UK and the USA, starting from 1970 and available from various sources, among them the OECD (Main Economic Indicators) and the US Bureau of Economic Analysis. For Germany the series, made available by the IFO, has been seasonally adjusted, corrected for working days and the level shift due to reunification, using the basic structural model with regression effects (Harvey, 1989). The Eurozone series is used for comparison. The second set is produced by Eurostat and provides a highly comparable set of statistics for real GDP based on the new system of national accounts (ESA95), but for a shorter sample.

6.1 Classical Cycles

Figure 6 presents the turning points of the classical business cycle for the Euro Area, Germany, France, Italy, UK and the USA, identified using the HP(1.25) filtered series on the first data set. We recall that this is a low-pass filter dampening the fluctuations with a period less than five quarters, which strictly do not pertain to the business cycle.

The identified dates for Germany are very similar to those for the Euro area and, once the two cycles at the beginning of the '80s are grouped into one, are coherent with the chronology established by the CEPR dating commettee for the Euro area. Similar findings hold for France, while for Italy more cycles are identified. Yet, imposing amplitude restrictions, the dates become again in line with those prevailing for the Euro area.

The UK cycles appear more in line with the US ones, and the recession dates in these two countries in general lead those for the Euro area.

To address the issue of synchronisation and concordance among the country specific business cycles in more detail, we now compute the standardized concordance indexes, following the approach outlined in subsection 3.10. The results in Table 3 indicate that for the euro area as a whole the concordance is lowest with the UK, and not statistically different from zero (Table 4), highest with the countries within the Euro Area, as expected, and intermediate with the US. Germany, France and Italy are also the group of countries with the highest cross concordances. The highest concordance for the UK is with the US, the lowest with Germany.

Harding and Pagan (2001, 2002, Pagan, 2002) also propose to regress the recession indicator for one country on the same indicator for another country, and evaluate BC independence using the t-statistic for the significance of the parameters, computed using HAC standard errors. The results of estimating such a regression, reported in AMP, confirm that the UK cycle is even independent of that of the EA, Germany and France, whereas there is a significant association with Italy and the US and cross independence between Euro Area countries is strongly rejected.

The analysis of the Eurostat series (see figure 7), available for a shorter time span, beginning in 1980 for most countries, is useful in pinpointing an additional peak that was not identified from the other Euro Area series considered before, taking place in the second quarter of 2001. This is mainly due to Germany, but is also anticipated in the series for Finland, Belgium, the Netherlands and Austria. The CEPR dating committee has reserved its position in identifying this peak, and the diffusion index analysis in Section 7 supports their decision.

Figure 8 illustrates that when high frequency dynamics, intended as those fluctuations with periodicity less than 5 quarters, are filtered out by a low-pass HP filter, fewer turning points are found.

6.2 Deviation Cycles

Figure 9 plots the Hodrick Prescott band pass based deviation cycles, highlighting more synchronization in the ’70s and ’90s than in the ’80s. The squared coherence between the Euro Area deviation cycle and that of the countries belonging to the first data set, also plotted in figure 9, suggests lower coherence with the US and UK cycles, confirming the previous finding for classical cycles.

To investigate further the issues of concordance and synchronisation we also report the standardised concordance index (table 5) and the robust test for cycle independence (table 6). The results largely confirm the previous outcome: there is a high degree of synchronisation within the Euro Area, with the lowest concordance for the US and intermediate for the UK; but now in all cases the hypothesis of business cycle independence can be rejected.

7 Diffusion and Multivariate Business Cycle Assessment

An index of business cycle diffusion measures the percentage of economic time series in a certain state, e.g. recession. It typically aims at assessing on a 0-1 continuous scale how widespread are business cycle movements throughout the economy, by looking at several phenomena that have a known nature, eg. coincident or leading.

There are two ways in which diffusion indices can be constructed. The first amounts to scoring each individual time series and then taking the cross-sectional average

$$D_t = \frac{1}{N}\sum_{i=1}^{N} S_{it}, \qquad t = 1, \dots, T$$

where S_{it} takes value 1 in recessions and zero otherwise, and N is the cross-sectional dimension.

It can be worth weighting the series considered according to their economic relevance and/or their proved efficacy in signalling recessionary events. If a system of (possibly time-varying) weights w_{it} is available then

$$D_t = \sum_{i=1}^{N} w_{it} S_{it}, \quad t = 1, \dots, T, \ \ \sum_i w_{it} = 1.$$

The underlying model is that the aggregate index, D_t, is a finite mixture of two-states Markov processes, the mixture probabilities being given by w_{it}. Suppose that the individual time series are the components of an aggregate $y_t = \sum_i w_i y_{it}$ and that we score recessions according to the calculus rule, that is $S_t = \mathrm{I}(\Delta y_t < 0)$, where $\mathrm{I}(\cdot)$ is the indicator function, then

$$E(S_t) = P(\sum_i w_i \Delta y_{it} < 0) > E(D_t) = \sum_{i=1}^{N} w_{it} E(S_{it}),$$

so that the diffusion index does not measure the probability of a recession in the aggregate series; rather it measures the proportion of the aggregate that is in a recession.

The second method of computing diffusion indexes, developed by AMP, exploits the dating algorithm of Section 3.1, where the transition probabilities are computed using the probability attached to expansion and recession terminating sequences (ETS and RTS, respectively) in the following way:

$$\mathcal{P}_t^{(ETS)} = \sum_{i=1}^{N} w_{it} \mathrm{I}(\mathsf{ETS}_{it}), \quad \mathcal{P}_t^{(RTS)} = \sum_{i=1}^{N} w_{it} \mathrm{I}(\mathsf{RTS}_{it}).$$

An expansion terminating sequence defines a candidate point for a peak, e.g. in the quarterly case, expansion is terminated at time t when both $(\Delta y_{t+1} < 0)$ and $(\Delta_2 y_{t+2} < 0)$ occur. On the other hand, a recessionary pattern is concluded by a trough at time t if both $(\Delta y_{t+1} > 0)$ and $(\Delta_2 y_{t+2} > 0)$ take place. Under the stated rule, the transition probabilities depend on the sum of the weights of the series that are in those two terminating sequences. Again, the underlying assumption is that the aggregate ETS_t is a finite mixture of cross-sectional ETS_{it} and the dating algorithm furnishes probabilities that must be interpreted as $P(D_t = 1)$, not as $P(S_t = 1)$, and loosely speaking are a smoothed version of the previous diffusion index.

Assessing the diffusion of the business cycle in the Euro area requires the evaluation of sector and country specific data, and many disaggregated time series; for this purpose we consider a set of time series drawn from the ESA95 quarterly national accounts of seven Euro area countries, Belgium, Finland, France, Germany, Italy, Netherlands and Spain (Source: OECD Statistical Compendium, 1991.1-2002.3), covering around 85% of the total Euro area GDP, referring to the breakdown of GDP by expenditure and by kind of activity; these are used to produce a multivariate assessment of the classical cycle in the Euro area, via the construction of weighted and unweighted diffusion indices, where the weights are proportional to the size of the aggregate.

The classical dating of the country specific GDP series is such that Belgium, Finland, Germany, Italy and the Netherlands spend in recession respectively the quarters 2001.2-2001.4 , 2001.1-2001.2, 2001.2-2001.4, 2001.4-2002.1, 2001.3-2001.4, with an output loss, expressed as a percentage of GDP, respectively of 0.8, 2.2, 0.5, 0.1, 0.2, which is very mild, except for Finland. On the other hand, France and Spain do not experience a downturn in the level of economic activity, as measured by GDP. It should be recalled a peak was identified on the Eurostat GDP series, but not on the AWM series (see Figure 3).

The idea is to score the transition probabilities of the Markov chain in section 3.1 underlying the dating algorithm according to the proportion of the coincident series that are respectively in an expansion terminating sequence (ETS) and in a recession terminating sequence (RTS). The resulting chronology is based on a Markov chain whose transition probabilities are determined by the consensus of the component series.

Figure 10 presents the log-odds of the recession probabilities, emerging from the second method of constructing diffusion indices, for a variety of aggregates expressing the demand and the supply side of the economy. Values greater than zero correspond to recession probabilities greater than 1/2.

The plot reveals the following: overall, the evidence for a classical recession in 2001 is weak; it did not spread to France and Spain, although it hit Germany and, with minor depth, Italy, and some smaller countries, so that it affected the majority share of the Euro area GDP. The aggregates that suffered most are investment, exports and the value added of the manufacturing sector. Comparing the situation to that in the previous recession of 1992-93, the resilience of consumption appears to be the force that avoided a deeper slowdown in 2001.

8 Conclusions

In the United States the NBER's business cycle chronology has established itself as an authoritative reference on the timing of cycles in the US economy. Researchers are prone to judge the excellence of alternative methods of cycle-identification by the standard implied in an ability to replicate the NBER history. In Europe the business of dating the cycle by an NBER-style methodology has just begun, with the CEPR's Euro area business cycle dating committee providing its first report in September 2003.

The methods and results reported in this paper can be regarded as providing technical background to an exercise such as that of the CEPR panel's. It is interesting and important that the main results are in close agreement.

Yet, the most important accomplishment of the paper is the illustration of a flexible dating algorithm which can be applied equally to dating deviation, as well as classical, cycles. The algorithm can accommodate duration and amplitude restrictions and can be readily adjusted to a monthly frequency. As designed, it can be applied to any univariate series. To take account of a requirement of coherence across countries, its application would require to be married to a criterion applied to a measure of diffusion or concordance.

In the paper we have applied this dating algorithm to provide estimates of the euro area cycle (using an updated AWM data set) and of its member countries, adopting both the deviation and the classical notion of business cycle. Moreover, we have explored measures of coherence and diffusion across countries, sectors, and various other measures of economic significance.

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Table 1: Classical BC dating of Euro Area time series: summary statistics.

	YER	PCR	ITR	MTR	XTR	GCR	LNN	LPROD	ULC	URX	SCR	Net Exp.
Number of cycles P-P	4.0000	3.0000	6.0000	5.0000	5.0000	1.0000	6.0000	5.0000	2.0000	6.0000	13.0000	9.0000
Number of cycles T-T	4.0000	3.0000	5.0000	5.0000	5.0000	1.0000	5.0000	5.0000	2.0000	6.0000	13.0000	8.0000
Average Expansion Prob.	0.9167	0.9470	0.7121	0.8485	0.8939	0.9848	0.6970	0.9091	0.9242	0.6548	0.5758	0.2652
Average Recession Prob.	0.0833	0.0530	0.2879	0.1515	0.1061	0.0152	0.3030	0.0909	0.0758	0.3452	0.4242	0.7348
Average Duration of Exp.	30.2500	41.6667	15.6667	22.4000	23.6000	130.0000	15.3333	24.0000	61.0000	15.1392	5.8462	3.8889
Average Duration of Rec.	2.7500	2.3333	7.6000	4.0000	2.8000	2.0000	8.0000	2.4000	5.0000	7.9957	4.3077	12.1250
Average Amplitude of Exp.	0.2107	0.2802	0.1640	0.3860	0.3900	0.9103	0.0395	0.1373	0.9680	0.3599	1.5304	0.1147
Average Amplitude of Rec.	-0.0086	-0.0061	-0.0719	-0.0508	-0.0328	-0.0017	-0.0149	-0.0081	-0.0178	-0.0827	-1.7025	-0.5485
Steepness of expansions	0.0070	0.0067	0.0105	0.0172	0.0165	0.0070	0.0026	0.0057	0.0159	0.0238	0.2618	0.0295
Steepness of recessions	-0.0031	-0.0026	-0.0095	-0.0127	-0.0117	-0.0009	-0.0019	-0.0034	-0.0036	-0.0103	-0.3952	-0.0452

Table 2: Deviation Cycles dating of Euro Area time series: summary statistics.

	YER	PCR	ITR	MTR	XTR	GCR	LNN	LPROD	ULC	URX	SCR	Net Exp.
Number of cycles P-P	9.0000	8.0000	5.0000	10.0000	8.0000	10.0000	5.0000	10.0000	7.0000	6.0000	10.0000	10.0000
Number of cycles T-T	8.0000	8.0000	5.0000	10.0000	9.0000	9.0000	6.0000	10.0000	6.0000	7.0000	11.0000	10.0000
Average Expansion Prob.	0.5833	0.6136	0.5682	0.6061	0.5909	0.5303	0.6212	0.5000	0.5455	0.3939	0.4848	0.5000
Average Recession Prob.	0.4167	0.3864	0.4318	0.3939	0.4091	0.4697	0.3788	0.5000	0.4545	0.6061	0.5152	0.5000
Average Duration of Exp.	8.5556	10.1250	15.0000	8.0000	9.7500	7.0000	16.4000	6.6000	10.2857	8.6667	6.4000	6.6000
Average Duration of Rec.	6.8750	6.3750	11.4000	5.2000	6.0000	6.8889	8.3333	6.6000	10.0000	11.4286	6.1818	6.6000
Average Amplitude of Exp.	0.0178	0.0134	0.0605	0.0523	0.0607	0.0090	0.0118	0.0134	0.0276	0.1186	1.4716	0.6737
Average Amplitude of Rec.	-0.0205	-0.0136	-0.0593	-0.0539	-0.0560	-0.0091	-0.0113	-0.0129	-0.0329	-0.0990	-1.3930	-0.6784
Steepness of expansions	0.0021	0.0013	0.0040	0.0065	0.0062	0.0013	0.0007	0.0020	0.0027	0.0137	0.2299	0.1021
Steepness of recessions	-0.0030	-0.0021	-0.0052	-0.0104	-0.0093	-0.0013	-0.0014	-0.0020	-0.0033	-0.0087	-0.2253	-0.1028

Table 3: Classical BC: Standardised Concordance Index.

	EA	D	UK	F	I	US
EA	-	7.15	2.48	6.29	6.35	3.40
D	7.15	-	1.93	5.41	5.43	4.43
UK	2.48	1.93	-	3.00	2.33	3.50
F	6.29	5.41	3.00	-	4.59	1.92
I	6.35	5.43	2.33	4.59	-	3.20
US	3.40	4.43	3.50	1.92	3.20	-

Table 4: Test for BC independence using HAC standard errors (Newey-West estimator with truncation parameter equal to 5).

	EA	D	UK	F	I	US
EA	-	52.52	1.80	4.41	12.15	2.62
D	7.85	-	1.53	3.07	6.73	3.33
UK	1.87	1.66	-	1.90	2.37	4.25
F	10.47	9.02	1.89	-	5.49	1.51
I	4.86	4.79	1.82	2.94	-	2.57
US	3.02	4.02	2.65	1.52	3.70	-

Table 5: Deviation cycles: Standardised Concordance Index.

	EA	D	UK	F	I	US
EA	-	4.83	3.42	4.71	5.77	2.75
D	4.83	-	2.95	2.66	3.48	2.53
UK	3.42	2.95	-	2.07	2.33	2.26
F	4.71	2.66	2.07	-	3.67	2.47
I	5.77	3.48	2.33	3.67	-	1.90
US	2.75	2.53	2.26	2.47	1.90	-

Table 6: Test for deviation cycle independence using HAC standard errors (Newey-West estimator with truncation parameter equal to 5).

	EA	D	UK	F	I	US
EA	-	15.27	4.96	12.93	11.12	4.45
D	8.89	-	2.06	4.53	4.49	2.75
UK	3.68	2.14	-	5.39	3.33	6.56
F	8.38	4.68	4.91	-	4.81	2.87
I	13.02	6.30	5.55	5.32	-	3.22
US	3.60	3.78	4.27	2.28	2.79	-

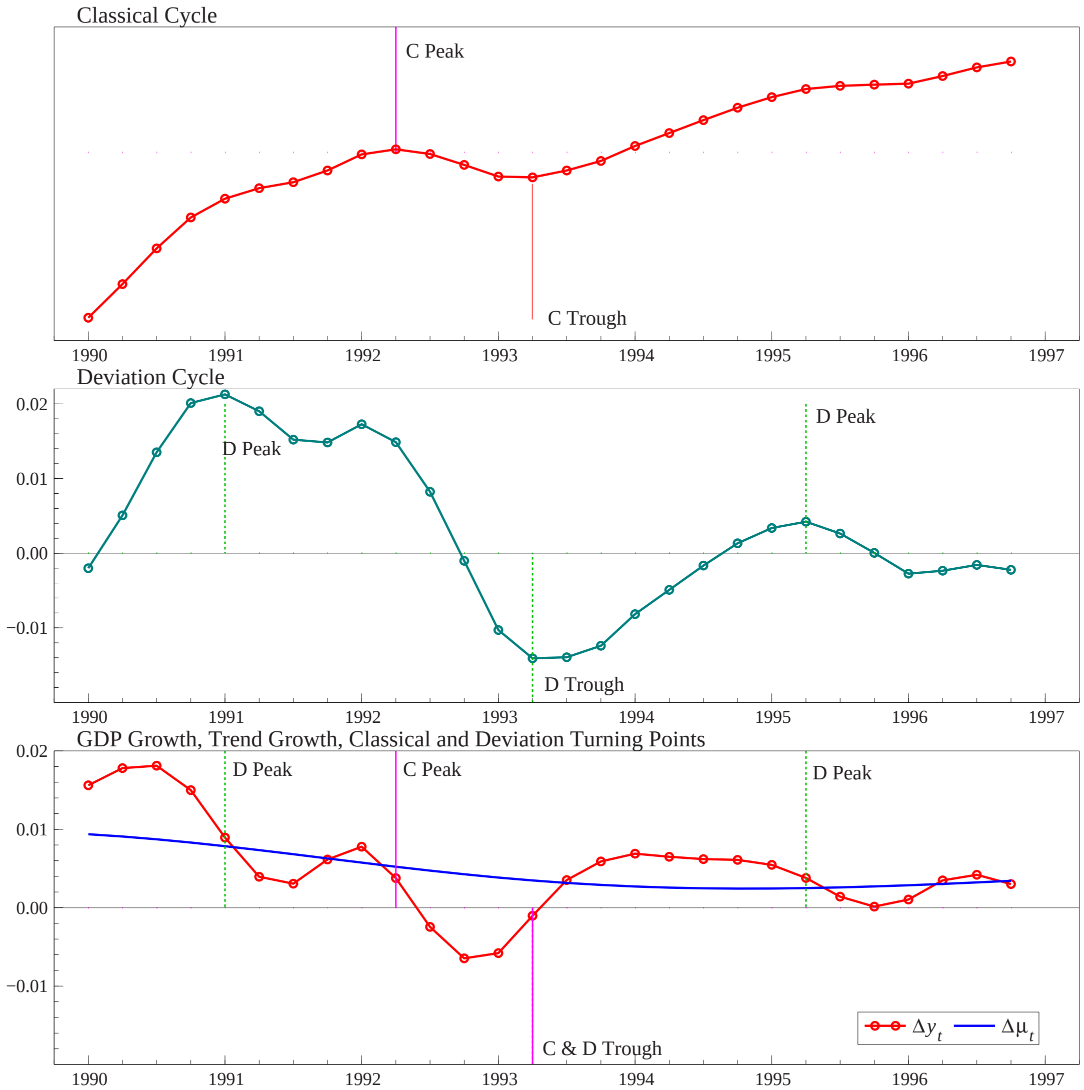

Figure 1: Classical and deviation cycles turning points and their relation with growth.

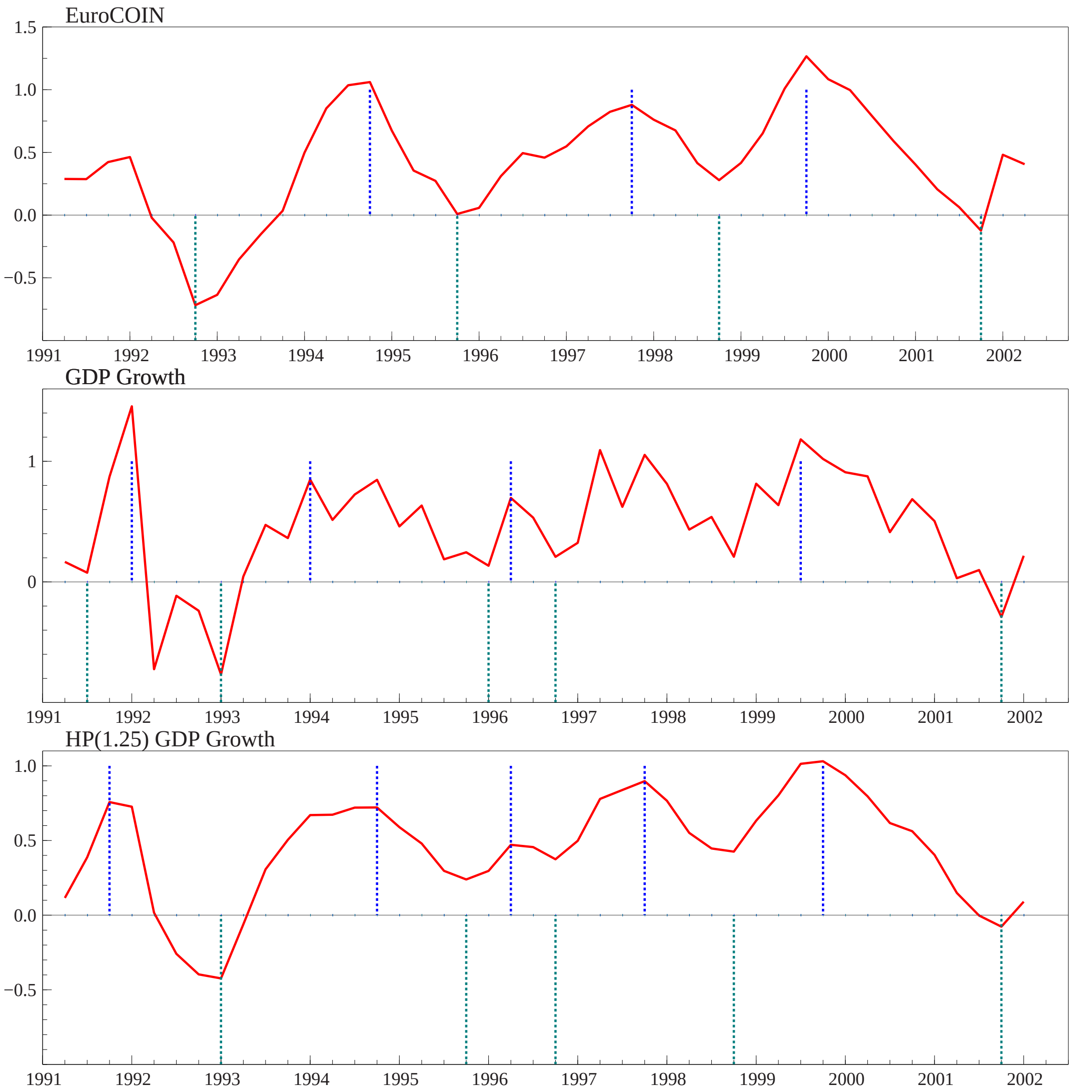

Figure 2: Growth rate cycles for EuroCOIN index and raw and filtered GDP growth.

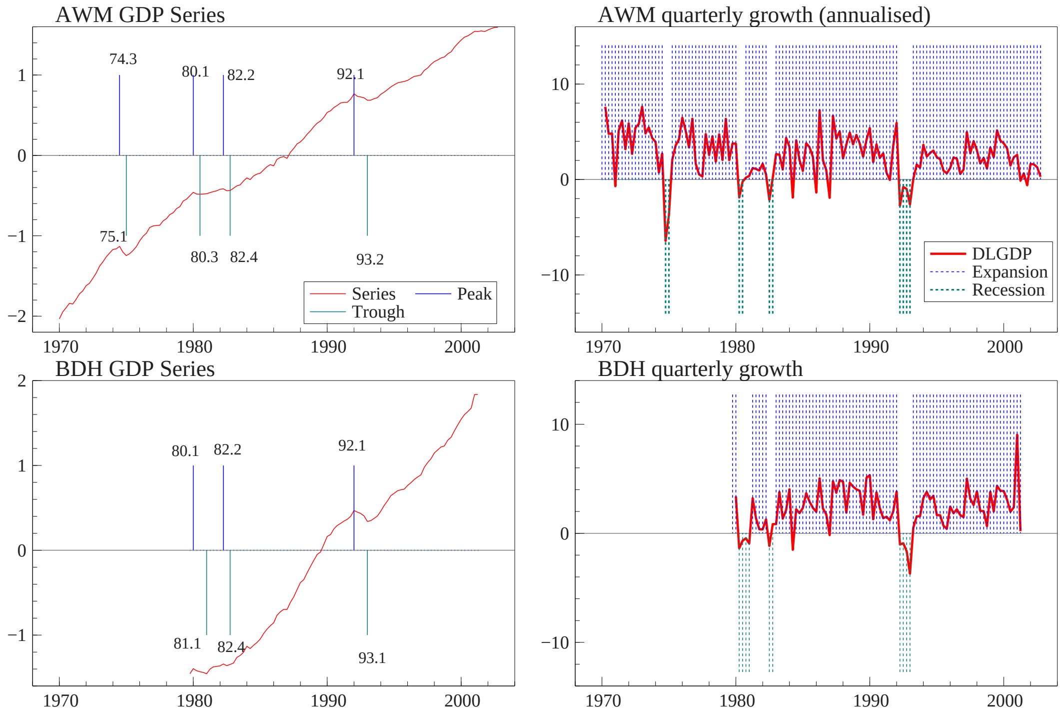

Figure 3: Classical cycle turning points, expansions and recessions, in the Euro area quarterly real GDP (seasonally adjusted, logarithms); ECB series and Beyer, Doornik and Hendry (2000) estimates.

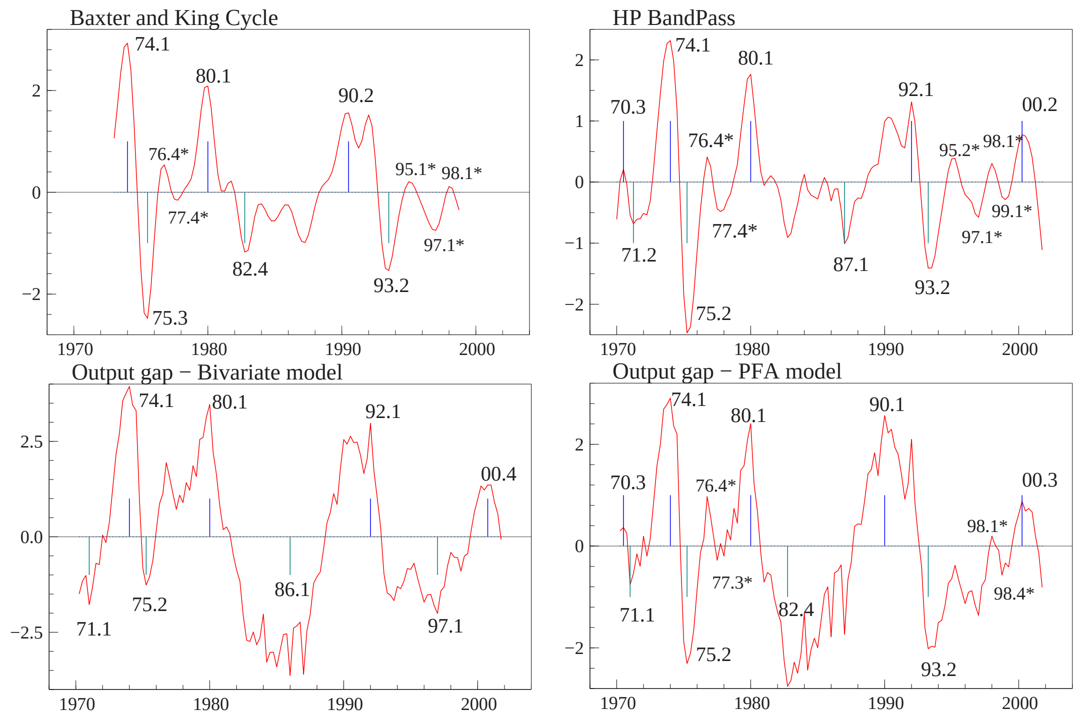

Figure 4: Turning points for four alternative measures of the Euro Area deviation cycle. An asterisk (*) denotes a turning point that was censored according to amplitude considerations (see text for details).

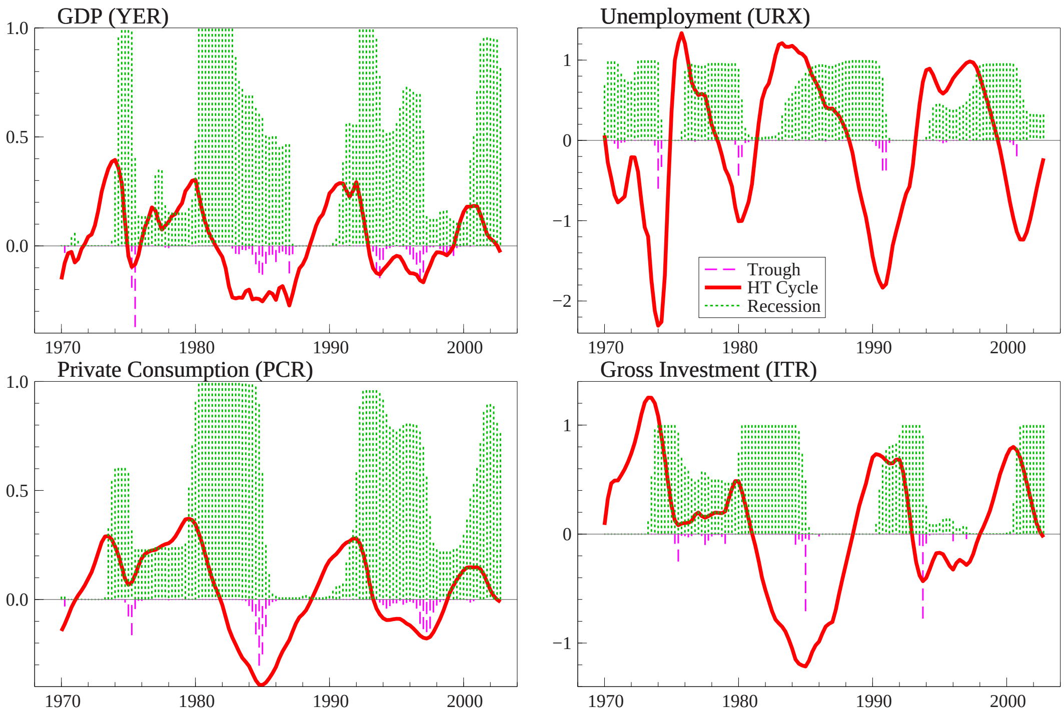

Figure 5: Harvey and Trimbur (2002) deviation cycles, recession probabilities, and trough probabilities (inverted scale), for selected Euro Area series.

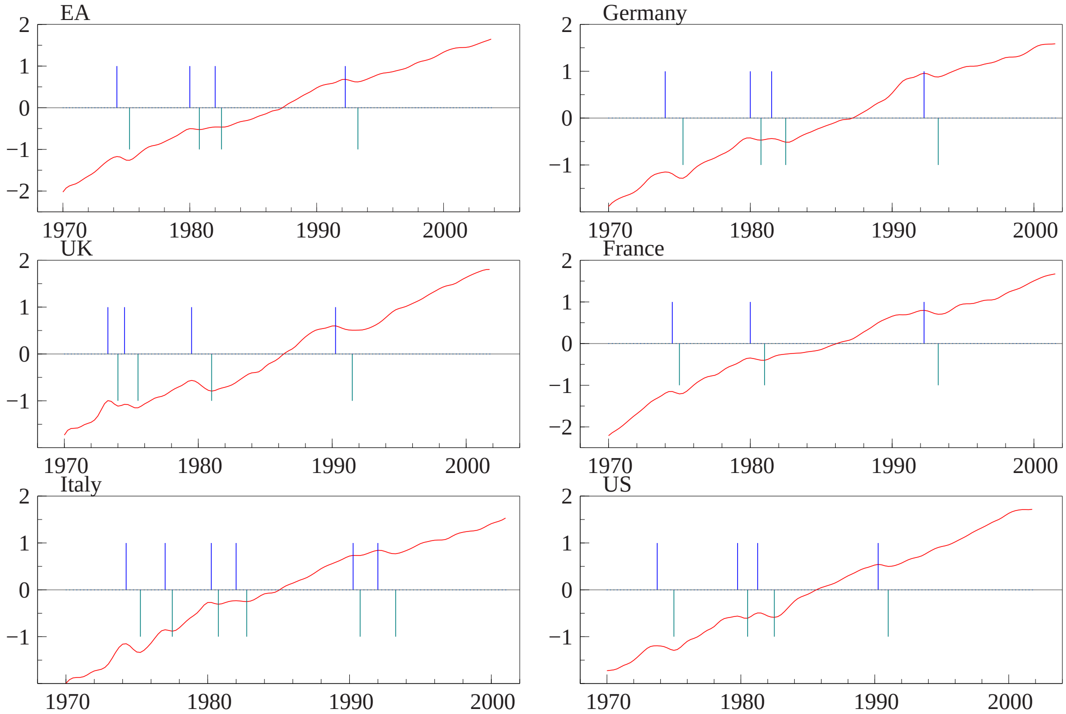

Figure 6: Classical cycle turning points for EA, Germany, France, Italy, UK and the USA, based on HP(1.25) filtered quarterly real GDP.

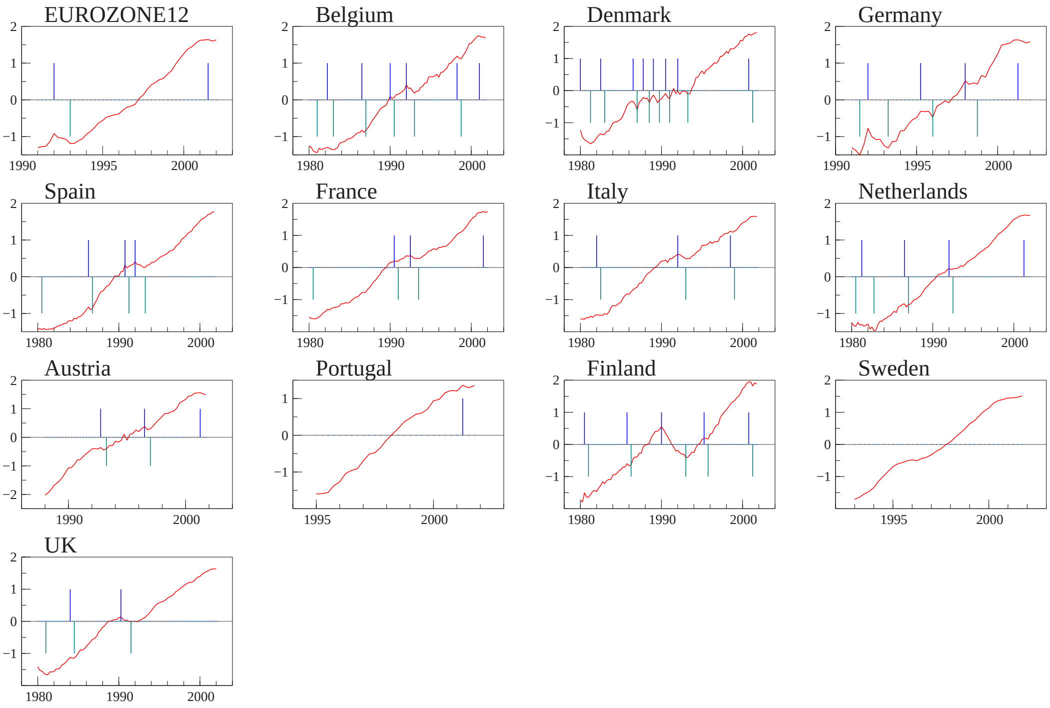

Figure 7: Classical cycle turning points, for the Euro zone countries based on quarterly real GDP (seasonally adjusted, logarithms); Eurostat series, 1980.1-2002.1.

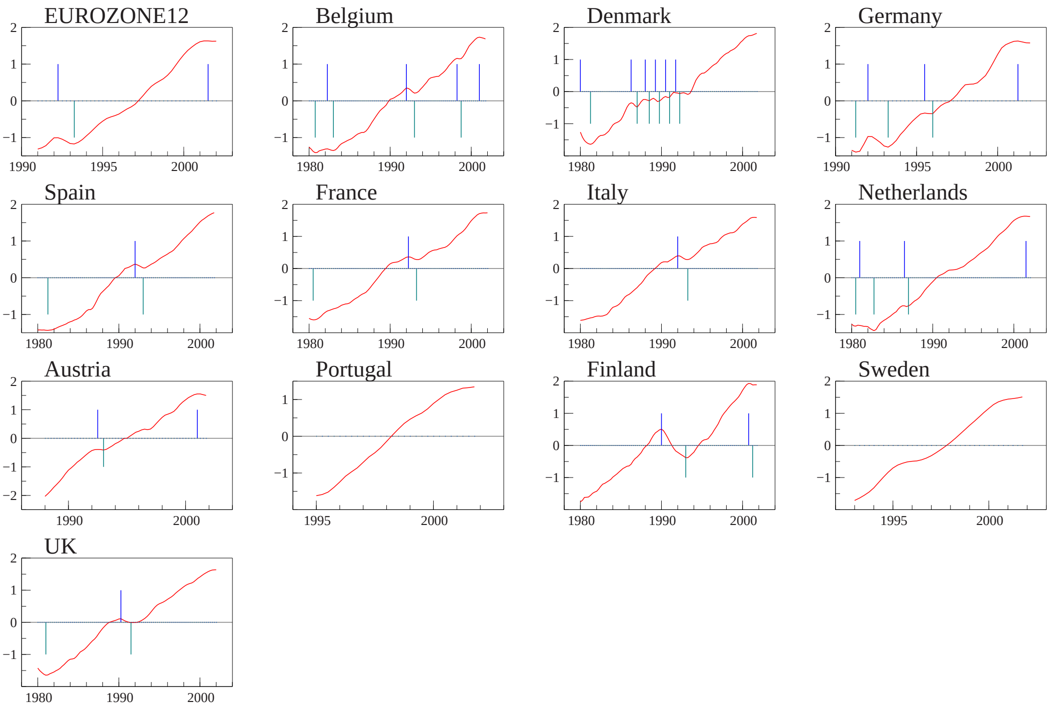

Figure 8: Classical cycle turning points, for the Euro zone countries based on estimates of a trend resulting from HP(1.25).

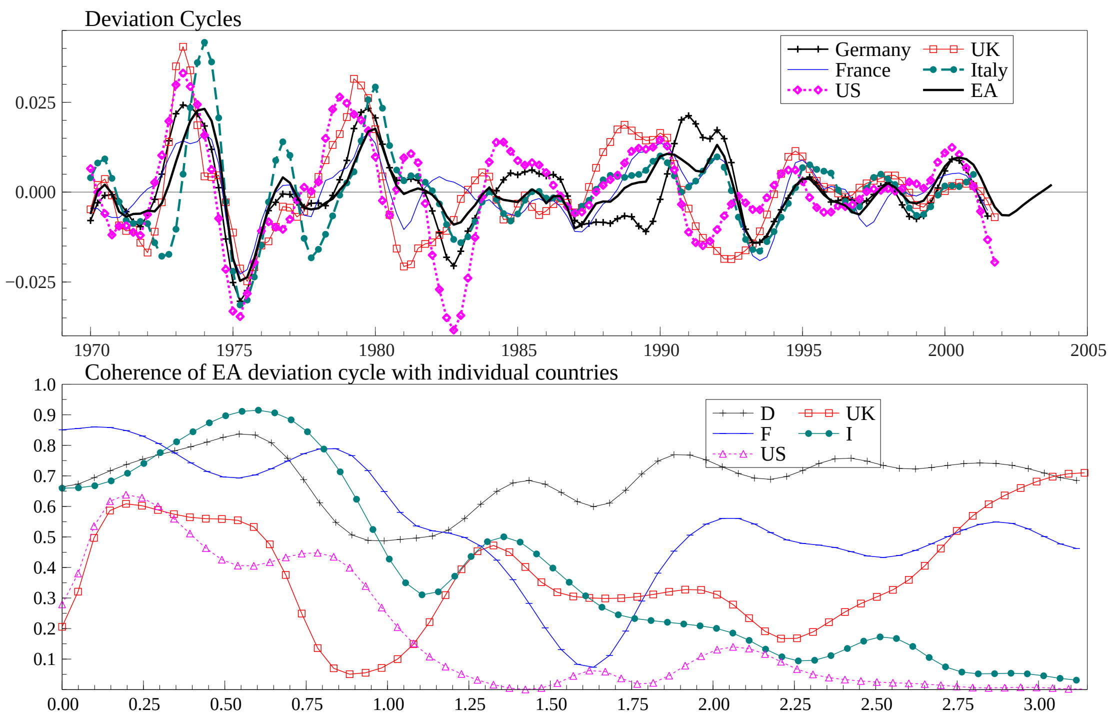

Figure 9: Coherence of the Euro Area HPB deviation cycle and those of selected countries.

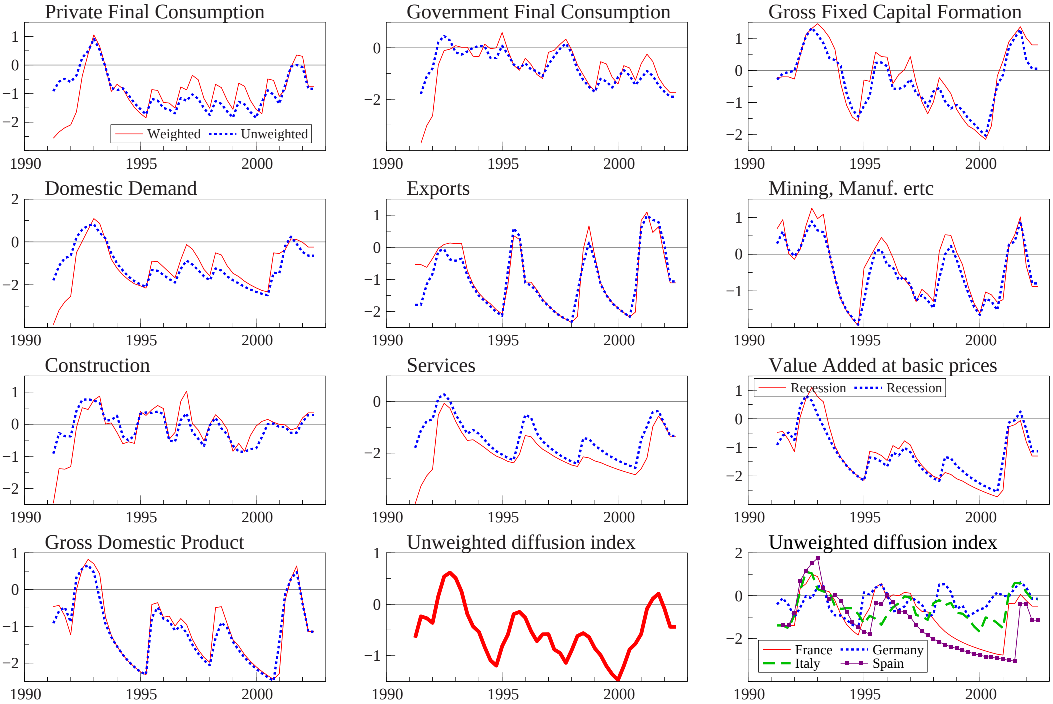

Figure 10: Diffusion indices for classical business cycles in the Euro area. Log-odds of the recession probabilities. Values greater than zero correspond to recession probabilities greater than 1/2.