Reconsidering the evidence: are Eurozone business cycles converging?*

Michael Massmann[†] and James Mitchell[‡]

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Abstract

This paper, using 40 years of monthly industrial production data, examines the relationship between the business cycles of the 12 Eurozone countries. Since estimates of the business cycle have been found to be sensitive to how the cycle is measured, a range of alternative measures are considered. We focus on both parametric and nonparametric univariate measures of the 'classical' and 'growth' cycles. We then investigate whether Eurozone business cycles have converged. This is based on an analysis of the distribution of bivariate correlation coefficients between the 12 countries' business cycles. This extends previous work that has tested for convergence, in a similar manner by focusing on correlation, but has not considered the entire distribution, instead focusing on the mean correlation coefficient or particular bivariate correlation coefficients. Although empirical inference about individual Euro-zone business cycles is found to be sensitive to the measure of the business cycle considered, our measure of convergence between the Eurozone business cycles exhibits common features across the alternative measures of the business cycle. Interestingly, we find that there have been periods of convergence, identified by the distribution tending to unity, and periods of divergence. Although further data are required to corroborate the story, there is evidence to suggest that the Euro-zone has entered a period of convergence after the clear period of divergence in the early 1990s in the aftermath of German unification and at the time of the currency crises in Europe. This is encouraging for the successful operation of a common monetary policy in the Eurozone.

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[†]University of Bonn and Lincoln College, University of Oxford; email: michael.massmann@uni-bonn.de; postal address: Institute of Econometrics and Operations Research, University of Bonn, Adenauerallee 24-42, 53113 Bonn, Germany.

[‡]National Institute of Economic and Social Research, London; email: j.mitchell@niesr.ac.uk; postal address: NIESR, 2 Dean Trench Street, Smith Square, London SW1P 3HE, UK.

1 Introduction

Economic and monetary union (EMU) in Europe has led to increased interest in studying convergence among business cycles, at both the national and regional levels. Both the causes of increased convergence and its consequences have been examined. Possible causes have included the exchange rate regime, international trade and geographical proximity; see Artis & Zhang (1997), Frankel & Rose (1998) and Clark & van Wincoop (2001), respectively. Turning to the consequences, it has been argued, for example by Christodoulakis et al. (1995), that synchronisation of business cycles among member countries of EMU is a prerequisite for its successful operation.

Several open methodological issues have emerged as a result of this work, the two most important of which are the following. Firstly, a controversy has arisen over the appropriate definition of a business cycle. Competing methods for the computation of a cyclical series have been suggested. One prominent view is that an economic time series can be decomposed into the sum of trend and cyclical components, although there remains disagreement over how the trend should be identified and estimated; indeed, a range of parametric and non-parametric algorithms can be considered. An alternative view rejects the concept of a trend-cycle decomposition and defines a business cycle in terms of the turning points in the original data series, hence not relying on the estimation and extraction of a trend series.

Secondly, there is no consensus on how convergence between time series in general, and business cycles in particular, should be gauged. Suggestions include looking for increased bivariate correlation, for decreased cyclical disparity or for evidence of an emerging common factor that drives individual countries' business cycles; see Artis & Zhang (1997, 1999), Massmann & Mitchell (2002) and Vahid & Engle (1993), respectively.

In this paper we address these methodological issues by looking for convergence, specifically through an analysis of (contemporaneous) correlation, between the business cycles of the 12 current Eurozone countries. This particular application is relevant not only for methodological reasons but also because the literature has not yet reached a consensus on whether Eurozone business cycles have converged in this sense. Table 1 illustrates this by summarising the main aspects of some representative studies. Differences are explained in part by the use of different data. Other reasons, however, include the use of different methods of both identifying business cycles and gauging convergence. In this paper to provide a common framework, and abstract from some of these differences, we take as our starting point the controversy initiated by Artis & Zhang (1997, 1999) and Inklaar & de Haan (2001) in *Oxford Economic Papers* – while Artis & Zhang (1997, 1999) conclude that European business cycles have become more synchronised, Inklaar & de Haan (2001), using the same but updated data, reach the opposite conclusion; Inklaar & de Haan (2001) discover that Eurozone cycles are better correlated (against Germany) in the period 1971-79 than the period 1979-87. They argue that is inconsistent with Artis & Zhang's (1999) view that increased monetary integration, specifically after the creation of the ERM in 1979, and business cycle synchronisation are positively related.

We re-consider the evidence that sparked this controversy and in so doing establish some important stylised facts about the nature of the Eurozone business cycle. Our work is characterised by the following two developments. Firstly, using the same raw data as Artis & Zhang and Inklaar & de Haan, again appropriately updated, we identify business cycles using a range of trend-cycle decompositions, as well as by a turning point rule. This is in contrast to the selective de-trending methods considered by Artis & Zhang and Inklaar & de Haan. It enables us to ascertain whether inference on convergence is contingent on the measure of the cycle. We thus build on and extend Canova's (1998) analysis; Canova showed that inference about business cycles can be sensitive to the chosen identification method. Secondly, in order to test whether Eurozone business cycles actually have converged, and there is evidence for a "common" cycle, we compute pairwise correlation coefficients using a method of moments estimator that also yields an associated measure of uncertainty. We then examine the evolution of this estimate over time using a series of rolling windows, rather than just two or four windows of fixed width as in Artis & Zhang and Inklaar & de Haan. Moreover, instead of focusing on the individual correlation of given countries with a reference country we look at the mean and variance, and indeed the entire distribution, of *all* bivariate correlation coefficients. This better captures 'general' movements within the Eurozone.

Our results can be summarised as follows. We confirm Canova's (1998) conclusion that the properties of the business cycle depend on how the business cycle is measured. However, we find that these differences do not translate into ambiguous inference about business cycle convergence between countries. Instead, inference about convergence is largely independent of both the detrending method used, and whether a detrending method or turning point rule is used to define a business cycle. We find that the Eurozone has been characterised by periods of convergence, associated with a rising mean correlation, a falling variance and with limited intra-distributional movement, and periods of divergence. We date these periods, and find the Eurozone to have 'switched' between periods of convergence and divergence many times in the last 40 years. These facts are not therefore consistent with Artis & Zhang's (1999) view that since the formation of the ERM in 1979 Eurozone business cycles have become increasingly in-line. Nevertheless, we do offer a tentative, and preliminary, interpretation of these facts that is consistent with Artis & Zhang's (1999) view that business cycle synchronisation is positively related to monetary integration, specifically the degree of exchange-rate rigidity. Moreover, we find that the most recent estimates suggest that the business cycles of the Eurozone have converged relative to the period of divergence in the early 1990s. This bodes well for the successful operation of a common monetary policy in the Eurozone.

The plan of the paper is as follows. Section 2 describes the data that we use in our empirical analysis as well as the transformations they were subjected to. In Section 3, an overview is given of the eight methods used to identify the cyclical component of our data series before Section 4 presents the method employed for measuring the convergence among the cyclical series. Our empirical results are presented in Section 5. Section 6 concludes.

2 Data

The data used for our empirical analysis are the industrial production indices (IIP) of Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain, as compiled and seasonally adjusted by the OECD. The data set is an updated version of that employed by Artis & Zhang (1997, 1999) as well as Inklaar & de Haan (2001).[1] The data are monthly and the chosen sample period is 1960-1 to 2001-8. Anticipating our results below, it is noteworthy that Irish IIP has grown very rapidly over recent years; extraction of an *a priori* sensible looking cycle for Ireland proved difficult. Ireland is retained in the discussion below but results were robust to her exclusion. See Table 2 for some other relevant country-specific notes.

The use of industrial production data for business cycle analysis is justified by appealing to the historically strong correlation, importantly in growth rates given their trending nature in levels, of industrial production and gross domestic product (GDP), the preferred measure of 'aggregate economic activity'; see Harding & Pagan (2002*b*). In contrast to GDP data, monthly observations on industrial production are available on a consistent basis for most OECD countries back to the 1960s. With over 40 years of data we can meaningfully identify and estimate business cycles. Note, however, that there are reports that the historically close relationship between industrial production and GDP has weakened. If confirmed, this would clearly make it more debatable whether meaningful inference about GDP can be made.

In order to ensure comparability of our results with those of Artis & Zhang (1997, 1999) and Inklaar & de Haan (2001), we did not take logarithms of the data.[2] It is worth pointing out, however, that "linearising" the data by means of logarithms did not result in altering the integration and normality properties of most data concerned. Tables 3 and 4 show the results of an ADF test for a unit root in the first differences and levels of the series, respectively. It is evident that the data of most countries are $\mathsf{I}(1)$, regardless of whether logs are taken. There is, however, weak evidence of logarithms *introducing* a unit root into Italian and Portuguese IIP! Table 5 illustrates that the null hypothesis of normality is rejected at the 1% level. This result holds irrespective of whether or not the data are transformed into logarithms.

We also considered the impact outliers might have on the level of the data series. This is important because aberrant observations can distort inference. In particular, we used the automatic procedure of the TRAMO-SEATS software package (see Caporello et al. (2002)) to detect and remove any outlying observations in the data series. Outlier corrected results, however, are qualitatively similar to those presented below. See also the discussion in Section 5.1.

[1]We are very grateful to Mike Artis for making the series available to us.

[2]We thank Mike Artis for confirming this in private correspondence with us.

3 Identifying the business cycle

In their analysis Artis & Zhang (1997, 1999) and Inklaar & de Haan (2001) make recourse to only a subset of the many detrending methods available for identifying a business cycle. In contrast, from within the family of univariate detrending methods we consider a wider spectrum of popular algorithms.[3] Additionally, we consider methods of identifying business cycles based on estimating turning points. The following two sections will give an overview of the detrending and turning point algorithms, respectively. For a detailed review of the alternative statistical approaches to measuring business cycles, see Massmann et al. (2003).

3.1 Trend-cycle decomposition

It is instructive to differentiate between parametric and nonparametric detrending algorithms. However, this distinction is made largely for expositional ease. It reflects a long standing methodological debate. It should be noted, however, that nonparametric methods can be rationalised as parametric ones. See in particular the paragraphs below on the Hodrick-Prescott and ideal band pass filters. Furthermore, the parametric methods, like the nonparametric ones, are 'simply' taking weighted averages of the data; see Harvey & Koopman (2000).

3.1.1 Parametric methods

Three parametric methods are considered: an ARIMA model resulting in the Beveridge-Nelson (BN) decomposition, an unobserved components (UC) model with a smooth stochastic trend, and a linear regression model with a constant time trend (TIM). The first two of these models were put in a state-space form and estimated using exact maximum likelihood. In particular, use was made of the SsfPack module for Ox to perform the calculations; see Koopman, Shephard & Doornik (1999) and Doornik (1998).

1. **ARIMA models and the Beveridge-Nelson decomposition (BN).** Beveridge & Nelson (1981) defined the trend component as the limiting forecast of a process $\{y_t\}$, adjusted for the mean growth rate. Specifically, the Beveridge-Nelson trend is defined as $\mu_t = \mathsf{lim}_{k\to\infty}\left(\hat{y}_{t+k|t} - k\tau\right)$ where $\tau = \mathsf{E}\left(\Delta y_t\right)$ is the mean growth rate of the process, k is the forecast horizon, and $\hat{y}_{t+k|t} = \mathsf{E}\left(y_{t+k} \mid Y_t\right)$ is the forecast of y_{t+k} made on the basis of available information at time t. The resulting cyclical component is found to be $c_t = \mu_t - y_t$.

   To compute μ_t and c_t, we adopt the traditional algorithms suggested by Beveridge & Nelson which proceeds in three steps. To start with, an ARMA model in first differences $w_t = \Delta y_t$ is estimated. This is used to produce the forecasts $\hat{w}_{t+1|t}, \ldots, \hat{w}_{t+k|t}$

[3] See Canova (1998) for a similar comparison.

on the basis of which the cyclical component

$$c_t = \mathsf{lim}_{k\to\infty}\left\{\sum_{j=0}^{k-1}\hat{w}_{t+k-j|t} - k\tau\right\}$$

is then computed.

In practice, of course, the forecast horizon k must be fixed, and we choose the value 100 since inspection showed that after that many time periods the difference $\hat{w}_{t+k-j|t} - k\tau$ is negligible, i.e. in the region of 10^{-15}. However, this approximation has been the main criticism of the Beveridge-Nelson algorithm, and a string of paper have suggested both computationally more efficient and exact procedures; see Cuddington & Winter (1987), Miller (1988), and in particular Newbold (1990). However, modern computing power is such that any reasonable number k could be chosen if it made a numerical difference.

The model in w_t that needed to be estimated in the first stage of this procedure was a multiplicative seasonal ARMA model of order $(p, q) \times (p_s, q_s)$: $\phi(\mathsf{L})\,\Phi(\mathsf{L}^s)\,w_t = \theta(\mathsf{L})\,\Theta(\mathsf{L}^s)\,\xi_t$ where s is the seasonal frequency, p_s and q_s are the seasonal AR and MA lag length, respectively, and $\xi_t \sim \mathsf{IID}\left(0, \sigma_\xi^2\right)$; see Harvey (1993, Section 5.6). Since our data are monthly observations we set $s = 12$. Moreover, p, q, p_s and q_s were chosen by selecting the model that minimised the Akaike Information Criterion among all possible combinations of $p, q = \{0, 1, 2, 3, 4\}$ and $p_s, q_s = \{0, 1, 2\}$. It is important to point out that although seasonal lags are included, this procedure does not constitute a method of seasonal adjustment. In contrast to the introduction of seasonal dummy variables, the seasonal lags are introduced into the time series model to improve fit but without having to include intermittent lags.

2. **Unobserved components models (UC).** Following recent experience (e.g. Koopman, Harvey, Doornik & Shephard (1999)), we estimated a so-called smooth trend model which decomposes the process y_t into $y_t = \mu_t + c_t + \xi_t$ where μ_t, c_t, and ξ_t are the trend, cyclical and irregular components, respectively. In particular, a smooth trend is obtained by setting the variance of η_t, σ_η^2, equal to zero in the general local linear trend formulation:

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

so that, effectively, $\eta_t = 0$ and the level of the trend, i.e. μ_t, is fixed while the trend's slope, viz β_t, remains stochastic due to $\zeta_t \sim \mathsf{IID}\left(0, \sigma_\zeta^2\right)$. Moreover, it was assumed that the cyclical component c_t follows a trigonometric function (e.g. see Harvey (1993, Section 6.5)), and that the irregular component is $\xi_t \sim \mathsf{IID}\left(0, \sigma_\xi^2\right)$.

The trend μ_t is extracted from the data using the Kalman smoother. Importantly, the cycle of y_t is taken to be the observed series less the trend component, i.e. $c_t = y_t - \mu_t$, and thus consists of the sum of the irregular and trigonometric cyclical components.

3. **Linear regression models (TIM).**With an intercept and a constant linear trend as the sole explanatory variables the linear regression model is given by $y_t = \alpha + \beta t + \varepsilon_t$ where $\varepsilon_t \sim \mathsf{ID}\left(0, \sigma_\varepsilon^2\right)$. The estimated cyclical component is then $y_t - \hat{\beta} t$.

It is instructive to relate these detrending algorithms to the ADF test mentioned in Section 2. Given that the hypothesis of the IIP data containing a unit root cannot be rejected, the TIM cycles are our least preferred measure of the business cycle. A simple deterministic time trend can only imperfectly approximate stochastic nonstationarity even if it is allowed to be subject to structural shifts.

3.1.2 Nonparametric methods

Nonparametric methods offer an alternative means of extracting trend and cyclical components from a time series. In contrast to parametric methods they do not rely on the specification of a statistical model. We consider four nonparametric methods:

1. **A centered moving average (MA).**[4] Simple moving average detrending of time-series is used widely; see Osborn (1995). We consider a 4-year moving average.

2. **The Hodrick-Prescott filter (HP).**[5] Use of the Hodrick-Prescott filter requires one parameter, say λ, to be chosen, where λ controls the smoothness of the trend. Ravn & Uhlig (2002) argue that for monthly data one should set $\lambda = 129600$.[6]

3. **The Baxter-King ideal band pass filter (BK).**[7] An ideal band pass filter is used to isolate the components of a time series that lie within a given range of frequencies. Economic theory can play a role in defining these frequencies. In particular, given our interest lies in extracting the periodic components of an economic time series that can be associated with the business cycle, the bands can be chosen consistent with priors about the duration of the business cycle. For example, it is widely believed that a business cycle lasts between 1.5 and 8 years; the lower band can then be set at 18 months and the upper band at 96 months.[8] This removes low frequency trend variation and smooths high frequency irregular variation, while retaining the

[4] Other types of moving average filter are also used widely. For example, the Henderson moving average is used by the U.S. Bureau of Census' X-11 and X-12 procedures to extract the trend component of a time series; see Findley et al. (1998).

[5] It is of theoretical interest that the Hodrick-Prescott filter also can be rationalised as a parametric method, see Harvey & Jaeger (1993) who interpret it as the optimal estimator in an unobserved components time series model.

[6] Pedersen (2001) derives the optimal estimator of λ for a stationary y_t process. This result is non-applicable in our context, however, since, as shown in Section 2, our data series contain a unit root. We thus adhere to Ravn & Uhlig's recommendation.

[7] Again it is of theoretical interest that ideal band pass filters can be rationalised as optimal estimators in unobserved components time series models; see Harvey & Trimbur (2002).

[8] Agresti & Mojon (2001) argue that 8 years is too low an upper band for business cycles in Europe. In fact our results do not support such an argument, see for instance Tables 6-7 below. In any case, results using the Baxter-King filter were robust to increasing the upper band to 10 years.

major features of business cycles. Since the ideal band pass filter requires a moving average of infinite order, in practice an approximation is required. We adopt the approximation of Baxter & King (1999) and set the length of the moving average to 3 years.[9]

4. **The Phase Average Trend (PAT)**. The computation of the phase average trend involves a number of steps. First, compute deviations of the series from a centered moving average. Second, break up the deviations into phases, according to the dates of cyclical peaks and troughs. Third, compute the mean values of the series for each successive phase, and smooth using three-item or two-item moving averages. The PAT is then given by connecting these midpoints of these triplets or doublets; see Zarnowitz & Ozyildirim (2002). Following Artis & Zhang (1999) we use the PAT calculated by the OECD.

3.2 Turning point analysis

Cycles computed in the manner discussed in Section 3.1 can be classified as "growth cycles", since they derive from deducting a trend, however estimated, from the original series. In contrast, "classical cycles" are defined in terms of the turning points in the levels of the original series. For example, a peak turning point indicates the end of an expansionary phase and the beginning of a recessionary one. This approach is typically associated with the National Bureau of Economic Research (NBER) and Burns & Mitchell (1946). There is a considerable controversy, however, over what the "real" definition of a business cycle is, some arguing that it is the growth cycle, others that it is the classical cycle. For a detailed account of the arguments, see, for instance, the discussion in Backhouse & Salanti (2000, pp. 69-81).

Again, both parametric and nonparametric measures of a cycle have been proposed. For a comparison of these two approaches see Harding & Pagan (2002*a*). Here we focus on the nonparametric measure proposed by Harding & Pagan (2000, 2001, 2002*b*). A related measure, motivated using the theory of Markov chains, is proposed by Artis et al. (2003).

Following the NBER tradition, Harding and Pagan advocate the use of a nonparametric dating rule to isolate turning points in the series. They suggest that the following three criteria need to be satisfied by the algorithm: (i) it picks the peaks and the troughs of a series, (ii) it ensures that peaks and troughs alternate and (iii) the cycle it defines has a minimum duration.

While this approach of characterising cycles has the attractive feature of not being dependent on applying an arbitrary detrending algorithm, it does also require some parameters to be chosen. The censoring rule that specifies the minimum duration of the cycle must be stipulated. We follow Harding and Pagan and require phases to last at least two quarters (six months) and completed cycles (peak to peak, or trough to trough) to last at least five quarters (15 months). Harding & Pagan (2001) show that if the dating

[9] Note that the approximation proposed by Baxter & King (1999) has been shown to fail to filter out the desired components when y_t is nonstationary; see Murray (2001) and Benati (2001).

algorithm is specified in this fashion it does a good job at approximating the turning points in quarterly U.S. GDP, as identified by the NBER; cf. Bry & Boschan (1971).

Therefore, in our setting, the process $\{y_t\}$ has a peak at time t_0 if both of the following criteria are met:

$$\left.\begin{array}{l}\Delta_i y_{t_0} > 0,\\ \Delta_i y_{t_0+i} < 0,\end{array}\right\} \text{ for all } i = 1, \ldots, 6,$$

i.e. if at time t_0 the series has a local maximum relative to the six months on either side. A trough is defined conversely. Application of the Harding-Pagan rule to the level of the series, $\{y_t\}$, yields a binary series with unity indicating a state of expansion, and zero a state of contraction.[10]

It may be of interest to use the Harding-Pagan rule to identify the turning points of the growth cycles as computed in Section 3.1. We can then compute the bivariate correlation coefficients of the resulting binary series with that based on the turning points for the level series $\{y_t\}$. This correlation C provides a criterion for ranking the de-trending mechanisms according to their ability to match the turning points of $\{y_t\}$. Robust standard errors for C, $se(C)$, can be estimated by the generalised method of moments (GMM). Although it may be argued that there is no theoretical reason to expect the classical cycle and the growth cycles to exhibit similar turning point behaviour this procedure provides an empirically based, sample specific, means of evaluating one detrending algorithm over another. Indeed, Canova (1999) conducted a similar comparison for NBER turning points of U.S. GDP.

4 Testing for convergence

We test for convergence by looking at whether the correlation between countries' business cycles has increased over time. Our approach encompasses and generalises previous work in several respects. Firstly, we compute robust standard errors associated with the correlation coefficients in order to have a measure of estimation uncertainty. This is similar to Wynne & Koo (2000) and related to Harding & Pagan (2001) who, however, derive robust regression coefficients. Secondly, following the work of Döpke (1999) we consider a series of rolling windows, rather than simply computing bilateral correlation coefficients for a small number of sub-periods. By contrast, Artis & Zhang (1999) consider two sub-periods, Inklaar & de Haan (2001) four. The rolling window approach is less arbitrary and presents a more complete picture of the correlation coefficient over time. This is important in establishing stylised facts about the Eurozone business cycle. Thirdly, and importantly, in order to capture the bilateral correlation coefficients of *all* countries under consideration we propose to look at their mean, their variance and, indeed, their entire distribution to answer the question of convergence. We also suggest a measure of intra-distributional dynamics. Previous work, by contrast, has focused on individual correlations such as that

[10]We would like to thank Don Harding for sending us GAUSS files to implement the Harding-Pagan rule.

of a given country with Germany or the US, as in Artis & Zhang (1999) and Inklaar & de Haan (2001), or with the Eurozone aggregate, as in Döpke (1999).

Consider n countries' business cycles identified *via* any of the detrending methods or the turning point rule. Let c_{it} denote country i's business cycle at time t; $i = 1, ..., n$; $t = 1, ..., T$; $\widetilde{c}_t$ denote the $n-$vector $(c_{1t}, ..., c_{nt})'$; $Corr$ denote contemporaneous correlation and $vech$ be an operator that stacks the elements of an $n \times n$ matrix below the main diagonal. For each available time period t and for each of the $j = 1, ..., n(n-1)/2$ bivariate combinations we estimate the correlation coefficient $\rho_{j,t}$ for a window of h months, where $(\rho_{1,t}, \rho_{2,t}, ..., \rho_{n(n-1)/2,t})' = vech(Corr\{\widetilde{c}_t\widetilde{c}_t'\})$, $\{t = t-h, t-h+1, ..., t\}$. Using GMM, we are able to estimate not only the correlation coefficient itself but also its variance and covariance. Let $\widehat{\rho}_{j,t}$ denote the GMM estimate, $Var(\widehat{\rho}_{j,t})$ its estimated variance and $Cov(\widehat{\rho}_{i,t}, \widehat{\rho}_{j,t})$ the estimated covariance between $\widehat{\rho}_{i,t}$ and $\widehat{\rho}_{j,t}$, $i \neq j$. The latter two quantities are provided by the Newey & West (1987) estimator, with the truncation parameter set equal to $4(h/100)^{2/9}$.

Consider as summary statistics the mean and variance of the $N = n(n-1)/2$ estimated correlation coefficients:

1. their mean, provided by $m_t = N^{-1} \sum_{j=1}^{N} \widehat{\rho}_{j,t}$. The variance of the sample mean can be computed as:

$$Var(m_t) = N^{-2} \left[\sum_{j=1}^{N} Var(\widehat{\rho}_{j,t}) + \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} 2Cov(\widehat{\rho}_{i,t}, \widehat{\rho}_{j,t}) \right], \tag{1}$$

2. their variance, given by $v_t^2 = (N-1)^{-1} \sum_{j=1}^{N} \left(\widehat{\rho}_{j,t} - m_t\right)^2$.

In fact, we also considered a weighted mean, where the bilateral correlation coefficients are weighted according to the combined 'size' of the two countries under consideration. Size is proxied by total population in 1985. Results were, however, similar to those presented below for the unweighted mean. It is of interest that weights derived from PPP GDP at constant prices, rather than population, again proved qualitatively similar.

As a minimum condition for countries' business cycles to be converging we require the following two conditions to be met. First, the mean m_t should tend towards 1 and, second, the variance v_t^2 should tend towards 0 over the sample period. If only the first condition were met it would be possible that the distribution of correlation coefficients is in fact widening, implying that the countries' business cycles are becoming less synchronised, not more. The need to examine both the mean and variance is analogous to why the economic growth literature considers both "beta" and "sigma" convergence when testing the *convergence hypothesis*; see Quah (1993, 1996).

A more complete picture of the behaviour of the N correlation coefficients can be obtained by estimating, using non-parametric density estimators, the entire distribution $f\left(\widehat{\rho}_{j,t}\right)$ of estimated correlation coefficients. The convergence of countries' business cycles requires that this distribution becomes more concentrated at unity over time. We examine this question by computing an estimate of the distribution for all cycle measures over all available time periods; see Quah (1993) and Bianchi (1997) for alternative analyses of distribution dynamics.

Moreover, a further necessary condition for meaningful convergence requires examination of the intra-distribution dynamics; see Quah (1993). Suppose, for example, that the business cycles of two specific countries that are relatively well correlated at the beginning of the sample, are relatively uncorrelated later on in the sample period. Then, even though the distribution of correlations as a whole might well become more concentrated at unity the evidence for convergence is in this sense weakened. We test for the degree of intra-distributional movement by computing the rank correlation between the observations. In particular, for each $t = h+1, \ldots, T$ let ρ_t^R denote the N-vector of correlation coefficients arranged in descending order. Then calculate the Spearman rank correlation coefficient between $\{\rho_t^R, \rho_{t-k}^R\}$ for $k = 12, 60$ and all available time periods t.[11] This provides an aggregate measure indicating the extent of intra-distributional movement within k time-periods. Our approach offers a nonparametric alternative to the Markov chain processes used by Quah (1993) to examine intra-distributional dynamics.

5 Empirical results

5.1 Properties of the alternative measures of the business cycle

We have seen that there are many ways to measure a business cycle, but does this actually affect the way Eurozone business cycles look? Yes; we find estimates of the business cycles for the Eurozone countries to be sensitive to measurement. This result is consistent with the findings of Canova (1998) for 'growth' cycles, and indeed confirms a well-known stylised fact. To illustrate, consider the results for Italy displayed in Figure 1 and Tables 6 and 7. The graphs and statistics associated with the remaining countries are comparable and available upon request.

Table 6 displays some descriptive statistics for Italian growth cycles; the first four statistics detail the statistical properties of the generated cycles, while the remaining statistics rely on identification of the turning points of the estimated cycles *via* application of the Harding-Pagan dating rule. The Beveridge-Nelson decomposition generates very erratic cyclical components with a low variance. This is explained by the unit root imposed on the trend component. Although the UC model also imposes such a unit root its cycle is less erratic due to the smooth trend specification. Linear detrending, the moving average filter and phase average detrending all tend to yield cycles which are longer, using both spectral and turning-point based measures of duration, than the other methods, and have higher variability; the period of the cycle, identified by either the spectrum ('spectra') or the Harding-Pagan turning point rule ('dur: PT' and 'dur: TP'), varies across measures of

[11] Unsurprisingly, since N is large in our application, results presented below for Spearman correlation are in fact similar to those for Pearson correlation.

the business cycle.[12] Moreover, the cycle with the highest variation (the highest standard deviation), i.e. TIM, does not even cycle in the sense that its spectral density peaks at frequency zero. However, a property common across these de-trending methods is that Italian business cycles are asymmetric, in the sense that expansions last longer than contractions, 'dur: PT' < 'dur: TP'. It should be noted that this finding was not specific to Italy, and was shared by the other Eurozone countries. The final two columns of Tables 1 present the correlation coefficient C, and its estimated standard error, between the turning points of the seven estimates of the growth cycle and the classical cycle identified using the Harding-Pagan rule. They indicate that the turning points of the growth cycles, aside from the Beveridge-Nelson cycle, explain a statistically significant amount of the variation in the classical cycle.

Table 7 provides summary statistics about the properties of the classical business cycles for the Euro-12 countries, identified using the Harding-Pagan rule. The mean duration of a cycle across the Euro-12 is approximately 60 months or 5 years, and expansions last much longer than contractions. This is broadly comparable to results for a sub-set of these countries seen in Harding & Pagan (2001). However, comparing the duration of the Italian classical business cycle with the two measures of duration for her growth cycle considered in Table 6, we find that classical business cycles appear longer, particularly in their expansionary phase.

Inspection of Figure 1 reveals that there may well be some outliers present in the estimated cycles. To guard against the possibility that this may distort inference about convergence we did also test for convergence of the Euro-12 business cycles when the underlying output series for each country had any outliers removed.[13] Results about convergence were again robust and below we present only the results based on the non-corrected series.

It is worth noting that none of the trend-cycle decomposition methods generate sensible looking business cycles for Ireland. This is because Irish output has grown very rapidly over the past four decades. It is widely accepted that Irish industrial production, like Irish GDP, provides inflated estimates of national income in Ireland since it includes both interest payments on the economy's foreign debt and, importantly, the profits of the growing number of multinational firms present in Ireland that have recently amounted to 13% of Irish GDP; see Barry et al. (1999, p. 14). Tests for convergence for the Euro-12 were therefore conducted both with, and without, Ireland. Results were similar, and for completeness below we present results using data for the entire Euro-12.

5.2 Convergence

Given that inference about individual Eurozone business cycles has been found to be sensitive to the measure of the business cycle considered, when testing for a 'common'

[12]Note that there is no theoretical relation, however, between these two measures of the duration of the cycle.

[13]This was achieved by means of the automatic outlier detection and correction algorithms in TRAMO, see Caporello et al. (2002).

Eurozone business cycle, it is clearly advisable not to restrict attention to just one measure of the business cycle, unless one has a strong preference for one measure over another. In the absence of such a preference, we take an eclectic approach when testing for convergence and consider all of the various measures of the business cycle.

Using the seven decomposition methods and the turning point-rule described in the previous section, we derive in total eight sets of estimates for the Euro-12's business cycles. The mean m_t and the variance v_t^2 of the bivariate correlation coefficients are then computed for each time period starting in 1962-1 and for window widths of 3.5 years ($h = 42$) and 7 years ($h = 84$).

For each detrending method, using the 3.5 year window, we present estimates of m_t and v_t^2 in Figures 2 - 3. Estimates are centered on the end-point of the window. Note that the period of analysis depends on the detrending method. Figure 4 presents the estimates of m_t and v_t^2 when the Harding-Pagan rule is used to identify the turning points. Due to the possibility of long sequences of zeros or ones, it proved possible only to consider a longer window of 14 years ($h = 168$); over shorter windows there is no cyclical variation for some countries.[14] Let us now summarise the results.

5.2.1 The mean

Figures 2 - 3 reveal that the estimated mean correlation coefficient, m_t, between the 12 European 'growth' business cycles is on average positive, and in a statistically significant manner. Re-assuringly, Eurozone business cycles are positively correlated. But there has been considerable volatility. Nevertheless, we can extract common features across the alternative measures of the business cycle. These include correlation trending upwards until the mid 1970s and reaching peaks of around 0.8, for all measures of the business cycle, except the Beveridge-Nelson cycle which is not considered further. Then, with for some measures a short-lived rise in the early 1980s, correlation in general falls to zero in the mid to late 1980s and is statistically insignificant. It is quite striking that this result is common across the alternative measures; indeed the results lend support to Inklaar & de Haan's (2001) finding that correlations of Eurozone countries with Germany are higher in 1971-79 than 1979-87. Correlation then rises in the late 1980s to values in the range 0.6 to 0.8, before slumping quite rapidly in the early 1990s. Since then correlation between the Eurozone countries has risen but remained volatile; indeed correlation appears to have declined during the mid 1990s. There is, however, some evidence of a rise thereafter. Certainly the most recent estimates suggest that correlation between the 12 European cycles is statistically positive, and has risen from the trough in the early 1990s. It is, of course, too early to tell whether these recent trends will continue.

By necessity our statistical approach to identifying and estimating business cycle relationships often requires a number of lead observations. This prevents us examining the current state of the Eurozone business cycle. Indeed our estimates of the business cycle

[14] Note that for this longer window estimates of $Var(m_t)$ in equation (1) are computed assuming independence, i.e. by setting $Cov\left(\hat{\rho}_{i,t}, \hat{\rho}_{j,t}\right) = 0$, $\forall i, j, t$. This avoided singularities in the variance-covariance matrix.

in 2001 will, in all probability, be revised when new data become available. Therefore the most recent estimates about the Eurozone are subject to change too. This problem is perhaps most acute for the PAT since it relies on firstly estimating turning points.

Figure 4 shows that use of a classical measure of the business cycle leads to similar results. Although the estimated mean correlation coefficient, m_t, between the 12 European 'classical' business cycles is much smoother, due to the use of the longer window, again a clear trough is revealed in the mid to late 1980s, with a rise in m_t thereafter.

Although in this paper we seek to establish the *facts* rather than explain them, it is interesting to relate this behaviour to the exchange-rate regime. An interesting hypothesis is whether rises in the mean correlation coefficient coincide with periods when the exchange-rate has been, to some degree, fixed.[15] This hypothesis has attracted considerable attention and controversy, as mentioned above; see Artis & Zhang (1997, 1999) and Inklaar & de Haan (2001). Consistent with the findings of Artis & Zhang (1999) that monetary integration and business cycle synchonisation are related, there is some supportive evidence in Figures 2- 3. For example, the fall in correlation that occurred in the mid 1970s was in the aftermath of the collapse of the Bretton Woods fixed exchange-rate regime. Then the rise in correlation from the late 1980s, and again after the trough of the early 1990s, was at a time when the EMS was relatively stable and credible; there were, for example, no exchange-rate re-alignments either in the late 1980s or from the mid 1990s, consistent with the entry requirements for EMU. By contrast the period of falling correlation in the early 1980s (specifically 1981-1986) was characterised by eleven re-alignments; see Gros & Thygesen (1998) for a more detailed chronology. The collapse in average correlation in the early 1990s can be explained away by German unification and the ensuing currency crises in 1992. These events, again see Gros & Thygesen (1998) for more details, temporarily disrupted the emergence of a 'common' Eurozone business cycle. Whether or not one subscribes to this story, and more work certainly is needed, it would be encouraging if in the run up to monetary union, and irrevocably fixed exchange-rates, correlation had been rising.

5.2.2 The variance

The evidence for convergence in the run up to monetary union appears stronger when one considers more than the mean correlation. As discussed above convergence requires not just that the mean, m_t, rises over time, but that the variance, v_t^2, falls. The failure of Artis & Zhang and Inklaar & de Haan to look beyond the first moment could lead to spurious inference.

Although the estimated variance, v_t^2, in Figures 2- 3 has not, except perhaps for the linear time trend, systematically fallen over time there is evidence that, aside from the PAT cycle, the variance has fallen in the most recent period from local peaks around 1995. This recent period was characterised by less exchange-rate volatility than the early

[15]Many other explanations for increased comovement between business cycles have been given. Increased correlation, for example, also has been related to international trade and geographical proximity; see Frankel & Rose (1998) and Clark & van Wincoop (2001), respectively.

1990s. Furthermore, there is some evidence across most of the detrending methods that the variance is lower at the end of the sample period than the beginning.

Further data are required to corroborate this conclusion, however. It is interesting that Figure 4 paints a similar picture; using a turning point rule, rather than a trend-cycle decomposition method, to define a business cycle we again find the most recent estimates suggesting that the variance is declining.

To more fully appreciate the relationship between m_t and v_t^2, Figure 5 plots for the smoother seven year rolling window, estimates of m_t alongside those for v_t^2. The results are striking. Except for the Beveridge-Nelson trend, which we have already established as unreliable, there is a clear negative relationship between m_t and v_t^2. Periods of increasing correlation are associated with decreased dispersion; historically there appear to be periods of convergence, as defined here, broken up by periods of divergence.

5.2.3 The distribution

To gain an impression of the evolution over time of not just the mean and variance, but the whole distribution of correlation coefficients Figures 6 - 8 provide estimates of the distribution of correlation coefficients based on the unobserved components, time-trend and Hodrick-Prescott growth cycle correlation using the 3.5 year window considered above. Results are presented for twelve selected points in time at two year intervals, from the late 1970s to 2001m8. These three cycles are representative of other measures of the cycle; moreover they reflect the distinction between parametric and nonparametric measures of the growth cycle.[16] We focus on the behaviour of the density in the last 20 years given our concern with establishing the stylised facts in this recent period.

Again, despite differences between these three measures of the cycle at the country-specific level, Figures 6 - 8 exhibit important common features across the alternative measures of the cycle. Inspection reveals the densities to have fluctuated considerably in the last 20 years. Consistent with the analysis above for the mean and variance, we see the density becoming increasingly concentrated at higher levels of correlation in the late 1980s after the period of divergence in the mid 1980s; note how the density in 1985m8 is almost symmetric about zero but by 1989m8 it is increasingly skewed to the left. The collapse in convergence in the early 1990s is clearly apparent again. Compare the figures for 1991m8 with those two years previously; the density in 1991 has a far heavier left-hand-tail than in 1989. The period of convergence immediately after 1991 is quite striking; the density in 1993m8 is far more skewed to the left than in 1991m8. The HP measure of the cycle, in particular, reveals that by 1993m8 the density is becoming increasingly concentrated, almost entirely, above zero. The fluctuations in the 1990s are again apparent; we can observe the dip in correlation in 1997. By 2001m8 the density certainly has not converged to unity but it is more concentrated above zero than ten years previously.

[16]Plots for the other cycles are qualitatively similar and available from the authors upon request.

5.2.4 Intra-distributional dynamics and persistence

Figures 9 and 10 plot the rolling Spearman rank correlation coefficient estimates for $k = 12$ and $k = 60$, i.e. for observations 1 year and 5 years apart, respectively. Again we present results, for completeness, for the 7 detrending methods (using $h = 84$), and for the Harding & Pagan rule (using $h = 168$). Both figures illustrate that there is considerable volatility in the estimates over time. Over 1 year there is, in general, limited intra-distributional movement from one year to the next – the Spearman correlation is in general high. The ranking of the N correlation coefficients tends to stay the same. However, it is interesting to note that there is evidence to suggest that the Spearman correlation fell quite sharply in the early 1990s. At a time when the mean correlation, m_t, was falling, there was increased volatility and movement within the distribution too.

Over 5 years there is increased movement within the distribution – the Spearman correlation coefficient has a much wider range. In the early to mid 1990s, a time of considerable uncertainty about the exchange-rate regime when the evidence above suggests that m_t was low and v_t^2 high, there appears to have been so much intra-distributional movement that the current ranking within the distribution bore no relationship to that 5 years previously. The collapse in m_t and rise in v_t^2 in the early 1990s in the aftermath of German unification and coinciding with the currency crises was accompanied by increased intra-distributional movement. It is interesting, however, that by the late 1990s when m_t had risen and v_t^2 fallen, relative to the early 1990s, that there was less intra-distributional movement and again quite a strong relationship, with correlation exceeding 0.5. This supports the view that periods of convergence are accompanied by less intra-distributional movement than periods of divergence. Additional support for this view comes from inspection of the figures in the 1970s. The period of divergence in the late 1970s, when, in general, m_t was falling and v_t^2 rising, was accompanied by increased intra-distributional movement reflected by a fall in the Spearman correlation coefficient.

6 Conclusion

Empirical inference about individual Eurozone business cycles is found to be sensitive to the measure of the business cycle considered. Examining seven measures of the 'growth' business cycle, and a measure of the 'classical' business cycle, we find that business cycles of Eurozone countries display different properties according to the measure used. Indeed the Beveridge-Nelson cycle clearly leads to implausible estimates of the business cycle.

However, our proposed measure of convergence between Eurozone business cycles, based on an analysis of the properties of the distribution of all bivariate correlation coefficients, exhibits common features across alternative measures of the business cycle.

Periods of convergence, with a rising mean correlation, a falling variance and with limited intra-distributional movement, are distinguished from periods of divergence. This *fact* is neatly summarised by the clearly negative relationship discovered between the mean correlation coefficient and the variance of the correlation coefficients. Although further data are required to corroborate the story, there is also evidence to suggest that the Eurozone has entered a period of convergence after the clear period of divergence in the early 1990s in the aftermath of German unification and at the time of the currency crises in Europe.

If indeed the 12 Eurozone economies are currently converging, this is consistent with the emergence of a 'common' Eurozone business cycle. Perhaps we can only expect this trend towards convergence to continue since the very existence of EMU, and irrevocably fixed exchange-rates, is believed to encourage the emergence of a 'common' Eurozone business cycle; for further discussion of such endogeneities see Artis (1999).

Finally it is important to make the following distinction. Eurozone business cycles can be *compatible* even if they are not *converging* in the sense considered in this paper. This can occur if Eurozone business cycles move 'closer' together, in the sense that the cyclical disparity between them declines. Any reduction need not be associated with increased correlation. One possible measure of closeness is to consider the root mean squared difference between the Eurozone 'growth' business cycles, expressed as a percentage of potential or trend output, for a series of rolling windows; for an application examining the relationship of the Eurozone with the UK see Massmann & Mitchell (2002).

authors	data used	measure of cycle	convergence measure	conclusions
Artis & Zhang (1997, 1999)	OECD data of industrial production	PAT, HP, linear trend	two sub-samples (pre- and post-ERM), lead and lag bivariate correlation with Germany and US	cycles have become more group-specific after ERM, correlations not different acoss filters after ERM
Inklaar & de Haan (2001)	dto.	dto.	pre- and post-ERM period again divided into two sub-periods, bivariate correlation	general decline in (contemporaneous) correlation
Wynne & Koo (2000)	Penn World Tables of GDP, annual data	Baxter-King	pairwise correlations, using GMM	null of no correlation between EU founding members rejected, but lower correlation with more recent members
Döpke (1999)	OECD data of 'big 5' Euro-area countries	HP, linear, segmented trend	rolling cotemporaneous correlations based on 5-year moving average of each country with Euro-area	correlation between each country and the Eurozone increases, but Belgium's falls
Agresti & Mojon (2001)	ECB AWM data of GDP	Baxter-King	contemporaneous and lagged cross-correlation between each country and the Euro-area	each country highly correlated with Euro-area as whole, with lowest values for periphery
Harding & Pagan (2001)	ECB AWM data of GDP for EA, OECD data for US	Harding-Pagan rule on level series and de-trended (linear, HP, PAT) series	correlation and regression methods on binary series	relatively low correlation between member countries and Euro-area

Table 1: summary of the literature

Belgium	through 1967-12: IIP excl construction (scaled); from 1968-1: IIP incl construction
Greece	start date: 1962-1
The Netherlands	IIP pertains to manufacturing
Spain	start date: 1961-1

Table 2: Country-specific notes on the data used

country	series	ADF test	lag	min AIC
Austria	ΔX_t	-5.583**	8	0.9463
	$\Delta \ln X_t$	-6.076**	8	-7.774
Finland	ΔX_t	-8.959**	4	1.098
	$\Delta \ln X_t$	-17.37**	2	-7.253
France	ΔX_t	-21.74**	1	0.7269
	$\Delta \ln X_t$	-17.65**	2	-7.371
Germany	ΔX_t	-20.00**	1	0.5666
	$\Delta \ln X_t$	-13.33**	2	-8.246
Ireland	ΔX_t	-5.046**	12	2.299
	$\Delta \ln X_t$	-8.848**	5	-7.011
Italy	ΔX_t	-19.96**	1	0.9269
	$\Delta \ln X_t$	-8.599**	5	-7.567
Luxembourg	ΔX_t	-24.46**	1	2.116
	$\Delta \ln X_t$	-11.92**	3	-6.728
Portugal	ΔX_t	-18.53**	2	1.235
	$\Delta \ln X_t$	-19.73**	2	-6.981
Belgium	ΔX_t	-22.86**	1	1.656
	$\Delta \ln X_t$	-22.98**	1	-7.342
Netherlands	ΔX_t	-8.659**	5	0.7894
	$\Delta \ln X_t$	-8.355**	5	-7.932
Greece	ΔX_t	-5.869**	10	1.501
	$\Delta \ln X_t$	-4.864**	10	-7.366
Spain	ΔX_t	-6.368**	7	0.8023
	$\Delta \ln X_t$	-4.589**	9	-7.784

Table 3: ADF test performed on ΔX_t as well as on $\Delta \ln X_t$. The regressions include a constant term. The null hypothesis is that of a unit root and a double asterisk denotes rejection of the null at the 1% level. The column labelled 'lag' denotes the maximum lag included in the ADF regression, selected on the basis of the Akaike information criterion whose minimised value is given in the column labelled 'min AIC'.

country	series	ADF test	lag	min AIC
Austria	X_t	-1.261	9	0.9457
	$\ln X_t$	-2.462	7	-7.781
Finland	X_t	-0.8066	5	1.098
	$\ln X_t$	-2.144	6	-7.253
France	X_t	-2.248	2	0.7229
	$\ln X_t$	-2.508	3	-7.381
Germany	X_t	-3.161	8	0.5548
	$\ln X_t$	-2.745	3	-8.258
Ireland	X_t	0.9663	12	2.432
	$\ln X_t$	0.09150	6	-7.015
Italy	X_t	-3.561*	6	0.8978
	$\ln X_t$	-2.593	6	-7.577
Luxembourg	X_t	-2.336	4	2.108
	$\ln X_t$	-2.862	4	-6.737
Portugal	X_t	-3.567*	11	1.215
	$\ln X_t$	-1.494	3	-6.986
Belgium	X_t	-2.458	2	1.649
	$\ln X_t$	-2.785	2	-7.354
Netherlands	X_t	-3.022	9	0.7683
	$\ln X_t$	-3.391	6	-7.961
Greece	X_t	-1.272	12	1.495
	$\ln X_t$	-2.453	4	-7.391
Spain	X_t	-2.174	9	0.7953
	$\ln X_t$	-2.427	10	-7.801

Table 4: ADF test performed on X_t as well as on $\ln X_t$. The regressions include a constant term and a linear trend. The null hypothesis is that of a unit root and one asterisk denotes rejection of the null at the 5% level while a double asterisk denotes rejection at the 1% level. The column labelled 'lag' denotes the maximum lag included in the ADF regression, selected on the basis of the Akaike information criterion whose minimised value is given in the column labelled 'min AIC'.

country	series	J-B test	D-H test
Austria	X_t	17.38**	32.12**
	$\ln X_t$	18.64**	35.37**
Finland	X_t	31.90**	61.31**
	$\ln X_t$	16.26**	28.15**
France	X_t	21.57**	44.81**
	$\ln X_t$	61.15**	176.3**
Germany	X_t	15.11**	25.37**
	$\ln X_t$	40.07**	100.5**
Ireland	X_t	434.9**	740.3**
	$\ln X_t$	28.65**	66.82**
Italy	X_t	25.34**	49.71**
	$\ln X_t$	46.00**	134.8**
Luxembourg	X_t	34.19**	84.11**
	$\ln X_t$	19.24**	33.50**
Portugal	X_t	31.48**	60.01**
	$\ln X_t$	37.78**	99.24**
Belgium	X_t	16.61**	24.06**
	$\ln X_t$	60.87**	107.3**
Netherlands	X_t	13.33**	17.57**
	$\ln X_t$	29.60**	66.75**
Greece	X_t	58.58**	235.2**
	$\ln X_t$	107.1**	458.4**
Spain	X_t	27.21**	63.50**
	$\ln X_t$	100.6**	320.2**

Table 5: The (J-B) asymptotic normality test, and the (D-H) small sample normality test. Both test statistics have a $\chi^2(2)$ distribution. The null hypothesis is that of normality and a double asterisk denotes rejection of null at the 1% level.

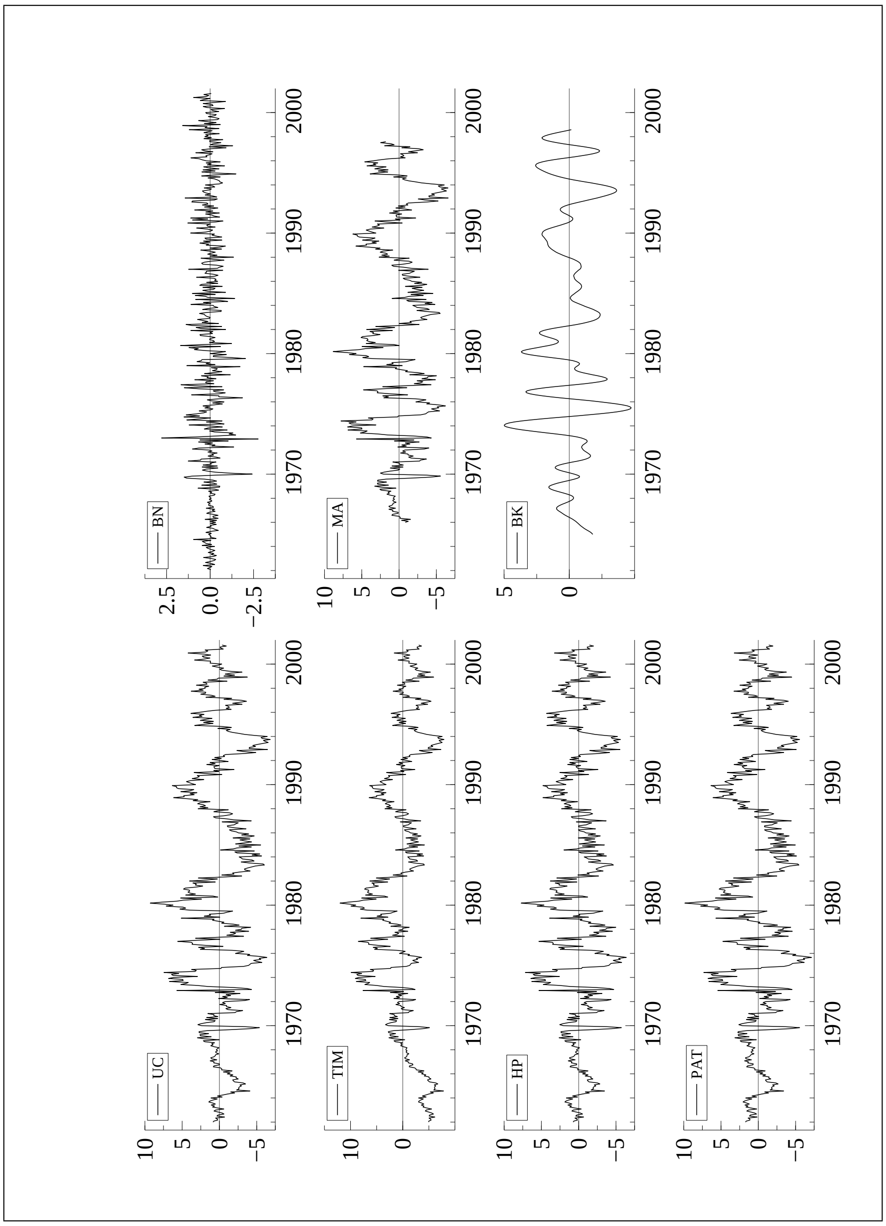

Figure 1: Growth cycle estimates: Italy

	s.d.	skew	kurtosis	spectra	peaks	troughs	dur:PT	dur:TP	PE	C	$se(C)$
UC	2.985	0.100	-0.310	79.333	10.000	10.000	18.556	29.500	61.975	0.789	0.081
BN	0.603	-0.034	2.533	2.870	9.000	9.000	22.444	32.500	57.474	-0.083	0.092
TIM	3.819	0.474	-0.122	∞	10.000	10.000	22.111	26.300	55.252	0.687	0.077
MA	3.122	0.117	-0.570	69.091	8.000	9.000	17.375	28.625	62.368	0.783	0.095
HP	2.527	0.068	-0.139	50.105	11.000	11.000	19.600	24.182	55.882	0.696	0.077
BK	1.775	0.056	0.165	44.889	14.000	13.000	12.846	15.538	56.683	0.380	0.092
PAT	2.931	0.156	-0.208	79.333	11.000	11.000	19.200	24.545	56.723	0.708	0.078

UC: unobserved components; BN: Beveridge-Nelson; TIM: time trend; MA: moving average; HP: Hodrick-Prescott; BK: Baxter-King; PAT: Phase Average Trend; s.d. denotes standard deviation; skew: measure of skewness equal to zero for symmetrical distributions; kurtosis: measure of kurtosis equal to zero for the normal distribution; spectra denotes the period of the cycle in months; ∞ denotes the peak was at frequency zero; peaks and troughs are the number of peaks and troughs identified by applying the Harding-Pagan rule to the estimated cycles; PT denotes peak to trough; TP denotes trough to peak; dur denotes duration in months ; PE is the percentage of time spent in an expansion state; C is the measure of coherence and $se(C)$ its robust estimated standard error

Table 6: Growth cycle characteristics: Italy

	AUS	BEL	FIN	FRA	GER	GRE	IRE	ITA	LUX	NET	POR	SPA
Mean Duration (months)												
PT	14.6	19.3	11.3	13.6	13.1	10.5	17.8	16.9	11.8	14.0	11.9	23.6
TP	45.0	49.7	54.9	34.1	34.8	51.6	78.2	43.0	23.6	33.8	40.6	35.5
Mean Amplitude (%)												
PT	-6.6	-16.6	-9.2	-8.7	-8.5	-9.3	-8.1	-9.9	-15.1	-6.4	-10.8	-8.185
TP	25.7	25.7	34.5	20.2	17.4	31.2	66.0	23.4	20.8	18.8	29.7	14.8

Table 7: Characteristics of classical cycles as identifed by the Harding-Pagan turning point rule.

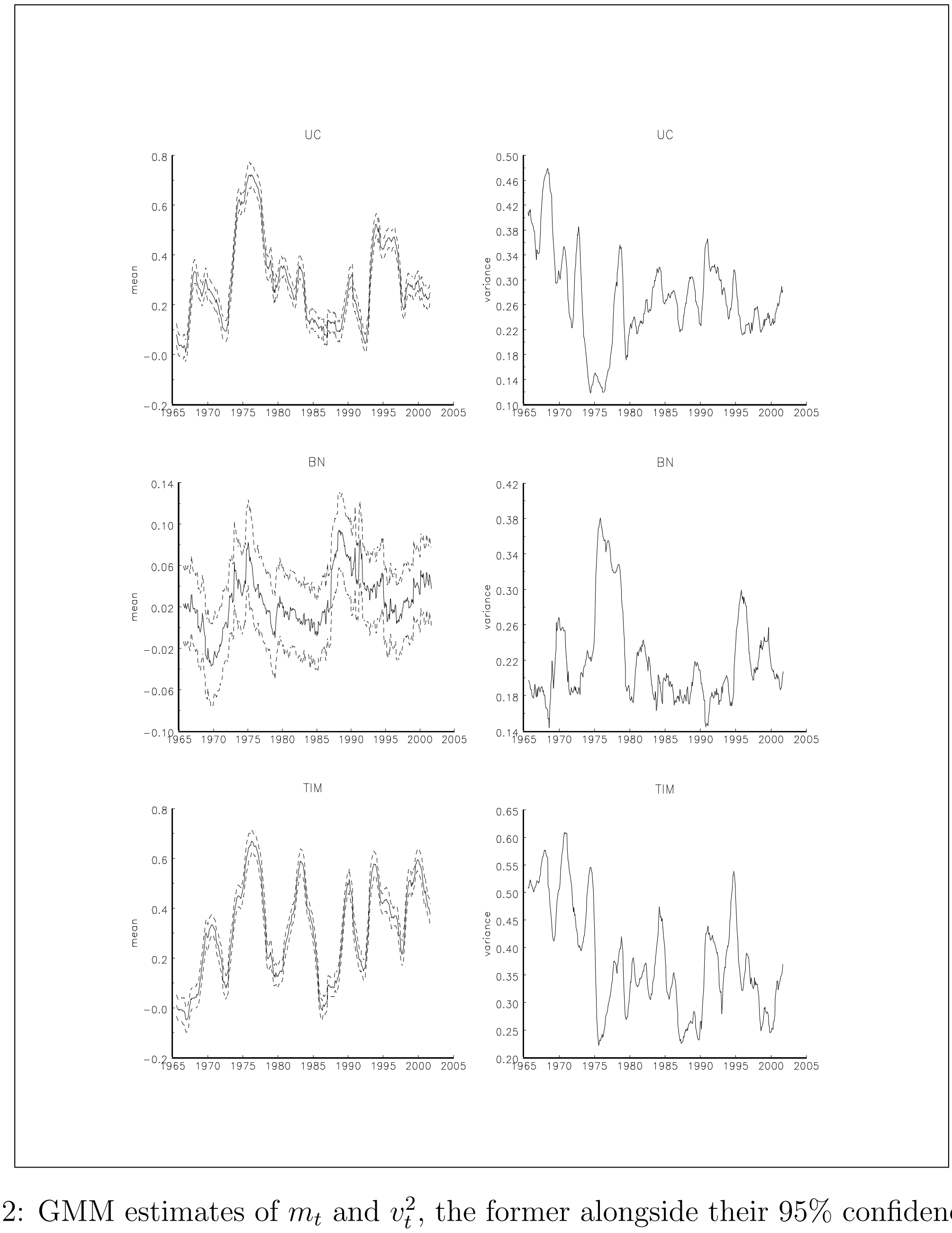

Figure 2: GMM estimates of m_t and v_t^2, the former alongside their 95% confidence intervals. Estimates are computed using a rolling window of 3.5 years.

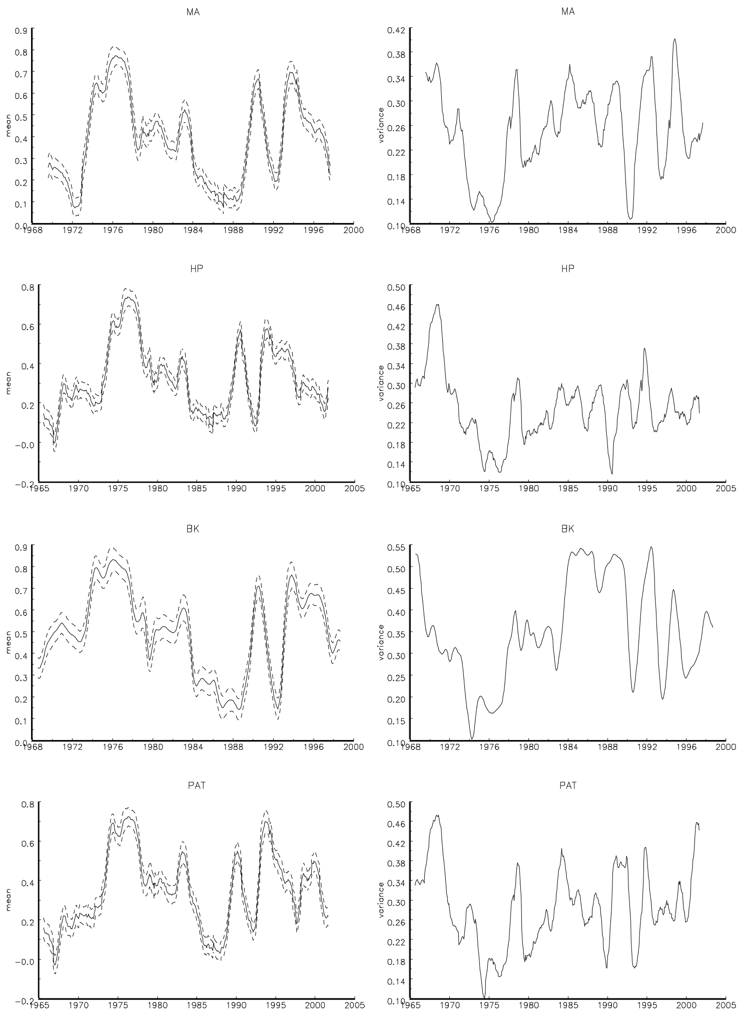

Figure 3: GMM estimates of m_t and v_t^2, the former alongside their 95% confidence intervals. Estimates are computed using a rolling window of 3.5 years.

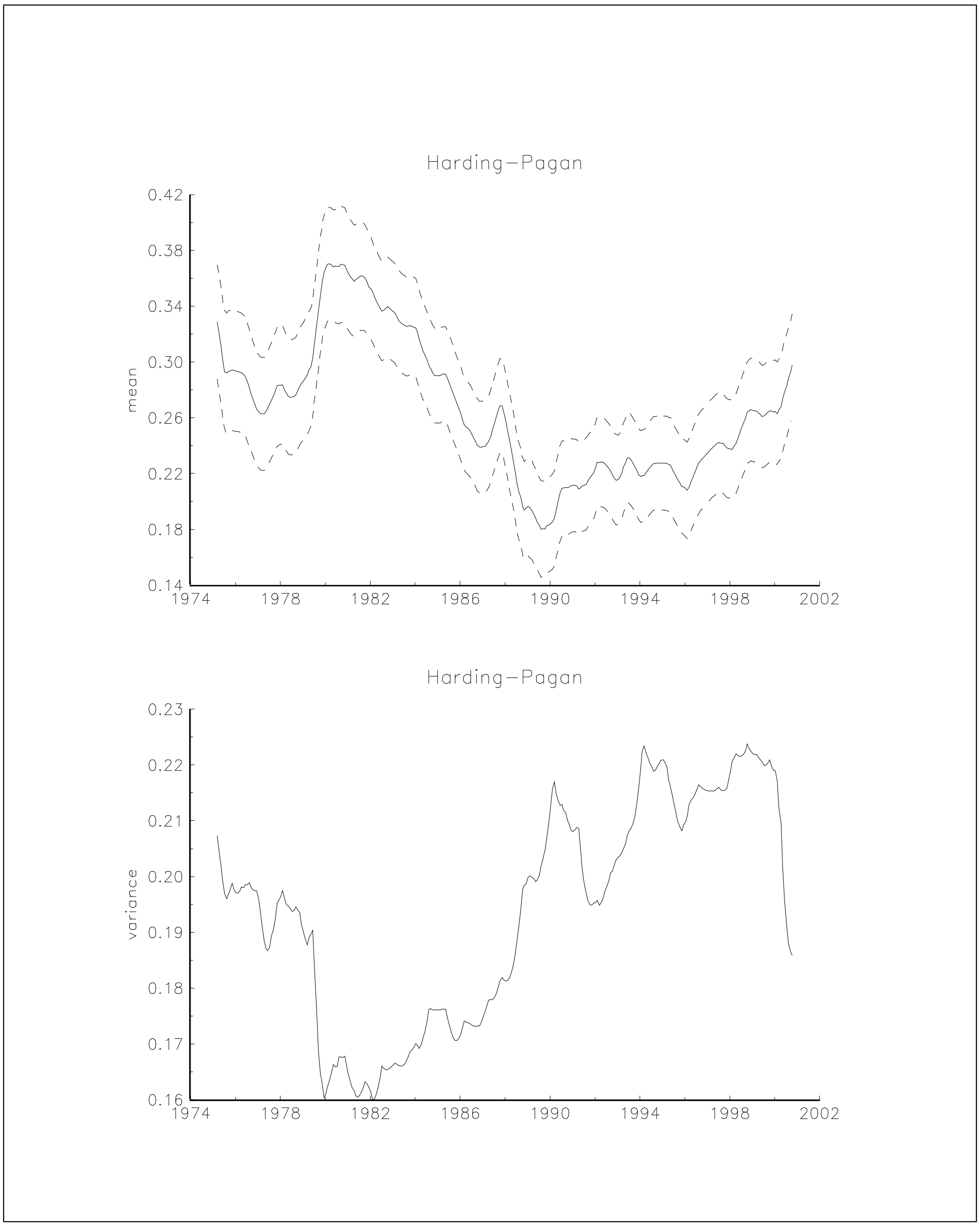

Figure 4: GMM estimates of m_t and v_t^2, the former alongside their 95% confidence intervals. Estimates are computed using a rolling window of 14 years.

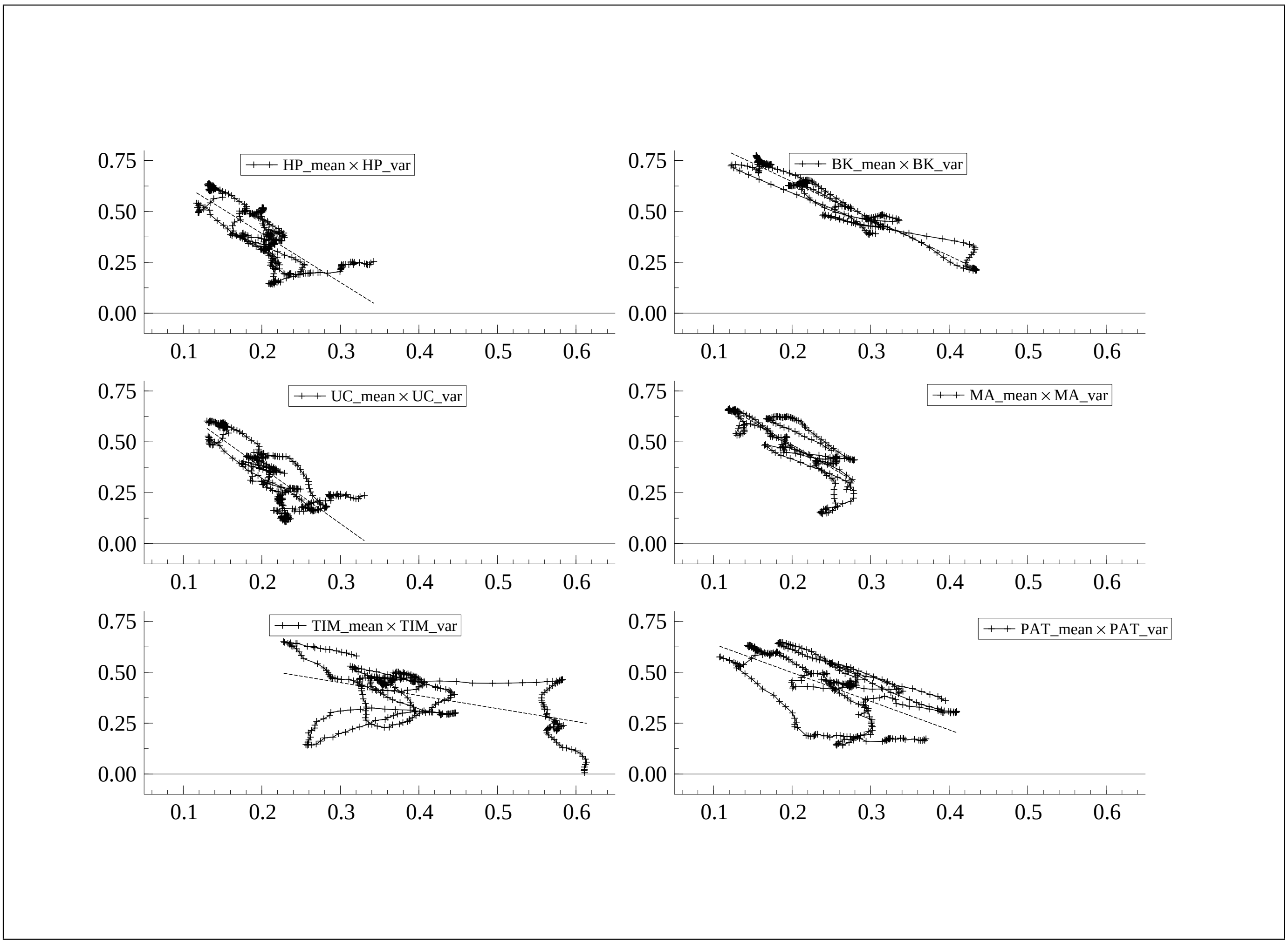

Figure 5: The relationship between m_t and v_t^2 across the detrending methods for the rolling 7 year window

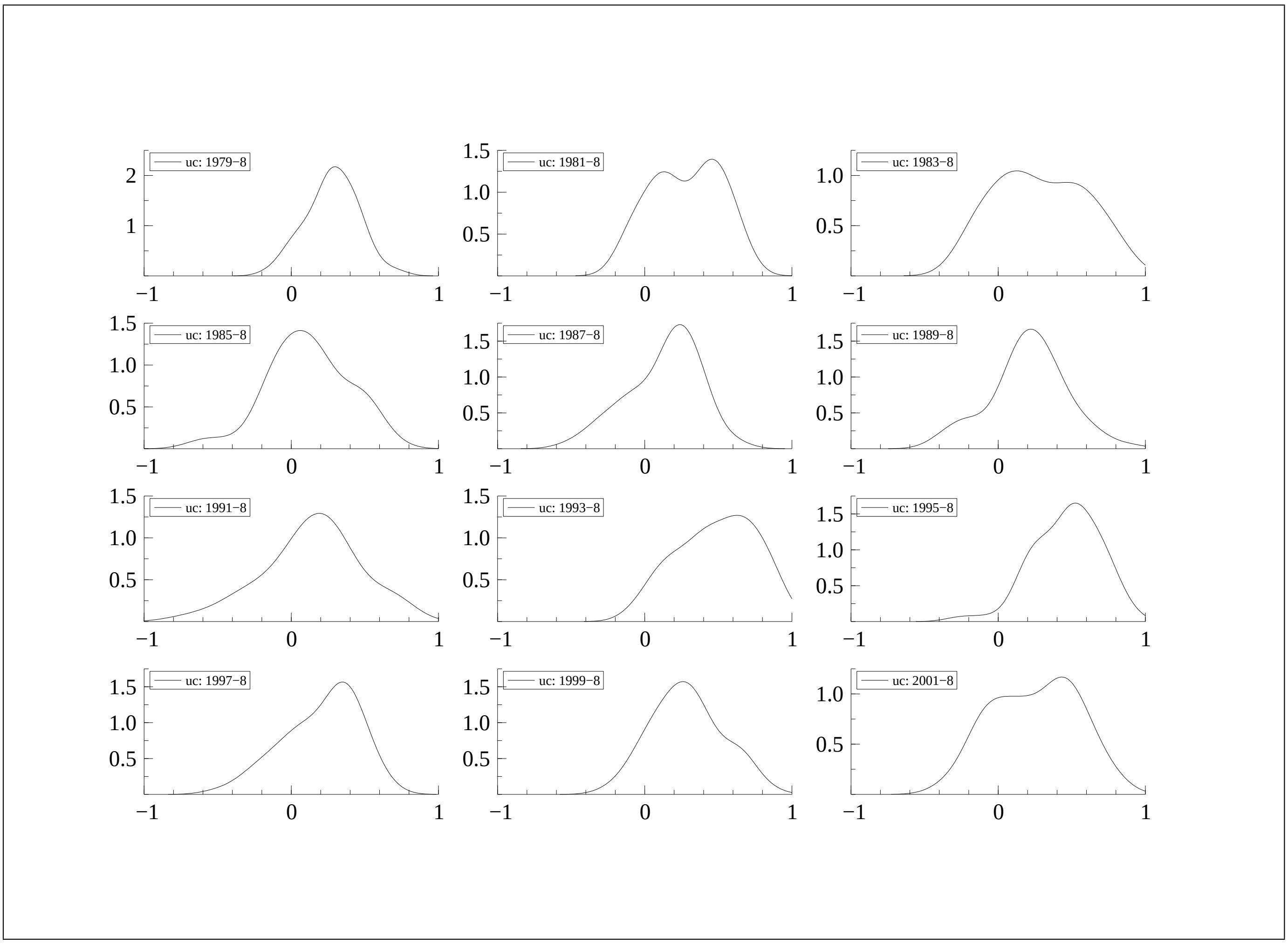

Figure 6: Density of correlation coefficients at 12 selected points in time: UC growth cycle

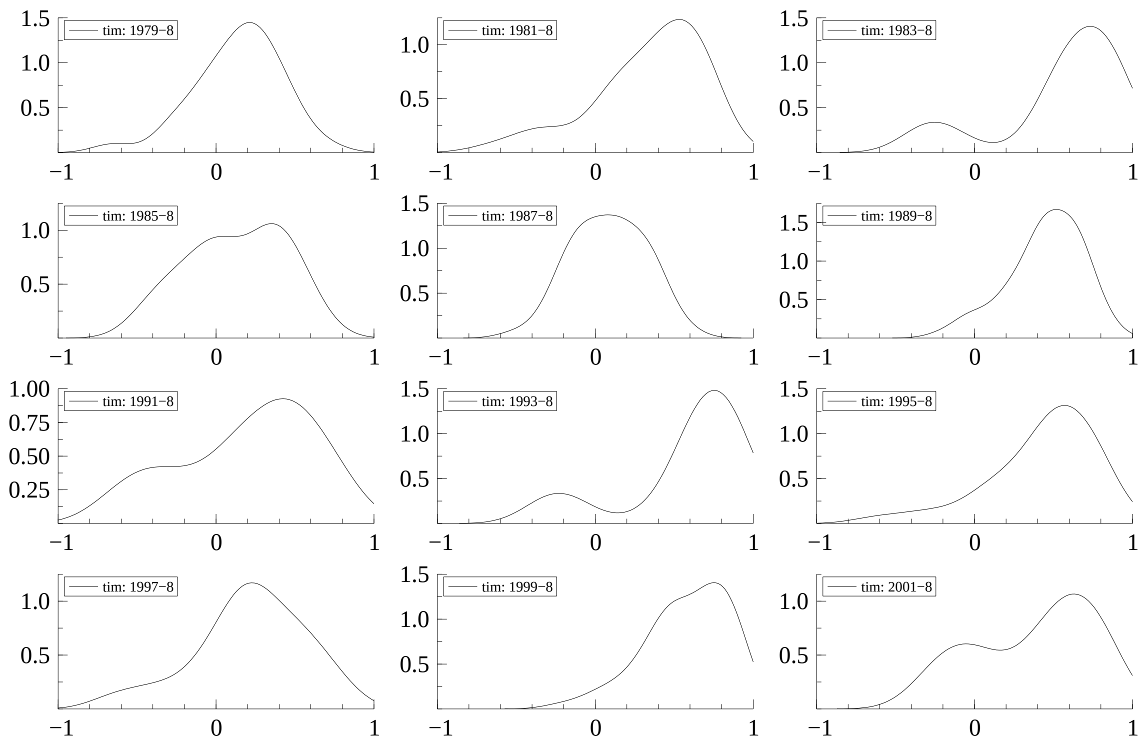

Figure 7: Density of correlation coefficients at 12 selected points in time: TIM growth cycle

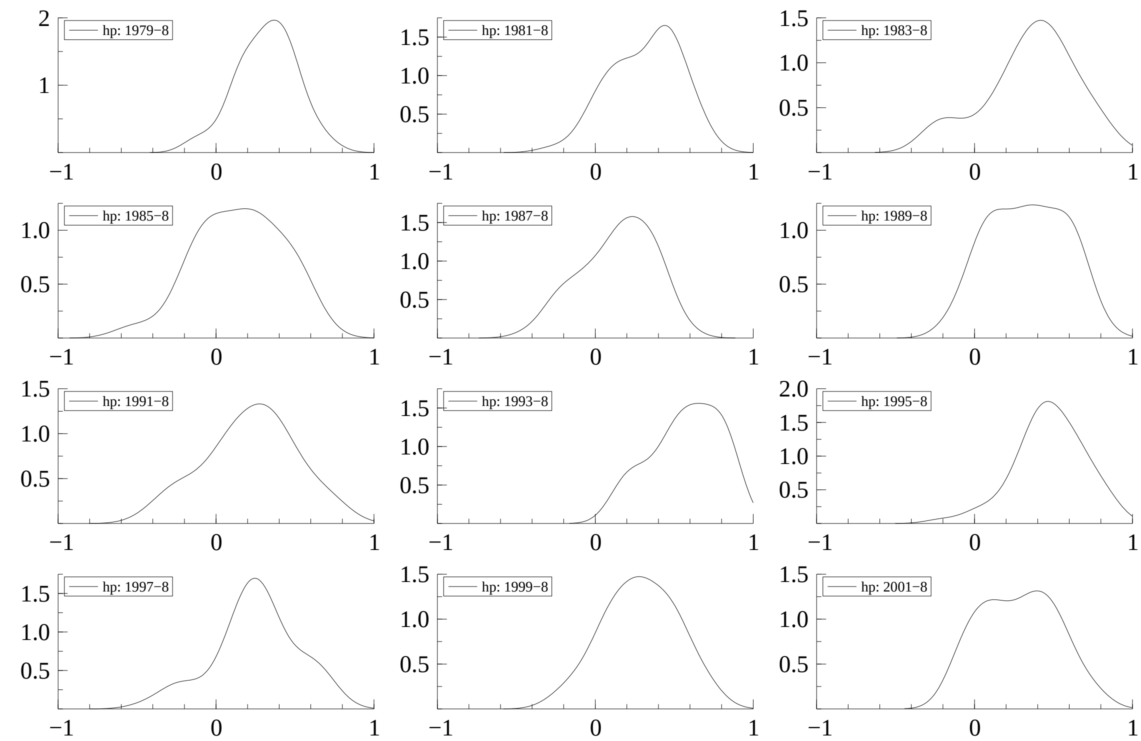

Figure 8: Density of correlation coefficients at 12 selected points in time: HP growth cycle

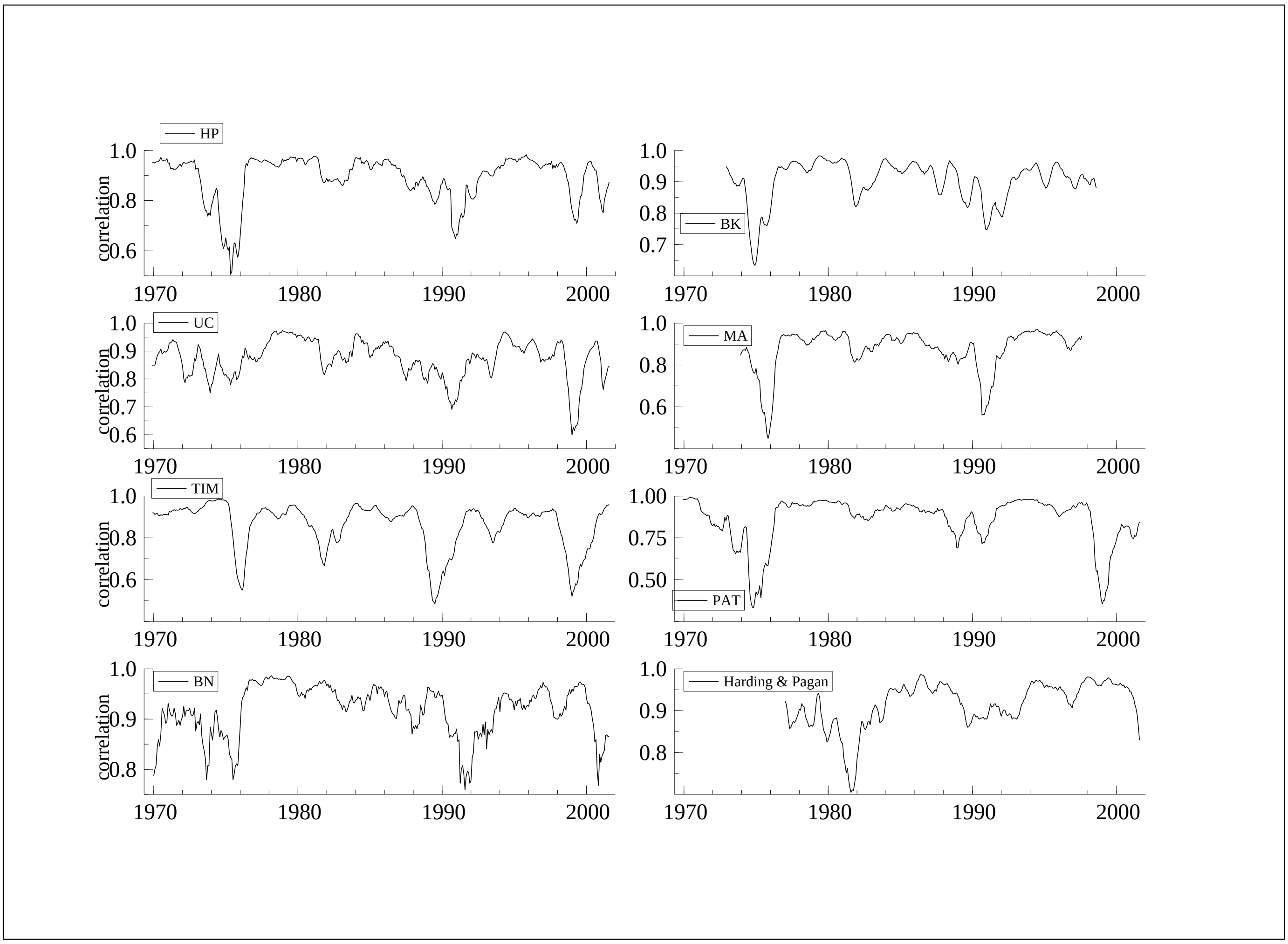

Figure 9: Rolling Spearman rank correlation coefficient when $k = 12$ (1 year)

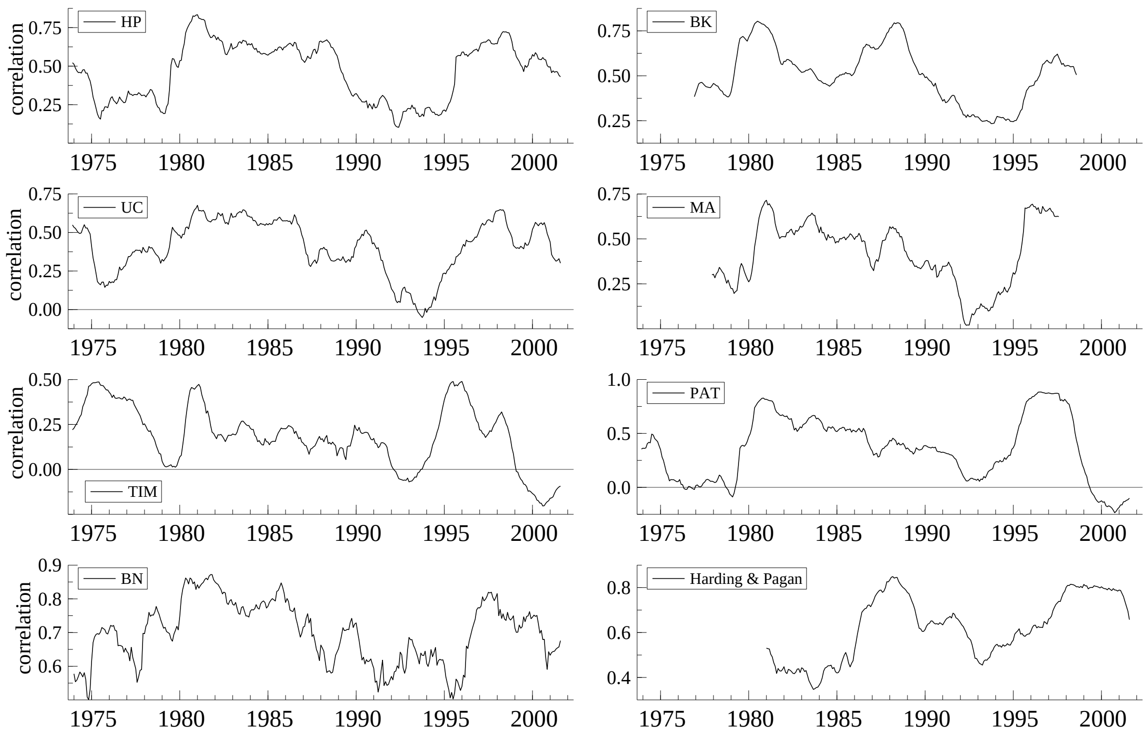

Figure 10: Rolling Spearman rank correlation coefficient when $k = 60$ (5 years)

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