«ΣΠΟΥΔΑΙ», Τόμος 54, Τεύχος 2ο, (2004) / «SPOUDAI», Vol. 54, No 2, (2004), University of Piraeus, pp. 23-46

THE DYNAMICS OF BUSINESS CYCLES STYLIZED FACTS USING QUARTERLY DATA FOR SIX INDUSTRIALIZED COUNTRIES

By

Erotokritos Varelas
University of Macedonia, Economics Department

Abstract

This paper examines the empirical evidence concerning the identification of cycles of the aggregate industrial production, prices and money for six OECD countries using quarterly data. We used Spectral Analysis (univariate and multivariate). An interesting result is that the monetary aggregates are procyclical. (JEL: E32, E10).

1. Introduction

In empirical business cycle research the regularity of economic fluctuations is an old finding, which goes back to the work of Juglar (1889). Based on the graphical analysis of financial series of France, United Kingdom and the United States, Juglar identified a cycle of about ten years. Subsequent to Juglar, a sizeable literature on business cycle emerged. What is important in the present context is that by 1940s and 1950s, certain features of the phenomenon were widely agreed upon. The inventory cycle with a duration of three to four years, the equipment cycle with a duration of seven to ten years and the building cycle with a length of about 20 years is an overview over this set of stylized facts. The length of each cycle was related to the speed with which the level of the associated capital stock could be adjusted.

In the 1960s, influenced by two decades of rapid and smooth economic growth, economists turned away from the study of business cycles. Connected with the vanishing interest in the phenomenon, the empirical knowledge embodied in the traditional view of business cycles also disappeared. During the 1970s, slowing and more erratic growth coupled with rising unemployment and inflation gave rise to a renewed interest in economic fluctuations. The new attempts at explaining fluctuations were monetarism, new classical economics and the real business cycle theory. The contemporary view of business cycles is seen to be considerably less specific than the traditional one, especially in that it does not postulate periodicities. Based on this, lists of stylized facts as the one in Lucas (1977), refer to co movements, not to cyclical structure.

The fact that any methodology leads to scientific progress must however be demonstrated. This paper applies to the phenomenon of cyclical growth, a methodology which emphasizes, that stylized facts must be established independently of explanatory models. It will be shown in this paper that it is possible to get much more detailed information on the structure of economic fluctuations by means of Maximum Entropy spectral analysis. More concretely, the method is able to answer the following questions:

— Are the observed fluctuations irregular or do they show cyclical structure, i.e. do they exhibit on average maxima and minima at regular time intervals?

— If they show cyclical structure, how many cycles can be identified?

— What can be said about the length of these cycles?

— How important are they?

— What can be said about the lead-lag relationships between cycles in different series?

Since we want to investigate the importance of cycles, it is natural to adopt the frequency domain approach, i.e. to use spectral analysis.

The purpose of the first section is to discuss both what business cycle stylized facts are and why they have not been established in contemporary econometric practice. In the second part, we briefly describe multivariate ME (Maximum - Entropy) spectral analysis. In the third part a univariate and multivariate analysis of the time series of 6 OECD countries, especially U.S.A., Germany, Italy, France, United Kingdom and Japan is given. So the empirical evidence concerning the identification of cycles of the aggregate Industrial Production (IP), Prices (P) and Money (M) for these countries is presented. The observation period is 1975 - 1993 with quarterly data.

2. Business Cycle Stylized Facts

The central issue is whether business cycles are merely serially correlated random disturbances, the Statistical View, or whether they can be approximated by a small number of periodic functions, the Genuine Cycle View. The Statistical View was advanced by Fisher (1925) and Slutsky (1937) and has become the currently dominant view. The Genuine Cycle View was advanced by Juglar (1862) on the basis of empirical investigations and was elaborated by Schumpeter (1939). The Genuine Cycle View dominated from about the middle of the nineteenth to the middle of the twentieth century. The Genuine Cycle View has been elaborated in considerably detail. Most importantly, it was found that a cycle of 8 - 12 years duration is primarily associated with equipment investment and a cycle of about 4 years with inventory investment. The cycle length can in each case be plausibly linked to the speed with which the relevant capital stock can be adjusted to its desired level.

Several tests of the Genuine Cycle View based on spectral analysis have rejected it. The best-known contribution is that of Granger (1966) who claimed the existence of a "typical spectral shape" of an economic variable in the form of a spectrum which is a monotonically declining function of the frequency. Hillinger (1992) argued that these results are due to the uncritical use of natural science methodology, which was developed for a quite different purpose. The standard methods of spectral analysis were developed to estimate a continuous spectrum given a large number of observations. Testing the Genuine Cycle View however, requires the identification of discrete elements in the spectrum. One reason why peaks at business cycle frequencies were not found in these studies is that they were averaged out by strongly smoothing "windows". The traditional techniques of windowing the data, (Priestley 1981) cannot offer a satisfying solution to this problem. Other reasons were inappropriate detrending and a failure to select the most relevant time series. The defects of the periodogram (Hillinger 1992, Woitek 1997), the classical spectral estimate, are mainly due to the assumption that the autocovariance function outside the observation period is zero. There are a huge number of spectra that are compatible with the sample autocovariances. One cannot expect that to choose out of this set of possible spectra that almost certainly wrong spectrum for which the underlying autocovariance function is zero will lead to a good estimate of the true spectrum (Jaynes 1985). With a small sample, this problem becomes even more important. We are searching for a spectral estimate which is compatible with the sample autocovariances, and we do not know anything about the out - of - sample autocovariance function. This is exactly the problem which previously was not solved and is solved by the application of the Maximum Entropy principle (Hillinger 1992, Reiter 1995, Woitek 1997, Woitek 2001).

The fact that phenomena are described independently of their explanation is a universal feature of everyday discourse as well as of empirical science. We know that empirical regularities (stylized facts) are the subject of scientific explanation. The philosophy of science (Nagel 1961) accordingly distinguishes empirical regularities and explanatory laws. In economics, under the influence of the statistical methodology of econometrics, the tendency has to disregard stylized facts and to concentrate instead on the fit of models to data. The determination of stylized facts plays a central role of my research program. This emphasis corresponds to the methodology of the natural sciences and stands in contrast to that of the mainstream econometrics.

3. Methodology

For the application of spectral analysis, it is necessary to have stationary series. But since most economic time series are non - stationary, a method has to be found which isolates the stationary part of the series without causing serious distortions of the cyclical structure. In the simplest case, the trend generating process is known, and one would apply the respective "optional" method. But in practice, the trend generating process is not known and therefore one has to use a method, which is reasonably robust against misspecification.

Basically, there are two types of non-stationarity: the difference stationary (DS-) model and the trend stationary (TS-) model. If the DS - model is the true model, one would make the series stationary using a difference filter; if the TS - model is the true model, one would detrend the series, using for example a linear time trend. Beginning with the influential work of Chan, Hayya & Ord (1977) and Nelson & Kang (1981), there is a number of studies analyzing the distortions caused by the wrong use of a detrending procedure. It has been shown that in the case where the TS - model is true, the difference filter exaggerates the importance of high frequency components, while in the case where the DS - model is true, the use of a linear time trend would exaggerate the importance of the low frequency components.

These results motivate the use of the Dickey - Fuller (DF-) test introduced by Dickey & Fuller (1976) to decide whether a series is DS or TS. Based on this test, the null hypothesis of a unit root cannot be rejected for a great number of economic time series [see Nelson & Plosser (1982)]. If we want to believe this test, this outcome suggests applying a difference filter to make the series stationary. It is well known that the DF - test has only low power against TS - alternatives which have similar characteristics as the null model. It was argued that this is not a problem, because in this case, the null and the alternative model would be so close that it would be impossible to give a different economic interpretation [see Nelson & Plosser (1982), p.152].

We thing that it is nevertheless important to distinguish reliably between the TS- and the DS-model. Besides the fact that assuming a wrong trend - generating process will lead to severe distortions in the cyclical structure of the series, Rudebusch (1992) and (1993) recently showed that the DF - test has low power not only against alternatives which are close to the null model but even against alternatives which have fundamentally different economic applications. Given this result, blind confidence in the reliability of the DF - test is equal to the automatic use of the difference filter, which leads to the well-known distortions in the cyclical structure. We decided therefore to use Hodrick-Prescott (HP-) filter (Hodrick & Prescott 1980), which in recent simulation study at SEMECON (Hillinger , Reiter & Woitek 1992, Woitek 2001) proved to produce less severe distortions than the other widely used detrending procedures, if carefully used.

The HP - filter is defined by

$$\min_{\tilde{y}_t}\left\{\sum_{t=1}^{T}(y_t-\tilde{y}_t)^2+\mu\sum_{\tau=2}^{T-1}[(\tilde{y}_{t+1}-\tilde{y}_t)-(\tilde{y}_t-\tilde{y}_{t-1})]^2\right\} \tag{1}$$

where the y_t are the original data and the y_t, are chosen to minimize the above expression. The parameter μ determines the relative weight between the first term, which measures the goodness of fit, and the second term, which is a measure of the variation of the trend.

The restriction to apply this filter carefully is due to the fact that in the case of a DS - model, this filter produces spurious cycles in the low frequency range [see Harvey & Jaeger (1991), King & Rebelo (1993), Canova (1996),(1998)]. As stated above, there is no method available to reliably distinguish between the DS- and the TS - model. Therefore, we analyzed the cyclical procedure of both the output series of the HP - filter and the difference filter. The modified Baxter-King filter (Woitek 2001) is an alternative which minimizes the risk of introducing spurious cyclical structure in the data when the type of non-stationarity in the data generating process is unknown. But if there are cycles in the series after taking differences, Hillinger et al. (1992) argue that it is better to apply the HP - filter, because a wrong use of the HP - filter causes less severe distortions in the structure of the output series than a wrong use of the difference filter. Otherwise, i.e. if we do not find cyclical structure in the output series of the difference filter, the procedure stops. The danger of distorting existing cyclical structure cannot be fully avoided, but we think that at least we can reduce the problem of generating artificial cycles to a minimum.

The optimal method of describing the cyclical characteristics of a linear time series is to transform it from the time domain to the frequency domain and to compute the spectral density function.

The spectral density function f(ω) of a univariate stochastic process is the Fourier transform of the covariance function of the process (see e.g. Brockwell and Davis 1991, pp. 114 - 158):

$$F(\omega)=\frac{1}{2\pi}\sum_{\tau=-\infty}^{+\infty}\Gamma(\tau)e^{-i\omega\tau}\quad;\ \omega=2\pi\lambda;\ \lambda=[-0.5,0.5] \tag{2}$$

with

$$\Gamma(\tau)=\begin{pmatrix}\gamma_{11}(\tau) & \cdots & \gamma_{1n}(\tau)\\ \vdots & \ddots & \vdots\\ \gamma_{n1}(\tau) & \cdots & \gamma_{nn}(\tau)\end{pmatrix}$$

$$F(\omega)=\begin{pmatrix}f_{11}(\omega) & \cdots & f_{1n}(\omega)\\ \vdots & \ddots & \vdots\\ f_{n1}(\omega) & \cdots & f_{nn}(\omega)\end{pmatrix}$$

Since F(ω) is an even function, it is sufficient to look at it in the interval [0, π]. The diagonal elements $f_{jj}(\omega),\ldots f_{nn}(\omega)$ are the real valued autospectra of the η individual series. The area under the spectrum equals the process variance $\gamma_{jj}(0)$:

$$\gamma_{jj}(0)=\int_{-\pi}^{\pi} f_{jj}(\omega)d\omega \tag{3}$$

In this paper, the normalized power spectrum is used, i.e. the power spectrum $f_{jj}(\omega)$ is divided by the process variance $\gamma_{jj}(0)$. Hence the area under the normalized spectrum $f_{jj}(\omega)$ equals one. Then the expression

$$\frac{2}{\gamma_{jj}(0)}\int_{\omega^*-0.1\omega^*}^{\omega^*+0.1\omega^*} f_{jj}(\omega)d\omega \tag{4}$$

can be interpreted as the part of the variance $\gamma_{jj}(0)$ which is explained by the variance of oscillations with frequencies in the range $\pm$ 10 per cent around the peak frequency ω^*. In the following, this expression is called peak power of a cycle with the frequency ω^*. A measure to judge the spread of a peak, i.e. the damping of the cycle, is the bandwidth, i.e. the range in which the peak halves: the sharper the peak at a frequency ω^*, the smaller the bandwidth (see Priestley 1981, pp. 513 - 517). This measure cannot be computed if the respective cycle is to strongly dumped or if two peaks are too close. Therefore, to describe the dumbing of a cycle we decided to look at the moduli of the corresponding complex roots of the characteristic polynomial of the AR - model used to estimate the univariate spectrum as is explained bellow. The signal - to - noise ratio measures the influence of the noise on a series and is defined as the ratio of the variance of the signal to the variance of the noise σ_u^2.

$$SNR = \frac{\int_{-\omega}^{\omega} f_{jj}(\omega)d\omega - \sigma_u^2}{\sigma_u^2} \tag{5}$$

The elements $f_{jk}(\omega)$, j k, are called cross spectra. In general, they are not real valued, since the cross covariances $\gamma_{jk}(\tau)$, j k, are not symmetric. Therefore, $f_{jk}(\omega)$ can be written as

$$f_{jk}(\omega) = \frac{1}{2\pi}\sum_{\tau=-\infty}^{+\infty}\gamma_{jk}(\tau)e^{-i\omega\tau} = c_{jk}(\omega) - iq_{jk}(\omega); \quad \begin{matrix} j=1,\dots,n; \\ k=1,\dots,n; \\ j \neq k; \end{matrix} \tag{6}$$

where $c_{jk}(\omega)$ is the cospectrum and $q_{jk}(\omega)$ is the quadrature spectrum. From the co- and the quadrature spectrum of two series j and k it is possible to compute measures for the lead - lag relationships between them. These measures are the phase lag, the gain and the squared coherency.

The squared coherency can be interpreted in the same way as the correlation coefficient in a regression model. It measures the degree of linear relationship between a cycle of frequency ω in the series j and a cycle of the same frequency in the series k. If it equals 1 at a frequency ω, there is an exact linear relationship between the cycles with frequency ω in the two series; if it equals 0, there is no relationship between the two cycles. The squared coherency is defined as

$$k_{jk}^{2} = \frac{\left|f_{jk}(\omega)\right|^{2}}{f_{jj}(\omega) f_{kk}(\omega)} \tag{7}$$

The gain spectrum and the phase spectrum can be interpreted in the same way as the impact of a univariate linear filter on an input series in the frequency domain. The multiplicative change of the amplitude of a cycle if transformed from series j to series k is called the gain, defined as

$$g_{jk}(\omega) = \frac{\left|f_{jk}(\omega)\right|}{f_{jj}(\omega)} \tag{8}$$

The phase spectrum

$$\varphi_{jk}(\omega) = \arctan\left[-\frac{q_{jk}(\omega)}{c_{jk}(\omega)}\right] \tag{9}$$

measures the phase lead of the series j over the series k at a frequency ω. If the squared coherency $k_{jk}^{2}(\omega)$ equals 1, there is a fixed linear relationship between the two series at the frequency ω. If it is less than 1, the phase and the gain have to be interpreted as expected values.

Since the classical spectral estimate, the periodogram, has well known defects, especially if applied to the description of the very short time series (sample size : 31 years) we want to analyze [see e.g. the discussion in Koopmans (1974), p. 294-336], we used Maximum - Entropy (ME-) spectral analysis (Burg 1975) to estimate the spectra.

Applying the ME-principle to spectral estimation, one has to choose that spectrum which maximizes the entropy, i.e. a measure for the non - knowledge concerning out - of - sample information, subject to the restriction that the resulting spectrum has to be the Fourier transform of the first ρ sample correlations, i.e. has to correspond to the inner - sample information. The resulting Maximum - Entropy (ME-) spectrum has the elegant property to be equivalent to the spectrum of an AR(p) - process, for which the ρ parameters are determined by an equation system which is formally identical to the Yule - Walker equations.

$$\tilde{f}(\omega)=\frac{\tilde{\sigma}_u^2}{\left|1-\sum_{j=1}^{p}\tilde{\alpha}_j e^{-i\omega j}\right|^2} \tag{10}$$

$$\begin{pmatrix} \tilde{\gamma}(0) & \tilde{\gamma}(1) \ldots & \tilde{\gamma}(p-1) \\ \tilde{\gamma}(1) & \tilde{\gamma}(0) & \vdots \\ \vdots & \ddots & \tilde{\gamma}(1) \\ \tilde{\gamma}(p-1) & \cdots \tilde{\gamma}(1) & \tilde{\gamma}(0) \end{pmatrix} \begin{pmatrix} 1 \\ \tilde{\alpha}_1 \\ \vdots \\ \tilde{\alpha}_p \end{pmatrix} = \begin{pmatrix} \tilde{\sigma}^2 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \tag{11}$$

To improve the estimation procedure for short time series, it is possible to use the property that (real valued) AR - parameters are valid in both time directions, since the covariance function is an even function. Therefore, time direction is not important, and we can estimate the parameters by minimizing both the forward (as it is the case for the OLS - estimates) and the backward prediction error. This procedure, which is called Burg - algorithm (Burg 1975), may lead to unstable results. If this is the case, it is replaced by the Fougere - algorithm (Fougere 1985), which forces a stationary estimate. For a more detailed description of these algorithms, we refer to Hillinger and Sebold - Bender (1992).

In the above part it was assumed that the order ρ of the AR - model is known. In practice, it has to be estimated. To do this, we use the CAT - criterion [criterion for autoregressive transfer functions, see e.g. Priestley (1981), p. 602]. The CAT criterion is defined by

$$\mathrm{CAT}(k)=\begin{cases} \left(\dfrac{1}{N}\sum_{j=1}^{k}\dfrac{1}{\tilde{\sigma}_k^2}\right)-\dfrac{1}{\tilde{\sigma}_k^2}; \; k=1,2,3\ldots \\ -\left(1+\dfrac{1}{N}\right); \; k=0 \end{cases} \tag{12}$$

where $\tilde{\sigma}_k^2$ is the unbiased residual variance estimate when fitting an AR(k) – process to the detrended data. The order p is chosen for which the CAT – criterion reaches a minimum. This criterion is known to overestimate the order in general, therefore we use it as an upper bound. The lower bound of the order can be derived by visual examination of the detrended data: for each cycle that can be seen in the data, the order has to be increased by 2.

For multivariate spectrum estimation, the problem to find an appropriate order estimate cannot be solved so easily. In simulation studies to judge the performance of different information criteria, Lutkepohl (1985), Lutkepohl (1991), pp. 135 - 139, finds that for data samples generated by low order VAR - processes, very parsimonious methods like the multivariate Schwarz criterion lead to better results than other criteria. But in practice it may as well be the case that the unknown data generating process is of infinite order and has to be approximated by a finite order model. In this case one may expect that less parsimonious criteria, like the multivariate CAT criterion, might perform better. Therefore Lutkepohl recommends comparing the results for VAR - processes of different order estimates. In this paper, the order is chosen for which the autospectra show similar characteristics as the respective univariate spectra, judged by visual examination.

4. Estimation of the IP/P/M1 - Spectra

This section describes how the methodology was utilized in order to obtain a description of the cyclical characteristics of the 6 OECD countries money, defined as Ml (currency in circulation and sight deposits), Industrial Production (IP) at constant prices, and Prices (P) (consumer price deflator at market prices). The observation period is 1975 - 1993 with quarterly data. As stated above, the business cycle stylized facts of these series are analyzed focusing on the following basic aspects: (1) The amplitude of the fluctuation; and (2) the degree of comovement with a measure for output, together with the phase shift of the series relative to the output cycle. Lucas (1977) claims that there are no country specific business cycle characteristics. Moreover, there are no significant changes in the cyclical pattern over time.

First, the data are detrended using the procedure described in section 3. If we want to use the Dickey - Fuller t - test to decide whether the trend stationary model (TS) or the difference stationary model (DS) is the true model, we have to estimate the augmented Dickey - Fuller equation. In the next step, the univariate ME - spectra of the detrended IP, Ml and P - series are estimated using the Burg - algorithm or the Fougere - algorithm, if the reflection coefficients estimated by the Burg - algorithm do not fulfill the stationary condition. After that, the multivariate ME - spectra for the time series are estimated.

TABLE 1

Augmented Dickey - Fuller test for the 6

	IP		P		M	
FRA	1.950	(0.83)	1.636	(0.97)	2.318	(0.89)
GER	2.181	(0.81)	1.943	(0.96)	2.108	(0.91)
ITA	2.458	(0.79)	1.718	(0.97)	2.435	(0.82)
JAP	2.713	(0.92)	1.993	(0.93)	1.848	(0.86)
U.K.	2.221	(0.90)	2.315	(0.98)	2.114	(0.93)
U.S.A.	2.535	(0.94)	2.818	(0.93)	3.018	(0.91)

In the parenthesis are the moduli of the series after taking differences.

The results, presented in Table 1, suggest that all variables are nonstationary in levels, so we cannot reject the null hypothesis. In order to avoid distortions of the cyclical structure of the series and wrong implications concerning the persistence of shocks, it seems that it would be preferable to make the series stationary assuming a DS - model rather than a TS - model. Proceeding in the way described in section 3, it can be seen that all series show cyclical structure after taking first differences (the moduli are less than one). Based on these outcomes we can be confident that the cyclical structure in these series is not generated by the detrending method.

In Table 2, the results of the univariate spectrum estimation are displayed. The order of the AR - model was chosen applying the procedure described in section 3, the upper bound is determined by CAT - criterion, the lower bound by the number of cycles identified by visual analysis of the detrended data. The empirical evidence, generally, supports the existence of two cycles for all magnitudes.

The HP filtered industrial production (IP), exhibit a long cycle with a median of 9.01 years. Looking the Table below the average long cycle is relatively above Germany, Italy & U.S.A., and relatively below U.K., Japan & France. The HP filtered industrial production exhibit a short cycle with a median of 3.49 years. The average short cycle is relatively above France, Italy and U.S.A. and relatively below Germany and U.K. The HP filtered money supply (Ml), exhibit a long cycle with a median of 8.69 years. The average long cycle is relatively above France, Italy and U.S.A. and relatively below U.K., Germany, Japan and Italy. The average short cycle for the Ml series has a length of 3.185 years. The period is relatively above France, Germany, Japan and U.S.A. and relatively below Italy and U.K. The HP filtered P (Prices) exhibit a long cycle with average 7.4 years.

TABLE 2

Univariate Analysis

		Period	Moduli	Peak Power	SNR
FRA	IP	9.40	0.91	0.18	8.15
		2.96	0.89	0.08	6.13
	P	7.29	0.87	0.26	13.22
		2.83	0.78	0.12	5.42
	M1	5.36	0.73	0.20	8.09
		2.56	0.69	0.09	7.19
GER	IP	7.98	0.92	0.16	8.89
		3.57	0.82	0.08	6.01
	P	9.15	0.81	0.40	13.96
		4.62	0.73	0.22	9.32
	M1	10.23	0.70	0.12	6.38
		3.18	0.58	0.09	4.23
ITA	IP	7.82	0.85	0.28	7.15
		3.42	0.76	0.09	6.15
	P	9.17	0.84	0.23	11.83
		4.12	0.73	0.08	8.11
	M1	8.22	0.84	0.27	7.32
		3.92	0.70	0.08	5.32
JPN	IP	11.20	0.83	0.20	10.25
		4.08	0.73	0.07	4.32
	P	6.53	0.88	0.18	6.36
		2.38	0.73	0.04	6.15
	M1	11.32	0.81	0.16	8.17
		3.07	0.75	0.06	5.22
U.K.	IP	10.23	0.92	0.32	12.99
		4.28	0.78	0.10	7.22
	P	5.50	0.71	0.21	8.32
		2.18	0.68	0.14	6.92
	M1	9.32	0.90	0.22	7.44
		3.39	0.78	0.07	6.15
U.S.A.	IP	7.48	0.82	0.30	10.05
		2.68	0.65	0.03	7.48
	P	6.79	0.77	0.23	10.45
		3.18	0.80	0.08	6.92
	M1	7.68	0.89	0.35	10.66
		2.99	0.75	0.02	5.05

The average long cycle is relatively above France, Japan, United Kingdom and U.S.A. and below average Germany and Italy. The average period of the short cycle is 3.22. The average cycle is relatively above France, Japan, U.K. and U.S.A. and relatively below Germany and Italy.

What can be said about the relative importance of the cyclical components for the structure of the fluctuations? The pp of the long cycle has median of 0.33, while for the short cycle it is only 0.05. The long cycle is more important for the cyclical structure than the short cycle. Looking the moduli, similar information can be obtained. The modulus gives an impression of the dumping of a cycle. We know that the higher the modulus, the sharper the peak in the spectrum, and the higher the pp of the respective cycle. The regularity of the fluctuations is measured by the signal - to - noise ratio (SNR). Looking the above Table we see that SNR vary between 5.22 and 13.94. The fluctuations of IP exhibit the most regular fluctuations.

TABLE 3

Multivariate Analysis IP/M, IP/P

	Period	Square Coherency	Phase Shift	Gain
FRA	9.22	0.62	- 0.19	0.36
	8.32	0.68	4.02	0.34
GER	7.94	0.68	- 0.30	0.49
	8.10	0.65	2.34	0.76
ITA	7.29	0.63	- 0.18	0.52
	8.42	0.73	3.48	0.49
JAP	12.01	0.78	- 1.92	0.48
	10.23	0.77	4.93	0.61
U.K.	10.83	0.67	- 0.48	0.54
	8.49	0.66	2.16	0.69
U.SA.	7.38	0.73	- 0.32	0.56
	6.91	0.82	2.73	1.31

First row: IP/Ml; second row: IP/P

The results of the multivariate spectral estimation for the IP and the other series are displayed in Table 3. As in the most part of the literature, I compare the cyclical structure of the component series, Ml and P with the respective IP cycles. Based on the procedure by Lutkepohl comparison of the estimated orders recommended by CAT, the BIC and the Hannan - Quinn criterion for multivariate time series suggests the fitting of second order filters to the detrended data. As it was to be expected, the peaks in the autospectra of the IP/Ml and IP/P systems differ from the corresponding peaks in the univariate spectra. But in most cases the differences are very small, i.e. cycles which can be found in the autospectra are also present in the univariate spectra.

From Table 3 it can be seen that the square coherency is relatively high for the IP/Ml relation in the countries. During the 1970s many major Central Banks moved toward targeting monetary aggregates to facilitate the control of inflation. A potential influence on the relationship between money and income is the acceleration in the development of new financial techniques and instruments. These developments have potential implication for the square coherency. If the money demand function is stable, and this is the case, fluctuations in the money - income relationship will be systematically associated with variations in the determinants of money demand. Therefore Ml affects the cyclical fluctuations of real industrial production with a relatively great power (the average degree of the linear relationship between IP and Ml with the same period is 0.61). So we attribute the high coherency in these countries (i) to the use of money against inflation and (ii) to the financial innovation. For P we see that again the results are the same as M1. The results for the phase shift show that the long cycle in Ml is procyclical (the negative phase shift indicates a lead of the first series). Given that the major part of the money supply is created by banks, it is evident that closer attention needs to be paid to the money generation process in business cycle models. If the rate of technological innovation does depend on availability of finance, then real and monetary impulses should not be regarded as separable. The median of the absolute phase shift at the long cycle for Ml is less than one year (0.56). The long cycle in the HP filtered P are countercyclical, with about the same absolute phase shift.

For the post war period, Backus and Kehoe (1992) have the following results. The price level is countercyclical and in the money stock, no pattern can be found. Using annual data, Woitek (1997) has found a small square coherency for the GDP cycles and the cycle in Ml for 11 OECD countries and for P the result is extremely sensitive to the detrending procedure. Blackburn and Ravn (1992) examine quarterly data (United Kingdom) in the time domain for the observation period 1956 - 1990. They apply the Hodrick - Prescott filter to achieve stationarity. Their main results are (1) the price level is countercyclical and (2) the monetary aggregates are procyclical. In contrast with our findings the real business cycle models attributes much less significance to the influence of money on the economy. King and Plosser (1984) introduce money as a factor of production, Williamson (1987) introduces financial intermediation. Litterman and Weiss (1985) focus on the behavior of the real interest rate and demonstrate that it is not caused by output, money, prices, or nominal interest rates. Eichenbaum and Singleton (1986), Mullineux, Dickinson and Peng (1993) notes that acceptance or rejection of real business models must be based on the plausibility of the variance and autocorrelations of shocks employed to generate realistic cycles. The analysis of money and its effects on the economy, which was discussed for the real business cycle models, generally used vector autoregressions and variance decompositions. This methodology has been employed more generally to evaluate the importance of real shocks in explaining output variation.

5. Conclusions

The aim of this study was to describe business cycle stylized facts by applying the Maximum Entropy spectral estimation for 6 OECD countries using quarterly data. We analyzed the cyclical structure of prices and money stock Ml in addition to the Industrial Production. Price cycles are countercyclical in the post war period, which is an important stylized fact with regard to real business cycle theory. Another interesting result is the lead - lag structure between industrial production and money supply. The monetary aggregates are procyclical. If the rate of technological innovation does depend on availability of finance, then real and monetary impulses should not be regarded as separable. The cyclical structure in macroeconomic time series has not to be country specific. So an extension of the analysis to the phenomenon of the international business cycle seems promising. Of course, it is necessary to examine the robustness of the cyclical structure in more detail. But based on the ME spectral analysis, the set of basic stylized facts of traditional business cycle theory could be convincingly confirmed and extended. We believe that in formations on business cycle structure obtained by spectral analysis are more detailed than obtained by time domain methods.

References

Abies. John G., "Maximum Entropy Spectral Analysis", in Donald G. Childers, ed., *Modern Spectrum Analysis,* New York: IEEE Press, 1978.

Barnett W, Gandolfo G, Hillinger C *Dynamic Disequilibrium Modeling,* 1996, Cambridge University Press.

Baxter M, King R.G., Measuring business cycles. Approximate band-pass filters for economic time series., 1995 *NBER Working Paper, Series No. 5022.*

Blanchard, O.J. & Watson, M.W., "Are Business Cycles All Alike?", in R.J. Gordon, ed., *The American Business Cycle,* New York: National Bureau of Economic Research, 1986.

Brockwell, Peter J. & Richard A. Davis, *Time Series: Theory and Methods,* 2nd ed., Berlin, Heidelberg, New York, Tokyo: Springer, 191.

Burg, John Parker, "Maximum Entropy Spectral Analysis", PhD dissertation, Stanford University, 1975.

Canova, Fabio, "Detrending and Business Cycle Facts", 1991. EUI Working Paper ECO No 91/58.

—, Three tests for the existence of cycles in time series. 1996 *Ricerche Economiche* 50, pp.135-162.

—, Detrending and business cycle facts: a users guide, 1998 *Journal of Monetary Economics,* 41, pp. 533-540.

Clan, K. Hung, Jack C. Hayya & J. Keith Ord, "A Note on Trend Removal Methods: The Case of Polynomial Regression Versus Variate Differencing", *Econometrica,* 1977 , 45 , pp. 737 - 744.

Cogley, Timothy & James M. Nason, "Effects of the Hodrick - Prescott Filter on Trend and Difference Stationary Time Series: Implications for Business Cycle Research", 1992. University of British Columbia, Department of Economics, Discussion Paper No 95 - 93.

Dickey, D. A., "Estimation and Hypothesis Testing in Nonstationary Time Series". PhD dissertation, Iowa State University, 1976.

—, and Wayne A. Fuller, "Likelihood Ratio Statistics For Autoregressive Time Series with a Unit Root", *Econometrica,* 1981, 49, pp. 1057-1072.

—, William R. Bell & Robert B. Miller, "Unit Roots in Time Series Models: Tests and Implications", *American Statistician,* 1986, 40, pp. 12-26.

Eichenbaum M and Singleton K.J, Do equilibrium real business cycle theories explain postwar U.S business cycles? 1986, *Macroeconomics Annual ,* Cambridge.

Fougere, Paul F., "A Review of the Problem of Spontaneous Line Splitting in Maximum Entropy Power Spectral Analysis", in C. Ray Smith & W.T. Grandy, eds., *Maximum Entropy and Bayesian Methods in Inverse Problems,* Dordrecht: D. Reidel Publishing Company, 1985.

Fuller, Wayne A., *Introduction to Statistical Time Series,* New York, Chichester, Brisbane, Toronto, Singapore: John Wiley & Sons, 1976.

Harvey, Andrew C. and Albert Jaeger, "Detrending, Stylized Facts and the Business Cycle", 1991. London School of Economics, Discussion Paper No. EM/91/230.

Hillinger, Claude, "The Methodology of Empirical Science", in Claude Hillinger ed., *Cyclical Growth in Market & Planned Economies,* London: Oxford University Press, 1992.

—, "Paradigm Change and Scientific Method in the Study of Economy Fluctuations", in Claude Hillinger, ed., Cyclical Growth in Market and Planned Economies, London: Oxford University Press, 1992.

—, and Monica Sebold-Bender, "The Stylized Facts of Macroeconomic Fluctuation", in Claude Hillinger, ed., *Cyclical Growth in Market and Planned Economies,* London: Oxford University Press,1992.

-, Michael Reiter and Ulrich Woitek, "Model-Independent Detrending for Determining the Cyclical Properties of Macroeconomic Time Series", 1992. Munchner Wirtschaftswissenschfktiche Beitrage.

Hodreck, R.J. and E.C. Prescott, "Postwar U.S. Business Cycles: An Empirical Investigation", 1980. Discussion Paper No. 451, Carnegie-Mellon University.

King, Robert G. and Sergio T. Rebelo, "Low Frequency Filtering and Real Business Cycles", *Journal of Economic Dynamics and Control,* 1993, 17, pp. 207-231.

—, and Plosser C.I., Money, credit and prices in a real business cycle economy, *American Economic Review,* 74, pp. 363-80.

Kwiatkowsky, Denis, Peter C.B. Phillips and Peter Schmidt, "Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root: How Sure are we that Economic Time Series have a Unit Root?", 1991. Cowles Foundation Discussion Paper No. 979.

Lastrapes, W.D. & Selin, G., "Buffer-Stock Money: Interpreting Short-Run Dynamics Using Long-Run Restrictions", *Journal of Money, Credit, and Banking,* 1994, 26, pp. 34-35.

Lutkepohl, Helmut, "Comparison of Criteria for Estimating the Order of a Vector Autoregressive Process", Journal of Time Series Analysis, 1985, 6, pp. 35-52.

—, *Introduction to Multiple Time Series Analysis,* Berlin, Heidelberg, New York, Tokio: Springer, 1991.

Marple, S. Lawrence, Digital Spectral Analysis with Applications, Englewood Cliffs: Prentice Hall, 1987.

-, and Albert H. Nuttal, "Experimental Comparison of Three Multichannel Linear Prediction Spectral Estimators", *IEEE PROC,* 1983, 130, pp. 218-229.

Morf, Martin, Augusto Vieira, Daniel T.L. Lee, and Thomas Kailath, "recursive Multichannel Maximum Entropy Spectral Estimation", *IEEE Transactions on Geoscience Electronics,* 1978, GE-16, 85-94.

Mullinex A, Dickinson D and Peng W, *Business Cycles* 1993, Blackwell Press, Oxford.

Nagel E, *The Structure of Science,* 1961, N. York.

Nelson, Charles R. and Charles I. Plosser, "Trends and Random Walks in Macroeconomic Time Series", *Journal of Monetary Economics,* 1982,10, pp. 139-162.

Priestley, M.B., *Spectral Analysis and Time Series,* London: Academic Press, 1981.

Reiter, Michael, "The Dynamics of Business Cycles. Stylized Facts, Economic Theory, Econometric Methodology and Applications". PhD dissertation, University of Munich, 1992.

Robinson, Enders A. and Ralph A. Wiggins, "Recursive Solution to the Multichannel Filtering Problem", *Journal of Geophysical Research,* 1965, 70, pp. 1885-1891.

Rudebusch, Glenn D., "Trends and Random Walks in Macroeconomic Time Series: A Re-Examination", *International Economic Review,* 1992, 33 (30), pp. 616-680.

—, "The Uncertain Unit Root in Real GDP", *American Economic Review,* 1993, 83 (1), pp. 264-272.

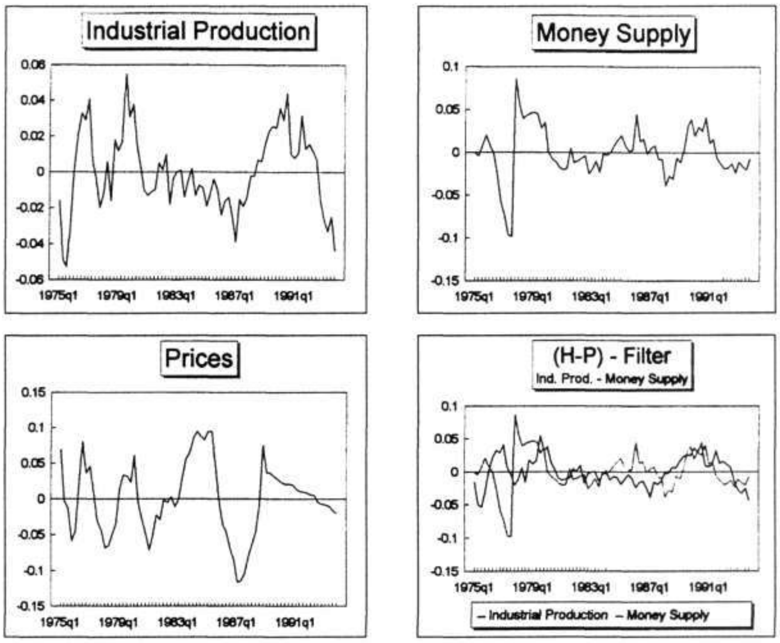
Swingler, D.N., "A comparison Between Burg's Maximum Entropy Method and a Nonrecursive Technique for the Spectral Analysis of Deterministic Signals", *Journal of Geophysical Research,* 1979, 84, pp. 679-658.

Woitek U., "The G7-Countries: A Multivariate Description of Business Cycle Stylized Facts", Conference on Dynamic Disequilibrium Modelling, Munich, 1993.

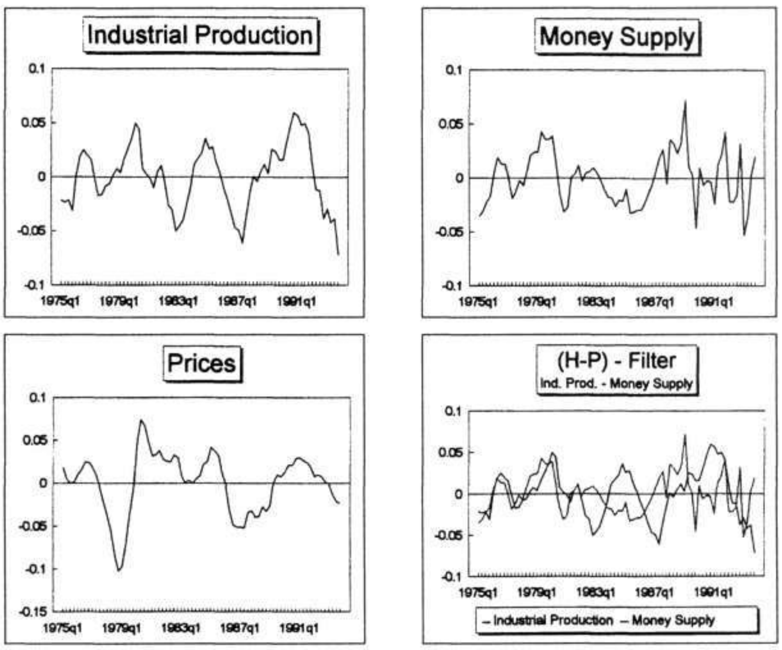
—, More International Evidence in the Historical Properties of Business-Cycles, *2001, Journal of Monetary Economis,* 47, pp. 321-46.

Varelas E., "Cycles in Greece: a Univariate Spectral Analysis", *Economie Appliquee,* 1995, pp. 139-156.

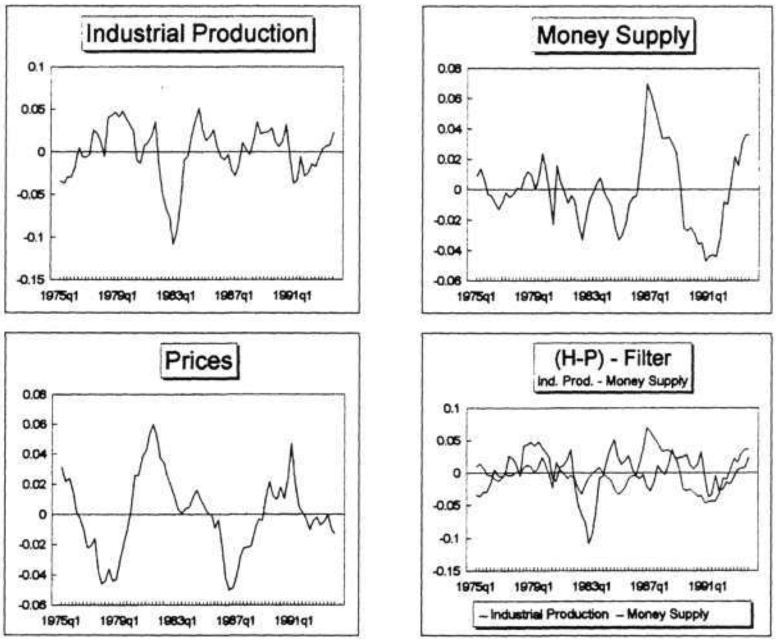
FRANCE



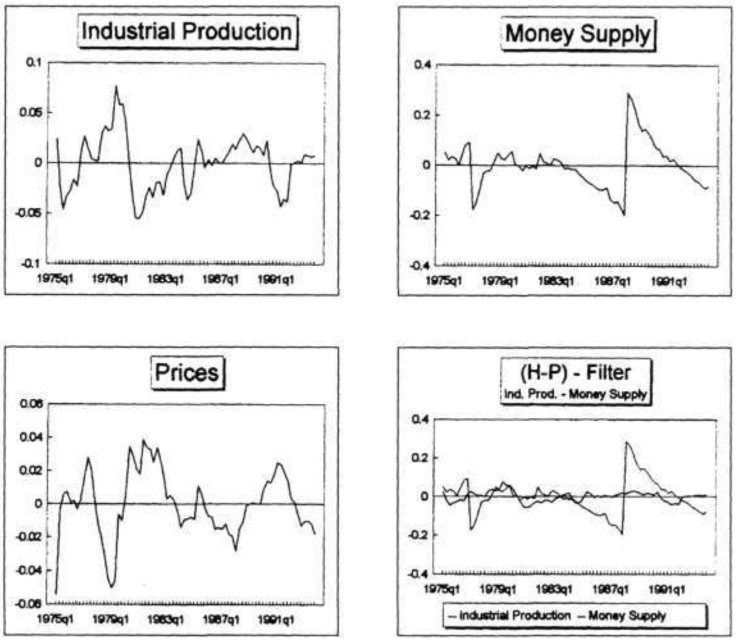
JAPAN



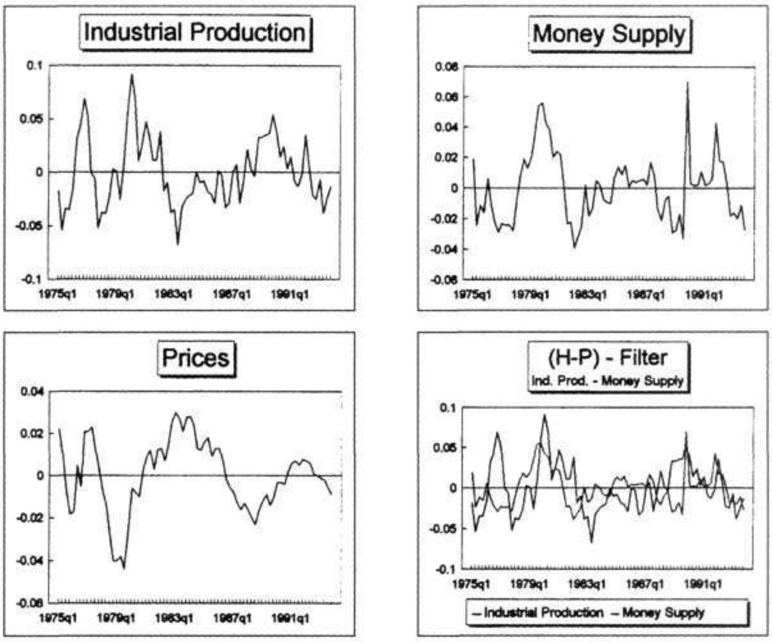
UNITED STATES



UNITED KINGDOM



ITALY



GERMANY