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Is the Greek Economy Periodic?

A Multivariate Description of the Business Cycle Stylized Facts

by Erotokritos Varelas* and Ulrich Woitek**

1. Introduction

Business cycle theorists want to explain the fluctuations of economic series around a time trend, an aim which requires information on the structure of these fluctuations. In this paper, the empirical evidence concerning the identification of cycles of basic economic magnitudes in Greece is presented and discussed. A useful method to answer important questions such as

- Are the observed fluctuations irregular or do they show cyclical structure?
- If they show cyclical structure, how many superimposed cycles can be identified?
- What is the length of these cycles?
- How important are they?

is provided by spectral analysis. The advantage of spectral analysis is that it contains the complete information about the cyclical characteristics of linear time series, and it displays this information in an easily inerpretable way. Hillinger and Sebold-Bender[1] contains an extensive description of the methods to estimate a univariate Maximum-Entropy (ME-) spectrum. For the equation, what can be said about lead-lag relationships between cycles in difference series, a multivariate extension is needed. In the first part of this paper, we briefly describe the univariate and multivariate spectral estimation. In the second part, a univariate and a multivariate spectral analysis of the GDP and its components for Greece are presented.

2. Methodology

For the application of spectral analysis, it is necessary to have a 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 simply apply the respective 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, for example using a linear time trend. Beginning with the influential work of Chan, Hayya and Ord and Nelson and Kang[2], there is a number of studies analyzing the distortions caused by the wrong use of a detrending procedure. It has 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[3] 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[4]. If we want to believe this test, this outcome suggests to apply 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[5].

We think 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, it was recently shown[6] 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 implications. 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 the Hodrick-Prescott (HP-)filter[7], which in

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[1] See Hillinger, Sebold-Bender (1992).

[2] See Chan and others (1977); Nelson, Kang (1981).

[3] See Fuller (1976); Dickey (1976).

[4] See Nelson, Plosser (1982).

[5] See Nelson, Plosser (1982), p. 1524.

[6] Rudebusch (1992) and (1993).

[7] Hodrick, Prescott (1980).

a recent simulation study at SEMECON[8] proved to produce less severe distortions than other wicely used detrending procedures, if carefully used. The HP-filter is defined by

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

where the y_t are the original data and the $\tilde{y}_t$ are chosen to minimize the above expression. The paameter μ determines the relative weight between the irst term, which measures the goodness of fit, and the second term, which is a measure for the variation of the trend.For annual data, this parameter is usually set to 100.

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[9]. As stated above, there is no method available to reiably distinguish between the DS- and the TS-model. Therefore, we analyzed the cyclical structure of both the ouput series of the HP-filter and the difference filter. If thereare cycles in the series after taking differences[10], it is bette 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 probem of generating artificial cycles to a minimum.

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

The spectral density function $f(\omega)$ of a univariate stochastic process is the Fourier transform of the covariance function of the process[11]. 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

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

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 ± 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[12]. This measure cannot be computed if the respective cycle is too strongly damped or if two peaks are too close. Therefore, to describe the damping 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 estinate the univariate spectrum as explained below. 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_μ^2.

$$SNR = \frac{\int_{-\omega}^{\omega} f_{jj}(\omega)\, d\omega - \sigma_u^2}{\sigma_u^2} \quad (3)$$

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

$$f_{jk}(\omega) = \frac{1}{2\pi} \sum_{\tau=-\infty}^{+\infty} \gamma_{jk}(\tau) e^{-i\omega\tau} = c_{jk}(\omega) - i q_{jk}(\omega) \; ; \quad \begin{matrix} j=1,\ldots,n; \\ k=1,\ldots,n; \\ j \neq k; \end{matrix} \quad (4)$$

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

$$k_{jk}^2 = \frac{|f_{jk}(\omega)|^2}{f_{jj}(\omega) f_{kk}(\omega)} \quad (5)$$

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

$$g_{jk}(\omega) = \frac{|f_{jk}(\omega)|}{f_{jj}(\omega)} \quad (6)$$

The phase spectrum

$$\varphi_{jk}(\omega) = \arctan\left(-q_{jk}(\omega) / c_{jk}(\omega)\right) \quad (7)$$

measures the phase lead of the series j over the series k at a frequency ω. If the squared coherency $k_{jk}(\omega)^2$ 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.

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[8] Hillinger, Reiter, Woitek (1992).

[9] See Harvey, Jaeger (1992); King, Rebelo (1993).

[10] Hillinger et al. (1992).

[11] See e.g. Brockwell, Davis (1991), pp. 114-158.

[12] See Priestley (1981), pp. 513–517.

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 used Maximum-Entropy (ME-) spectral analysis to estimate the spectra of the Greek GDP and its components[13].

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 p 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 p parameters are determined by an equation system which is formally identical to the Yule-Walker equations.

$$\tilde{f}(\omega) = \frac{\tilde{\sigma}_u^2}{|1 - \Sigma_{j=1}^{p} \tilde{\alpha}_j e^{-i\omega j}|^2} \tag{8}$$

$$\begin{pmatrix} \tilde{\gamma}(0) & \tilde{\gamma}(1) & \cdots & \tilde{\gamma}(p-1) \\ \tilde{\gamma}(1) & \tilde{\gamma}(0) & & \vdots \\ \vdots & & \ddots & \tilde{\gamma}(1) \\ \tilde{\gamma}(p-1) & \cdots & \tilde{\gamma}(1) & \tilde{\gamma}(0) \end{pmatrix} \begin{pmatrix} 1 \\ \tilde{\alpha}_1 \\ \vdots \\ \tilde{\alpha}_p \end{pmatrix} = \begin{pmatrix} \tilde{\sigma}^2 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \tag{9}$$

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[14], may lead to unstable results. If this is the case, it is replaced by the Fougere-algorithm, which forces a stationary estimate[15]. For a more detailed description of these algorithms, we refer to Hillinger and Sebold-Bender[16].

In the above part it was assumed that the order p 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[17]. The CAT-criterion is defined by

$$CAT(k) = \begin{cases} \left(\frac{1}{N} \sum_{j=1}^{k} \frac{1}{\tilde{\sigma}_k^2} \right) - \frac{1}{\tilde{\sigma}_k^2} \; ; k = 1,2,3,... \\ -\left(1 + \frac{1}{N}\right) \qquad ; k = 0 \end{cases} \tag{10}$$

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 spectral 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, one 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[18]. 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 Lütkepohl recommends to compare 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.

3. Estimation of Spectra

This section describes how the methodology was utilized in order to obtain a description of the cyclical characteristics of the greek Gross Domestic Product and its components (at constant 1970 prices): Gross Investment (GI), Inventory investment or changes in stocks (CI), and the residual demand (RD), which sums private consumption, governmental comsumption, and the exports minus the imports. The reason for this special kind of breakdown was the interest in the results for the investment series, which are traditionally looked upon as being mainly responsible for the cyclical structure of the GDP. The observation period is 1960-1990, with annual data. The data was obtained from the National Accounts of Greece and the Bank of Greece. Although questions may be raised about the quality of certain series they may still be accepted because of lack of alternative sources.

First, the data are detrended using the procedure described in Section 2. Then the data are analyzed using simple descriptive statistics to get a first impression of the cyclical characteristics. In the next step, the univariate ME-spectra of the detrended GDP, GI, CS, and RD-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. In the last step, the multivariate spectral analysis is presented.

Table 1 gives a first impression of the cyclical characteristics of the greek GDP and its components. First a measure for the share of a component in the original data of GDP is displayed. It can be seen that Residual Demand (RD) con-

[13] Burg (1975).

[14] Burg (1975).

[15] Fougere (1985).

[16] See Hillinger, Sebold-Bender (1992).

[17] See e.g. Priestley (1981), p. 602.

[18] Lütkepohl (1985); Lütkepohl (1991), pp. 135-139.

Table 1

Descriptive Statistics

	GDP	GI	CS	RD
Share of GDP[1)]	1.000	0.25!	0.029	0.715
SD/MEAN[2)]	0.354	0.48·	0.762	0.252
SD/SD of GDP[3)]	1.000	0.51!	0.322	0.371

[1)] mean of component / mean of GDP. - [2)] standard deviation (sd) of detrended / mean of componer — [3)] sd of detrended component / sd of detrended GDP.

(RD) contributes the largest part byfar to total GDP. The share of Inventory Investment (CS) i less than 1 per cent. The share of Gross Investment is 2!per cent. Second we have a measure for the variability of aeries: The ratio of the standard deviation (sd) of the detrened series to the mean of the series. Inventory investmentfluctuates extremely, Residual Demand is least variabl and as the largest variable also causes the Gross-Domstic-Product (GDP) to be relatively smooth. Gross Investhent variability is intermediate. Third we measure the exend to which the component fluctuations contribute to th fluctuation of GDP. Because the components are posively correlated, the contributions add to more than 100 er cent. The value of Gross Investment is the largest, whilthe value of inventory investment is the lowest.

This result may be seen as a conrmation of the importance of the investment componnts of the GDP in economic fluctuations. In connectio to changes in stocks (CS), particularly, it has been arued that although it usually consists a low percentage othe GDP, it accounts for a much higher one of its movment. The empirical evidence, generally, supports the exitence of cycles for all magnitudes, that can be decompsed into a long one (equipment) and a short one (inventry).

In Table 2 and in Figure 1 the resultfrom univariate spectral estimation are displayed. The cder of the AR-model was chosen applying the procedure escribed in Section II. The upper bound is determined byhe CAT-criterion, the lower bound by the number of cycls identified by visual analysis of the detrended data. The verage of the long cycle (equipment) for all component is7.686 years. The long cycle periods of GDP and CS are abve average and those

Table 2

Univariate Analysis

	GDP	GI	CS	RD
cycle length	9.376	7.522	7.838	6.010
	3.455	3.080	2.987	0.032
moduli	0.765	0.787	0.706	0.584
	0.671	0.628	0.714	0.654
PP	0.137	0.171	0.096	0.112
	0.087	0.097	0.184	0.157
SNR	6.835	5.431	4.598	4.344
AR-order	4	4	4	4

of GI and RD are below average. Next the average period of the short (inventory) cycle is 3.139. Only the period of GDP is above average, those of GI, CS, and RD are below it.

The peak power (pp) in Table 2, is a measure of the "importance of each cycle in the variation of the residuals of each economic magnitude". For the GDP and GI the most dominant cycle is the long one. We see that there is a long cycle in GDP with a length of about 9.5 years and a peak power of about 14 per cent, while the short cycle with a length of about 3.5 years has a peak power of less than 9 per cent. In the Gross Investment (GI) with a length of about 7.5 years has a (pp) of 17 per cent, while the short cycle with a length of about 3 years has a peak power of less than 10 per cent.

The short cycle is more important for (CS) and (RD). The long cycle in (RD) has a peak power of 11 per cent, while the short cycle has a peak power more than 15 per cent. The long cycle in the CS with a length of about 8 years has a peak power of less than 10 per cent, while the short cycle with a length of about 3 years has a peak power of more than 18 per cent.

If we compare GI and CS we have: The long cycle has the highest peak power in Gross Investment and the short cycle has the highest peak in the Inventory Investment. An additional result is that the higher the modulus of a complex root, the higher the peak power of the corresponding cycle. The signal to noise ratio is highest for the GDP and lowest for the Inventory Investment. The moduli is highest for GI and lowest for the RD. We have here to note that the Inventory Investment is more noise driven than the Gross Investment.

It is not easy to give an explanation for this matter at that level of analysis, but the following points are possibly of some interest.

a) The periods concerning the dominant cycles of the GI, CS, and the GDP in Greece are possibly close to the respective ones of the relevant magnitudes of certain countries that have close traditional relations with the Greek economy (e.g. Germany, France, U.S.A, and Italy). The above point may be related within the context of a small economy as that of Greece.

   Looking Table 3 the long cycle period of GDP in Greece (9.5 years) is relatively above Germany, U.S.A. and Italy and relatively below France. The long cycle period of Gross Investment in Greece (7.5 years) is like Italy, relatively below France and Germany, and relatively above U.S.A. The short cycle period in Inventory Investment in Greece (2.9 years) is relatively above France and relatively below Germany and Italy. We have to note that the very long period in Residual Demand spectrum of France and Italy is probably spurious[19].

   If we compare Greece with the average value of the length of the period (in Table 3) we have: The dominant

[19] Woitek (1993).

Table 3*

Cycles

DOMINANT CYCLES (1960-1991)								
	Cycle length				Peak Power			
	GDP	GI	CS	RD	GDP	GI	CS	RD
Germany	8.01	8.25	3.35	3.78	0.23	0.67	0.26	0.23
France	10.07	9.44	2.85	11.21	0.24	0.26	0.25	0.07
U.S.A	7.30	6.87	2.95	8.95	0.37	0.51	0.25	0.50
Italy	8.67	7.51	3.18	11.11	0.32	0.29	0.31	0.48
Average	8.51	8.01	3.08	—				
Greece	9.4	7.5	2.9	3.0				
* See for more details: Woitek (1993).								

long cycle of GDP in Greece is relatively above average, the dominant long cycle of Gross Investment is relatively below average, and the dominant short cycle of Inventory Investment is relatively below average.

b) A visual inspection of the diagrams (detrended Data) shows, that the cycles seem to change pattern, though not all of the same degree, their amplitude becoming wider after approximately the oil crisis of 1974. This is possibly indicative of an increased instability related to international economic factors and the structure of the Greek economy. Structure may include concepts like: (a) the open character of the economy, (b) the existence of a significant underground economy, (c) the superfluous service sector, (d) the large percentage of small scale industry and its difficulty to keep up at the technological level.

Corrective measures of economic policy not taken on time may have also contributed in sustaining and/or prolonging that pattern after 1974. In relation to this increased variation, it is interesting to note the behaviour of Gross Investment. It showed an increased variability after 1973-1974 that tended to diminish after 1981. This latter may be explained by the serious slackening of the investment activity after 1979.

In connection to peaks and troughs there is a greater degree of coincidence of the GDP with its components in the former than in the latter case. When a peak or a trough occurs there is at least a "partial" coincidence combined with a movement towards the same direction of approximately the rest of the magnitudes in most cases. There is one relatively clear exception to this "rule" in 1977 that may be worth noting as it is possibly related to the political characteristics of Greece. The 1977 GDP trough appears to be mainly influenced by the deep trough in inventories despite the fact that both investment and residual demand were increasing. However, to the extent the political phase may affect economic policy and this in its turn expectations, an indirect political factor may be considered to be introduced in the analysis of the cycle. Furthermore, the converse influence of the economic cycle on political events is not easy to be established, despite the fact of the coincidence of the main political turning points with the GDP troughs or GDP turning points.

Still, it could possibly, be accepted that the former cycle may have provided a suitable framework for the second (its main political turning points, the establishment and fall of the military regime, the elections of 1977, as well as the political change of 1981 are meant).

The results for the multivariate analysis are given in table 5. Only the lead-lag relationships between the GDP and its components are discussed here; the GDP series is taken as reference.

Based on the procedure by Lütkepohl[20] comparison of the estimated orders recommended by the CAT, the BIC and the Hannan-Quinn criterion for multivariate time series suggests the fitting of second order filters to the detrended data. From the visual comparison of the univariate spectra and the autospectra it can be seen that results are similar to the univariate spectra.

As it was to be expected, the peaks in the autospectra of the GDP/GI/CS/RD system 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 5(a) in can be seen that the squared coherency is relatively high for the GDP/GI-relation, while the phase shift is very low. The negative phase shift indicates a lead of the first series. From table 5(b) and (c) it can be seen that the squared coherencies are low for GDP/CS and GDP/RD relations. The squared coherency of GDP/GI at the long cycle is greater than the squared coherency of GDP/CS at the short cycle.

[20] See Lütkepohl (1991).

Table 4

Major peaks — Major troughs

	4a: Major peaks of the magnitudes							4b: Major troughs of the magnitudes							
GDP	65		73		79	85	89	68		74	77		83		87
GI	65		73		79	85	89	67/68		74/75		81		84	87
CS	65	70	73		80	85	88	67/68	72		77		82		87
RD	66	72		76	81	86	89	65	68	73		79	82		88

Table 5

Multivariate Analysis

	a) Multivariate Analysis GDP/GI (Dominant Cycle) Period	Squared Coherency	Phase Shift	Gain
Greece	7.407	0.857	−0.004	0.795
Germany	7.35	0.91	−0.11	1.30
USA	8.77	0.86	0.79	2.27
France	9.80	0.94	0.20	1.32
Italy	9.09	0.95	−0.51	1.95
	b) Multivariate Analysis GDP/CS (Dominant Cycle) Period	**Squared Coherency**	**Phase Shift**	**Gain**
Greece	2.967	0.386	−0.014	0.663
Germany	3.7	0.89	0.20	1.54
USA	5.5	0.91	0.85	6.05
France	2.9	0.87	−0.16	0.87
Italy	3.6	0.96	0.08	1.49
	c) Multivariate Analysis GDP/RD (Dominant Cycle) Period	**Squared Coherency**	**Phase Shift**	**Gain**
Greece	3.021	0.183	1.499	0.299
Germany	6.76	0.50	−0.86	2.50
USA	9.26	0.96	−0.67	1.42
France	9.62	0.71	−1.65	2.22
Italy	9.35	0.95	0.16	1.70

If we compare the squared coherency of GDP/GI, GDP/CS and GDP/RD relations of Greece with the squared coherency of GDP/GI, GDP/CS relations of Germany, Italy, U.S.A, and France we have: The squared coherency of GDP/GI relation of Greece is relatively below, the squared coherency of GDP/CS and GDP/RD relations are extremely below Germany, Italy, U.S.A, and France.

It is important for this differences to note, that during the 30 year period covered by our analysis the Greek economy passed from the state of underdevelopment to semi-industrialization. As a consequence some of the characteristics typical of low-income countries were quite prominent at the beginning of the period but have since been smothered out, although they have not been completely eliminated. The existence, however, of these special features calls for the following two observations.

The activity of at least one major sector of the economy is almost completely determined by autonomous or exogenous factors or exhibits a sector-specific cyclical pattern. A case is Greek agriculture. Its share in GDP was 25 per cent in 1960 and fell to about 14 per cent in 1990, while the corresponding share of employment shrank from 56 per cent to 30 per cent. Some significant cobweb type interactions between urban and rural sectors should not be precluded, there exists considerable evidence that cyclical fluctuations in Greek agriculture may be attributed mainly to non-economic factors.

The structure and the functioning of financial markets in countries with the characteristics of Greece, was until 1985 very little developed. The banking system was virtually the sole financial intermediary, interest rate was fixed by the monetary authorities according to various criteria and total credit as well as its allocation was controlled through several instruments. In such markets, changes in single monetary aggregates are likely to be much more closely associated with the evolution of real magnitudes in a quantity theory of money fashion.

5. Conclusion

In this paper cycles for each economic magnitude have been identified and the volatility of the investment components of the GDP verified. In the detrended GDP a long and a short cycle can be found with a length of about 9.5 years and about 3 years, respectively. The long cycle has the highest peak power in GI (gross investment) and the short cycle has the highest peak power in the CS (changes of stock or inventory investment). In the inventory investment a long cycle can be seen, too, but with clearly less importance for the cyclical structure. The inventory investment is more noise driven than gross investment.

The empirical results are very interesting insofar as the about same frequency parameters could be found in other Studies[21]. The business fluctuations are without doubt an international phenomenon whose occurrence in Greek economy is not astonishing, because of the great dependence on capital and industrial transfer from abroad.

An important fact concerning all cycles in general except residual demand is their increased variability after 1974. This may be interpreted as a symptom of increased instability of the economy and/or the application of certain wrong policies with the political characteristics of Greece.

[21] See Hillinger (1992); Woitek (1993).

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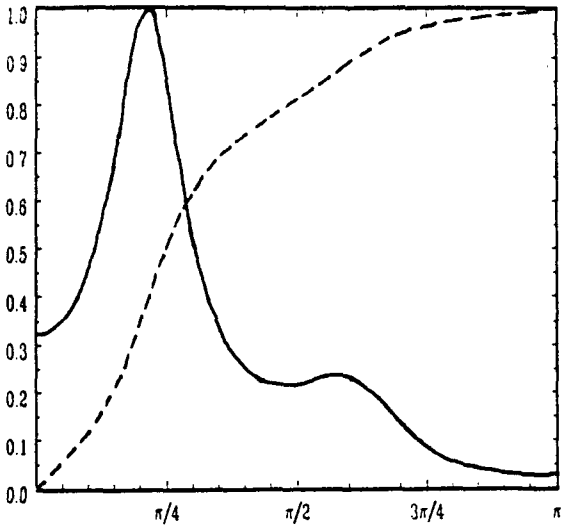
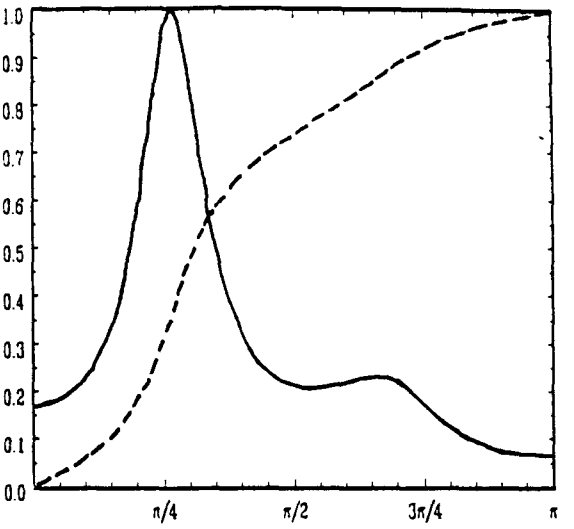
GDP



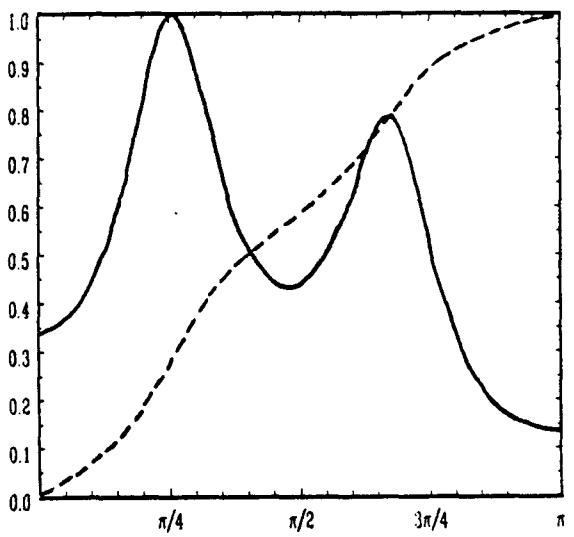
maxima at period : 9.38 3.46
peak power : 0.14 0.09

Gross Investment



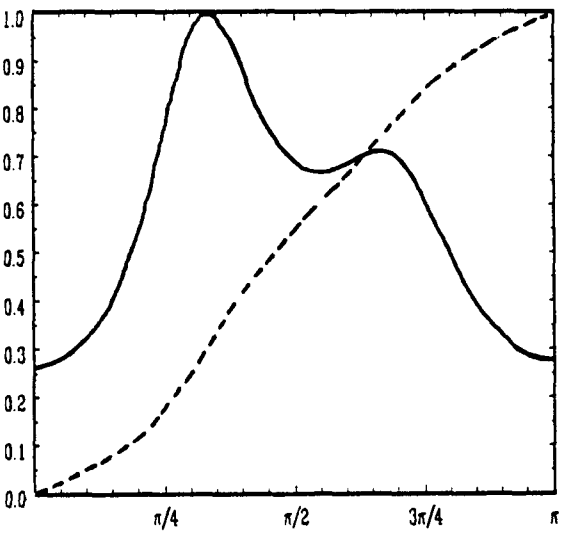
maxima at period : 7.52 3.08
peak power : 0.17 0.10

Changes in Stocks



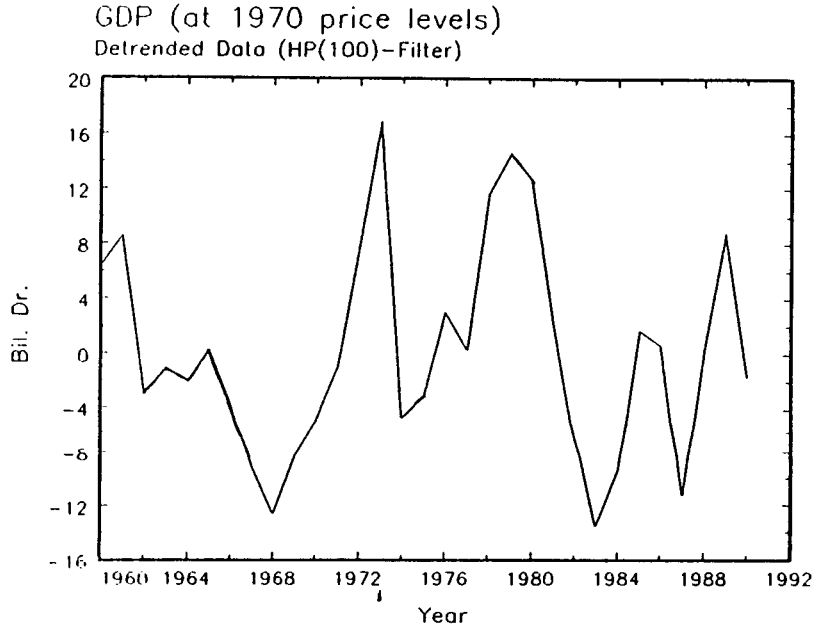
maxima at period : 7.84 2.99
peak power : 0.10 0.18

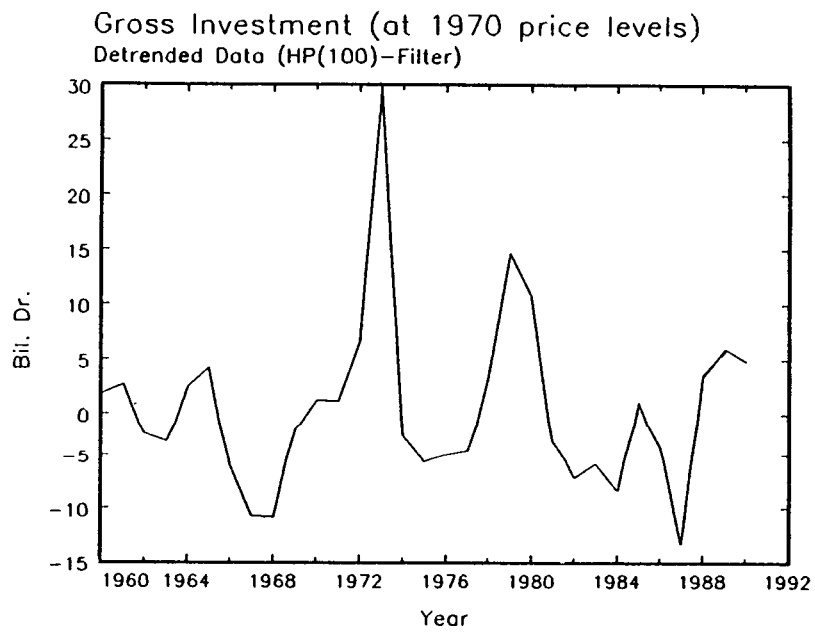
Residual Demand

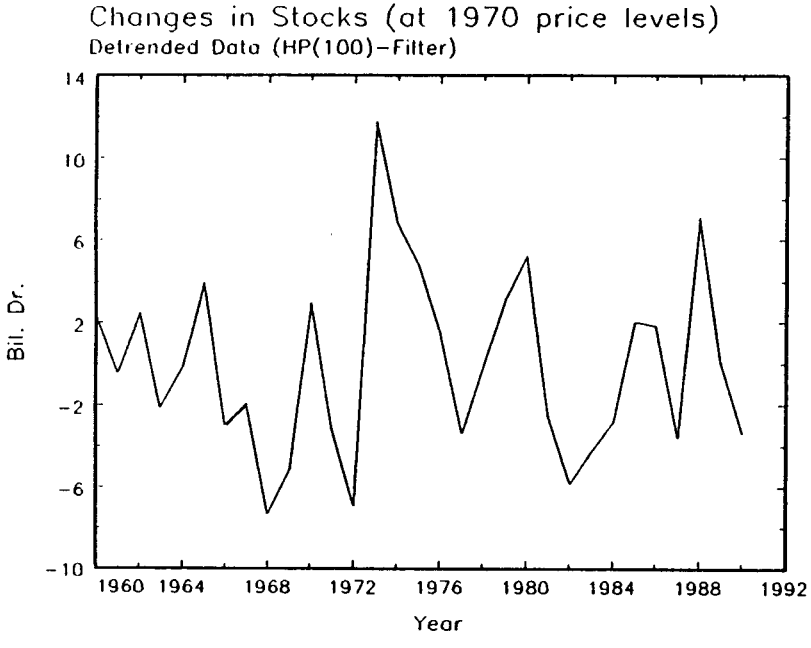


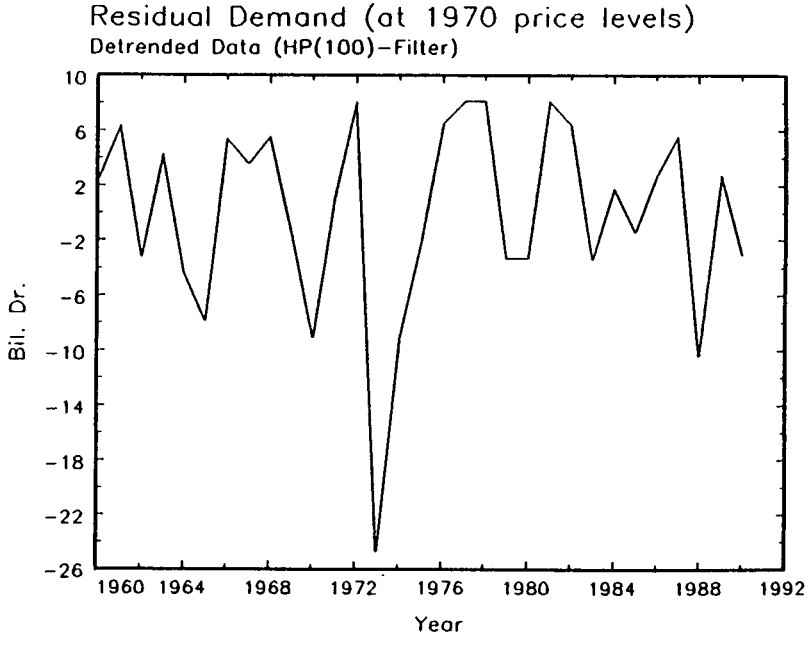
maxima at period : 6.01 3.03
peak power : 0.11 0.16

power spectrum (standardized)
normalized integrated spectrum


GDP (at 1970 price levels)
Detrended Data (HP(100)-Filter)
Bil. Dr.
20
16
12
8
4
0
-4
-8
-12
-16
1960 1964 1968 1972 1976 1980 1984 1988 1992
Year


Gross Investment (at 1970 price levels)
Detrended Data (HP(100)-Filter)
Bil. Dr.
30
25
20
15
10
5
0
-5
-10
-15
1960 1964 1968 1972 1976 1980 1984 1988 1992
Year


Changes in Stocks (at 1970 price levels)
Detrended Data (HP(100)-Filter)
Bil. Dr.
14
10
6
2
-2
-6
-10
1960 1964 1968 1972 1976 1980 1984 1988 1992
Year


Residual Demand (at 1970 price levels)
Detrended Data (HP(100)-Filter)
Bil. Dr.
10
6
2
-2
-6
-10
-14
-18
-22
-26
1960 1964 1968 1972 1976 1980 1984 1988 1992
Year

Summary

Is the Greek Economy Periodic?

The aim of this paper is to investigate stylized facts of GDP, and its components for the Greek economy, using the Maximum-Entropy Principle of Univariate and Multivariate Analysis. The empirical evidence, generally, supports the existence of cycles for all magnitudes, that can be decomposed into a long one and a short one. The empirical results are interesting insofar as the about same frequency parameters could be found by Hillinger (1992) in 15 OECD countries and by Woitek (1993) in the G7 countries.

Zusammenfassung

Ist die griechische Wirtschaft zyklisch?

Ziel dieser Arbeit ist die Darstellung stylisierter Faktoren des Bruttosozialprodukts und seiner Komponenten für die griechische Wirtschaft, wobei das Maximum-Entropy Prinzip der univariaten und multivariaten Analyse zur Anwendung kommt. Die empirischen Ergebnisse der Untersuchung lassen erkennen, daß für alle relevanten Größen Zyklen existieren, die jeweils in einen langfristigen bzw. kurzfristigen Zyklus zerlegt werden können. Ein interessanter Aspekt der Ergebnisse ist, daß die aus der vorliegenden Arbeit hervorgehenden Frequenzen auch bei den Untersuchungen von Hillinger (1992) für 15 OECD-Länder und Woitek (1993) für die G7-Länder zu finden sind.