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LEAD-LAG RELATIONS BETWEEN MONEY AND REAL MAGNITUDES IN THE FLUCTUATION OF GDP.
(A Multivariate Spectral Analysis for Greece)

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Abstract

The paper describes a method of determining the characteristics of economic fluctuations, which is applied to the real and money magnitudes for Greece. The results of univariate and multivariate spectral estimation confirm established business cycle stylized facts for Greece. (JEL CIO, E10, E50)

1. Introduction

The first aim of busines cycle model is to identify the basic dynamics of economic fluctuations, which are manifest in the most obvious stylized facts. These stylized facts are robust to the different types of noise in the data, such as measurement errors, influences of other, less important variables, etc.

Econometricians have been puzzled for a long time by the fact that their models usually yield high R^2 within the sample, but that the forecast errors of these models are typically much higher than should be expected. But the good fit is a matter of change, and breaks down outside the sample. My experience in modeling in the last years shows that it is easy to get a model with a good fit, much harder to get one that explains the stylized facts, and extremely difficult to find one that does both. If one accepts the basic premise from the philosophy of science that one has to subject one's theories to the most stringent tests possible,

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it is necessary to do a thorough analysis of the data to obtain as many sharply characterized stylized facts as possible.

Are the observed fluctuations irregular or do they show cyclical structure i.e. do they exhibit maxima and minima at reglar time intervals? If they show a cylcical structure, how many superimposed cycles can be identified? What can be said about the lenght of these cylces? How important are they? What can be said about lead-lag relationships between cycles in difference series?

There is a number of stylized facts concerning these questions, which have been identified beginning with the work of Juglar (1862). An overview of the literature on stylized facts of business cycles may be found in Hillinger (1992a).

The optimal method to answer the above questions 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 interpretable way. In recent years Maximum-Entropy (ME)-spectral estimation, a method developed by Burg (1975), was successfully applied at Seminar for Mathematical Economics (SEMECON), University of Munich, to the description of stylized facts regarding macroeconomic fluctuations.

Univariate spectral analysis can only answer the first four questions. For the last question i.e. the lead lag relationships between cycles in different series, a multivariate extension is needed.

Attempts to connect monetary phenomena, and business cycles often have been the province of economist who also accepted the Walsarian full employment paradigm. Monetary explanations of business cycles preceded Keynes (Zarnowitz 1985), and in the post Keynesian era Monetarists (Poole 1978) have tried to integrate monev into a disauilibrium account of fluctuations.

In this paper, first, the empirical evidence concerning the identification of cycles of the aggregate GDP, money supply (M1), (M2), private and public investment (Pr. In.), (Pub. In.), total credit (TC) and credit in the private sector (CPS) for the greek economy is presented and discussed. Second, we try to compare the lead-lag relations between monetary and real magnitudes in the fluctuation of GDP. We measure the degrees of relationship between the cycle in money (M1)/(M2)/total credit (TC)/Credit in private sector (CPS) and the cycle in GDP, and then we measure the degrees of relationship between the cycle in private (Pr. In.) /public investment (Pub. IN) and the cycle in GDP.

In the second part, we briefly describe multivariate ME-spectral estimation and discuss soime of the problems connected with the application to economic series. In the third part, a univariate and multivariate analysis of the time series for Greece is given. The GDP series is taken as reference.

2. Methodology

For the application of spectral analysis, it is necessary to have a stationary series. But since 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, for example using a linear time trend. Beginning with the influential work of Chan, Hayya and Ord (1977) and Nelson and Kang (1981), 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 introduced by Fuller (1976) and Dickey (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 and Ploesser (1982)). If we want to believe this test, this outcome suggests tp 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 is would be impossible to give a different economic interpretation (see Nelson and Plosser) (1982), p. 152).

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 by Rudebusch (1992) amd (1993) the DF-test has low power not only against alternatives which are close to the null model but even against alterantives 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 cuclical structure. We decided therefore to use tyhe Hodrick-Prescott (HP-) filter (Hodrick and Prescott 1980), which in a recent simulation study at SEMECON (Hillinger, Reiter and Woitek 1992) proved to produce less severe distortions than other widely used detrending procedures, if carefully used.

The Hp-filter is defined by

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

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 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 (see Harvey and Jaeger (1991), King and Rebelo (1993)). As stated above, there is no method available to reliably distinguish between the DS- and the TS-model. Therefore, we analyzed the cyclical structure of both the output series of the HP-filter and the difference filter. 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 $f(\omega)$ of a univariate stochastic process is the Fourier transformation of the covariance function of the process (see e.g. Brockwell and Davis 1991, pp. 114-158):

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

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 $F(\omega)$ is an even function, it is sufficient to look at it in the interval $[0, \pi]$. The diagonal elements $f_{11}(\omega), \ldots, f_{nn}(\omega)$ are the real valued autospectra of the n 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 expained 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 (See Priestley 1981, pp. 513-517). 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 estimate 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 *al.*

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

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

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

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

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

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

$$\gamma_{jk}(\omega) = \frac{|f_{jk}(\omega)|}{f_{jj}(\omega)} \tag{8}$$

The phase spectrum

$$f_{jk}(\omega) = \arctan(-q_{jk}(\omega) / c_{jk}(\omega)) \tag{9}$$

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.

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 of the Greek GDP and its components.

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.

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

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

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 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, see e.g. Priestley (1981), p. 602). The CAT-criterion is defined by

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

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 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, 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 to compare the results for VAR-processes of different order estimates. In this paper, the order is based on what the autospectra shows similar characteristics as the respective univariate spectra, judged by visual examination.

3. Estimation of the GDP/Pr. In./Pub.In./Ml/M2/TC/CPS -Spectra

The section describes how the methodology was utilized in order to obtain a description of the cyclical characteristics of the money, defined as Ml (currency in circulation and sight deposits), the M2 (Ml plus time deposits), the total credit (TC), the credit in private sector (CPS) at nominal prices, the private investment (Pr.In.), the public investment (Pub.In.) and the gross domestic product (GDP) at constant 1970 prices. The observation period is 1960-1990, with annual data. The data were obtained from the National Accounts of Greece and the Bank of Greece.

First, the data are detrended using the procedure described in Section 2. In the next step, the univariate ME-spectra of the detrended GDP-M1-M2-TC-CPS-Pr.In.-Pub.In. series are estimated using the Burg-algorithm or the Fougere-argorithm, if the reflection coefficients estimated by the Burg-argorithm do not fulfil the stationarity condition. After that, the multivariate ME-spectra for the time series are estimated.

In order to remove any structural changes (we see it at time 1973) we have estimated a changing-growth model:

$$y_t = \mu + \beta t + \gamma DT_t + J_t \ ; \ t = 1, ..., TB, ..., T; \tag{13}$$

with

$$DT_t = \begin{cases} t - T_B & \text{for} \quad t > T_B \\ 0 & \text{for} \quad t \leq T_B \end{cases} \tag{14}$$

T_B is equal 14 and J_t is a AR(2) process:

$$J_t = \rho_t \, y_{t-1} + \rho_2 \, (1 - \Lambda) \, \upsilon_{t-2} + u_t \ ; \ u_t \sim NID\,(0, \sigma^2).$$

We test whether the coefficient of pi is zero against the alternative that it is negative. If the null hypothesis is true, then this regression has an 1(0) variable on the first difference and 1(1) on the level (Perman, 1991). The results, presented in table (1), suggest that all variables are nonstationary in levels, so we can't reject the null hypothesis, whereas they are stationary in first difference. (The calculation of critical values for these tests is not straightforward since the exact critical values are themselves functions of the data generation process. Engle and Grager (1987) provide exact critical values using Monte Carlo methods for two different data generating process. Their computations suggest that a 95 per cent confidence interval is given by -3.96 for the ADF statistic). So it is not possible to reject the hypothesis that the data generating process can be represented by random walk with drift. Given this result, blind confidence in the reliability of the DF-test is equal to use of the difference filter which leads to the well known distortions in the cyclical structure. Proceeding in the way described in section 2, it can seen that all series show cyclical structure after taking first differences. Based on these outcome we can be confident that the cyclical structure in these series is not generated by the detrending methods.

In Table 2 the results from univariate spectral estimation are displayed. The order of the AR- model was chosen applying the procedure described in Section 2. The upper bound is derermined by the 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 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/Pr.In./Pub. In. - univariate spectral analysis 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 (Pr. In.) with a length of about 9.6 years ha s (pp) of 41 per cent, while the short cycle with a length of about 4 years has a peak power of 9 per cent. In the (Pub. In.) with a length of 10.4 years has a peak power of 28 per cent, while the short cycle with a length of 4 years has a peak power of about 12 per cent. If we compare (Pr. In.) and (Pub. In.), we have: The long cycle has the highest peak power in (Pr. In.). An additional result is that the higher the modulus of a complex root, the higher the peak power of the corresponding cycle.

It is very important to note, that Ml has the same length of period with GDP. For the money supply Ml the most dominant cycle is the long one. We see that there is a long cycle in Ml with a length of about 9.6 years and a peak power of about 23 per cent, while the short cycle with a length of about 2.7 years has a peak power of less than 5 per cent. For the money supply M2 the dominant cycle is the long one. We see that there is a long cycle in M2 with a length of about 5.5 years and a peak power of 32 per cent, while the short cycle with a length of about 2.5 years has a (pp) of 10 per cent. For the total credit and for the credit in the private sector the dominant cycle is the short one. We see that there is a long cycle in (TC) with a length of about 13.5 years and a peak power of about 12 per cent, while the short cycle with a length of 3 years has a (pp) 13 per cent. In the (CPS) with a length of about 14 years has a peak power of less than 7 per cent, while the short cycles with a length of about 4 years has a peak power more than 12 per cent.

A visual inspection of the diagrams (GDP, Pr.IN., Pub.In.) shows, that the cycles seem to change pattern, though not always in the same degree, their amplitude becoming wider after approximately the oil crisis of 1972. This is possibly indicative of an increased instability related to international economic factors and the structure of 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.

The results for the multivariate analysis are given in table 3. Only the lead-lag relationships between the GDP, the private investment (Pr.In.), the public investment (Pub.In.), the total credit (T.C.), the private credit (CPS), the money supply (Ml) and money supply (M2) are discussed here; the GDP series is taken as reference.

Based on the prodecure by Lutkepohl (1991) a comparison of estimated orders recommended by CAT criterion for multivariate time series suggests the fitting of second order filters to the detrended data. From the visual comparison of univariate and the autospectra it can be seen that results are similar to the univariate spectra. As it was expected, the peaks in the autospectra of GDP/Ml/M2/TC/CPS/Pr.In./Pub.In.- 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 3 it can be seen that the squared coherency is relatively high for the (GDP/Pr.In.) - relation and for the (GDP/Pub.In.)- relation. The squared coherency of (GDP/Pr.In.) - relation is greater than the squared coherency of (GDP/Pub.In.) - relation. So the degree of the linear relation between the cycle of private investment with period 9.8 years and the cycle of GDP with the same period is 60.7 per cent. The degree of the linear relation between the cycle of public investment with period 10 years and the cycle of GDP with the same period is 60.1 per cent. It is important for these very small 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. In general we think that, this evidence supports the conclusion, that both private and public sector respond in the same way, to the circumstances promoting the desicion to invest. This is at least a general trend, though the post 1982 period appears to have been subject to non-economic forces that created temporarily a deviation from that trend.

The squared coherency of GDP/Ml is relatively low. This means that money supply affects (exist a linear relationship) the cyclical fluctuation of real GDP, but without a great power. The degree of the linear relation between the cycle of Ml with period 8 years and the cycle of GDP with the same period is 52.6 per cent. The degree of the linear relation between the cycle of M2 with period 4.4 years and the cycle of GDP with the same period is 41 per cent. If we compare the squared coherency between Ml and M2 we shall have: The squared coherency of GDP/Ml is relatively above the squared coherency of GDP/M2. The squared coherency GDP/TC and GDP/CPS-relations are relatively low. If we compare the GDP/Pr. In. and GDP/Ml-relations we have: The squared coherency of GDP/Pr.In. is relatively greater than the squared coherency of GDP/Ml relation. The phase shift of GDP/Pr.In. is smaller than the phase shift of GDP/Ml relation.

It is important to note that, the structure and the functioning of financial markets in countries with the characteriostics of Greece, were until 1987 very little developed. Historically the functioning of the financial system in Greece has been heavily regulated. The role of monetary and credit policies in Greece was not limited to controlling the overall expansion of credit and money aggregates. Throughout the post-war period until 1987, the controls over credit aggregates and the allocation of credit were supplemented by a comprehensive system of interest rate regulation. Qualitative changes in the credit market have been pursued along with the quantitatives ones. Prior 1986, the authorities determined the sectoral allocation of credit within the overal credit ceilings for each specialized credit institution as well as the conditions and terms under which loans should be granted. Only recently, in 1987 and 1988, did the authorities take steps to dismantle this system. In the financial area, several initiatives have been taken: the compulsory investment by commercial banks in treasury bills was reduced, long-term capital movements were liberalized, restrictions on consumer credit and on foreign currency loans to residents were lifted. However, the structure of rates is still effectively influenced by the authorities through their control of interest rates on saving deposits. In order to play a greater role in money supply and affect more the real fluctuations in GDP, the interest rate should be totaly determined by the money market.

4. Conclusions

The above analysis has confirmed that traditional univariate business cycle stylized facts apply to the greek -GDP, the private investment, the public investment, the total credit, the private credit, the money supply (Ml) and money supply (M2). To these results multivariate stylized facts concerning the lead-lag relationships of the series were added. It has been shown that spectral analysis is a powerful tool for the description of cyclical characteristics of macroeconomic time series.

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. In the detrended money supply (Ml) a long and a short cycle can be found with the same length of period of GDP. In the detrended (M2) the dominant cycle is the long run with a length of 5.5 years. In the detrended (TC) a long cycle can be found with a length of about 13 years. The dominant cycle is the short one. The period of this cycle lasts 3 years. In the detrended (CPS) a long and a short cycle can be found with a length of about 14 years and 4 years, respectively. The dominant cycle in this series is the short one. In the (Pr.In.) the dominant cycle is the long one. The period of this time series is 9.6 years. In the detrendet (Pub.In.) a long and a short cycle can be found with a length about 10 years and 4 years, respectively. The peak power of the (Pr.In.) is greater than the peak power of the (Pub.In.).

An important result is that money supply affects the fluctuations of GDP, but without a relatively great power. The degree of the linear relation between the cycle of Ml with period 8.1 year and the cycle of GDP with the same period is 52.6 per cent. From the other hand, the degree of the linear relation between the cycle of (Pr.In.) with period of about 10 years and the cycle of GDP with the same period is 61 percent. The squared coherency of GDP/Ml is smaller than the squared coherency of GDP/Pr.In.relation. The phase shift of GDP/Pr.In. is smaller than the phase shift of GDP/Ml relation.

The business fluctuations are an international phenomenon whose occurrence in greek economy is not astonishing, because of their great dependence on capital and industrial transfer from abroad.

Appendix

TABLE 1

Greece, ADF- and Perron- Test

	μ	β	γ	ρ_1	ρ_2	$\hat{\tau}$	R^2
GDP	53663.98 (14697.4)	7013.07 (2234.42)	-3245.23 (1048.5)	0.584 (0.135)	0.166 (0.181)	-3.075	0.996
Pr.Inv.	11425.26 (4159.53)	1384.06 (813.8)	-1419.20 (1026.15)	0.539 (0.203)	0.385 (0.212)	-2.374	0.856
Pub. Inv.	5236.68 (1897.14)	458.16 (217.41)	-454.57 (267.53	0.517 .	0.506	-3.012 (0.160)	0.829 (0.198)
M_1(logs)	1.153 (0.809)	0.020 (0.014)	-	0.891 (0.086)	0.056 (0.198)	-1.270	0.999
M_2(logs)	0.443 (0.220)	0.020 (0.014)	-	0.906 (0.072)	-0.070 (0.208)	-1.310	0.999
TC (logs)	2.243 (0.898)	0.041 (0.016)	-	0.790 (0.083)	0.182 (0.226)	-2.542	0.999
CPS (logs)	0.397 (0.259)	0.015 (0.017	-	0.905 (0.094)	0.372 (0.196)	-1.018	0.999

In parenteses are the s.e. GDP (Gross Domestic Product), Pr. Inv. (Private Investment), Pub. Inv. (Public Investiment), M1 (Money Supply M1), M2 (Money Supply M1), TC (Total Credit), CPS (Credit in Private Sector).

moduli of the series after taking differences
GDP (0.88) Pr. Inv. (0.73) Pub. Inv. (0.545) M1 (0.861) M2 (0.938) TC (0.766) CPS (0.799)

TABLE 2

Greece, Univariate Analysis

	GDP	M1	M2	Total Credit	Credit in Private Sector	Private Invest-ment	Public Invest-ment
Period	9.376 3.455	9.645 2.66	5.483 2.525	13.366 3.156	13.803 4.253	9.629 3.890	10.368 4.109
moduli	0.765 0.671	0.857 0.563	0.855 0.777	0.823 0.829	0.619 0.718	0.939 0.815	0.908 0.838
pp	0.137 0.087	0.228 0.049	0.325 0.104	0.128 0.130	0.064 0.127	0.417 0.081	0.280 0.116
S.N.R.	6.835	6.818	7.835	6.354	9.191	8.844	11.574
AR-Order	4	4	6	4	4	5	5

TABLE 3

Greece, Multivariate Analysis

	Cycle Length at maxima of Autospectra	Squared Coherency	Phase Shift	Gain
GDP / M1	8.197	0.526	2.083	3.075
GDP / M2	4.386	0.411	-1.582	2.846
GDP / TC	3.413	0.372	-0.103	4.452
GDP / GPS	4.032	0.303	-0.095	3.749
GDP / Pr.In.	9.804	0.607	-0.312	1.581
GDP / Pub.In.	10.000	0.601	-0.418	1.376

TC (Total Credit), CPS (Credit in Private Sector), Pr.In. (Private Investment), Pub.In. (Public Investment), M1 mCurrency and sight deposits), M2 (M1+time deposits)

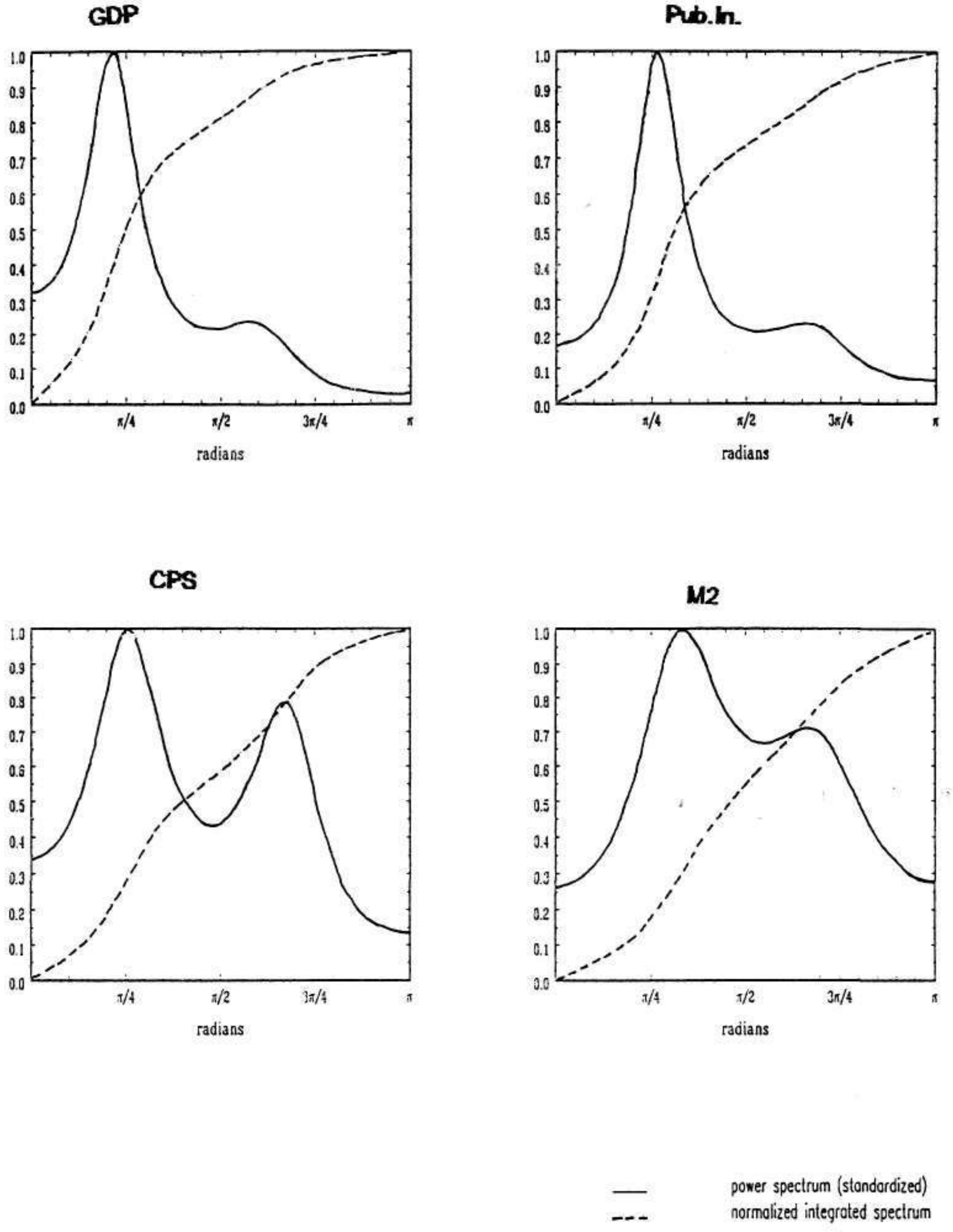

Fig. 1. (Maximum Entropy) Spectra

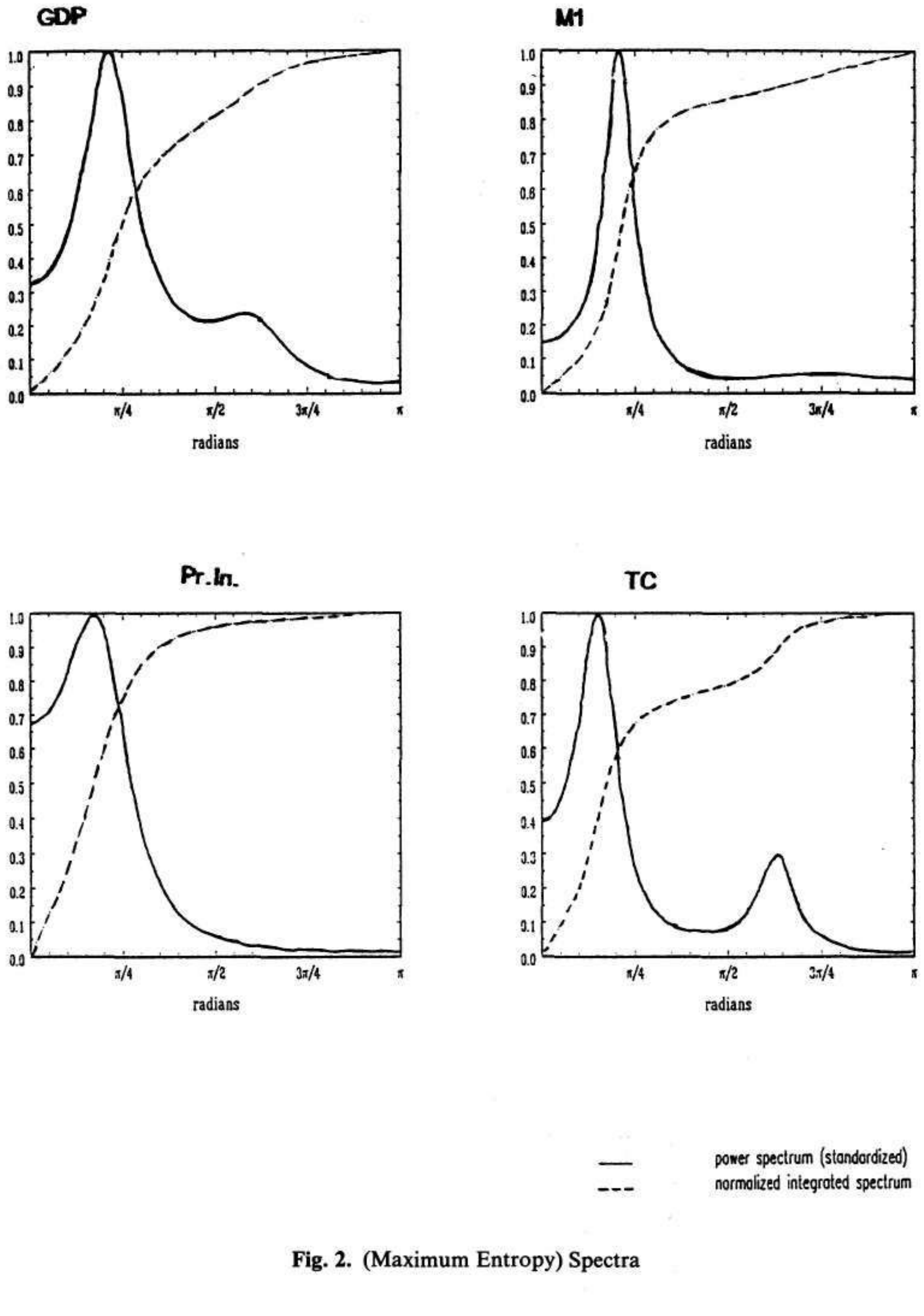

Fig. 2. (Maximum Entropy) Spectra

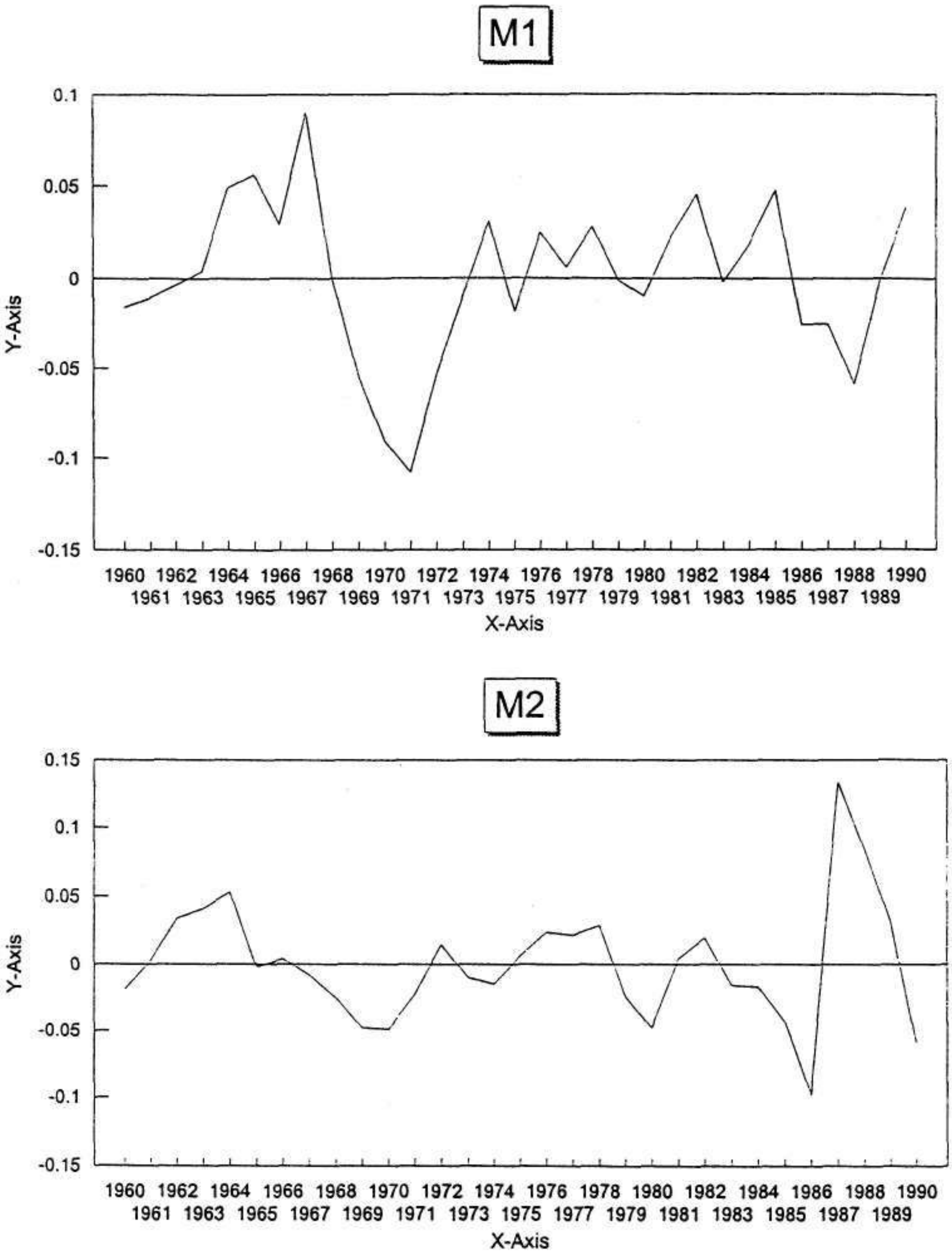

Fig. 3. Diagrams of the Detrended Data

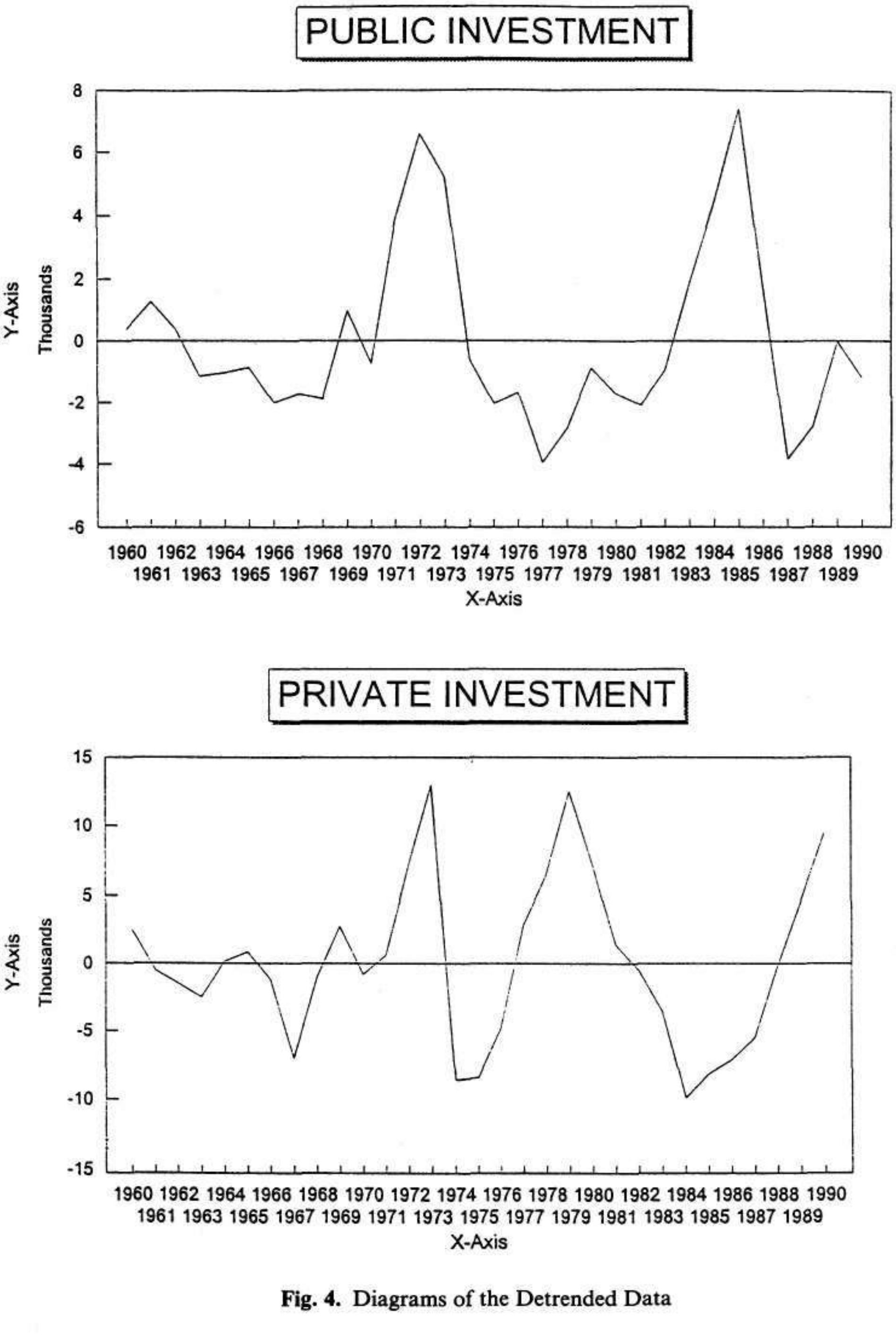

Fig. 4. Diagrams of the Detrended Data

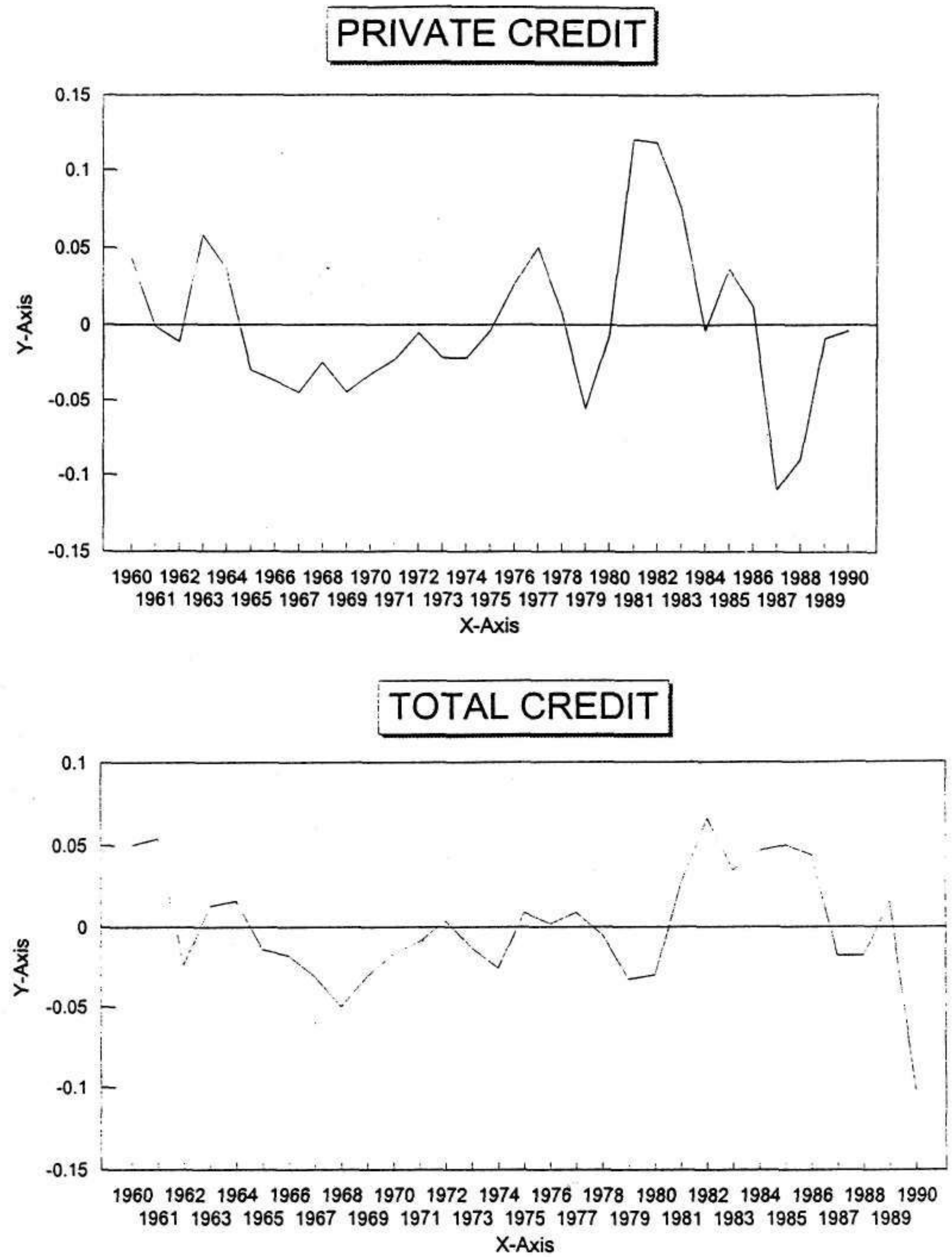

Fig. 5. Diagrams of the Detrended Data

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