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Choosing the best type of wavelet: Case study-business cycle in Iran

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Abstract

The main purpose of this paper has been determined the best type and length of the wavelet used the case study business cycles of Iran during the period 1978-2010 and on the bases on quarterly data. Therefore Haar, Daubechies, Symmelets, Coiflets and biorthogonal wavelets was used to level 5, and the quarterly log GDP were decomposed to 370 series of (185 series of quarterly business cycle and 185 series of trend). First by using the correlation index, the same series was removed and then by wavelet simulation, series were simulated for the period 2005-2010. Our findings indicate that while the majority of research conducted have chosen Daubechies wavelet, the biorthogonal wavelet have a higher quality and comprehensiveness than the Haar, Daubechies, Symmelets, Coiflets wavelets. The study of types of biorthogonal wavelet shows that bior2.2, bior3.1, bior2.6, bior5.5, bior1.1, bior1.5 and bior1.3 respectively, have the highest quality of decomposition and smoothing the business cycle in Iran. In order to provide more accurate results, the business cycle was also examined on an annual basis. The results showed that the business cycle shows high sensitivity and inverse to the level and type of the selected wavelet. It is proposed that when annual data are used, the choice of wavelet level is low (maximum 3) and If the data is monthly or quarterly, high-level wavelet (minimum of 4) is selected.

Keywords: Wavelet, filtering, simulation, business cycle, daubechies and bi-orthogonal

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Introduction

After nearly a century, of the first scientific study of the business cycle, there are some conflicts about causes and how to handle this important variable in the economy. Traditional analysis methods of business cycles, such as correlation analysis and the spectral analysis of the fictional character does not considered historical data (transition time) in the terms of their reviews. According to the Lucas (1977) article, "Understanding Business Cycles" shows that variations repeatable business cycle of real GDP is around its long-run.

This perspective caused a lot of methods development to determine the business cycle so that current, determine the appropriate methods of smoothing time-series analysis methods are difficult. This difficulty has led researchers to use filtering methods to taste the results with errors.

The significance of this error in economic planning and predicted future developments in the economy has resulted in recent years, that time series analysis methods developed within the framework of linear filters, such as Hodrick - Prescott (1997), Bandpass (Baxter and King, 1999), and wavelets and their generalizations strongly considered. Theoretical Reviews show that the wavelet method is an appropriate mathematical tool for signal analysis and display them at various levels. In this method, a time series of the frequency amplitude could be studied in different times and with different views.

According to Ramsey (1999 and 2002), this method is a useful tool for the study of business cycles. However, the wavelet methods, has a different tools for different wavelengths and frequency smoothing. In these circumstances, the problem of selection is difficult.

This paper tries to illustrate the difficulty and how to choose the appropriate method using wavelet technique, between the Haar wavelets, Daubechies, Symmelets, Coiflets, of two Biorthogonal wavelength maximum of 5 levels, the best type to wavelet smoothing in the business cycle in Iran, seasonality during the period 1389-1357 to examine the use of MATLAB software. To address this issue, the paper is organized in five sections. After the introduction, the second section presents the theoretical model. Research carried out in the background and theoretical foundations are presented. The third section is a review of research methods and data analysis. Then findings were analyzed and results will be presented in the fifth section.

Theoretical framework model

Theoretical foundations of wavelet

In 1822, French mathematician and physicist, Jean Baptiste Joseph Fourier, in the book of Analytical Theory of Heat showed that any periodic function (signal) can be defined as an infinite set of the periodic complex exponential functions (Ozgonenel *et al.,* 2004). Graps (1995) showed that the wavelet decomposition, such as Fourier transform, is not a set of the basic functions signal that the cosine and sine functions are used. Wavelet decomposition consists of an infinite set of the possible basis functions which, unlike other methods, there is instant access to information. Therefore, according to analysis is based on Fourier, Wavelet analysis of time series can be analyzed at different time scales, or different investment horizons to be parse (Kim *et al.,* 2002). Whereas other statistical methods, only time domain or frequency range for the analysis of financial time series are considered.

This feature is has caused time frequency of the wavelet analysis in time series modeling economic and financial time series widely used (Gencay *et al.,* 2002). In wavelet analysis, a signal is shown as a linear combination of the wavelet functions (Cifter and Ozun, 2007; 2008). According to length of the data, there are two main wave of wavelet. The first wave is the continuous wavelet transform (CWT) which defined to work with time series on the whole real axis design. Second wavelets, is discrete wavelet transform (DWT).The wavelet might study to isolate a series of tests at different frequencies in depth (Conlon *et al.,* 2008). In this field wavelet decomposition can be divided into two types: The father wavelet (φ) and mother wavelet (Ψ).

$$\int \psi(t)dt = 0 \qquad \int \varphi(t)dt = 1 \qquad \text{---------------------------(1)}$$

These wavelets are defined as follows: Flat and low-frequency components of a signal, shown using wavelet is a father and mother wavelets, in order to show more detail and high-frequency components are used. Father and mother wavelets, is shown in order equation (2) and (3).

$$\varphi_{j,k}(t) = 2^{-\frac{j}{2}}\varphi\left(\frac{t-2^j k}{2^j}\right) \qquad \text{--- (2)}$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi\left(\frac{t-2^j k}{2^j}\right) \qquad \text{--- (3)}$$

Functions which turn approximation of wavelet are and translated and scaled versions of Ψ and by the scale or dilation factor is 2j. The estimate of an orthogonal Wavelet series to a signal is obtained by equation (4).

$$f_j(t) = \sum_k S_{j,k}\varphi_{j,k}(t) + \sum_k d_{j,k}\psi_{j,k}(t) + \ldots + \sum_k d_{l,k}\psi_{l,k}(t) \qquad \text{----------------------- (4)}$$

In this equation, j is Multi-scale analysis of the relation and k is a range from one to the number of coefficients in the corresponding parts. Also, the detail coefficients ($d_{j,k}$,...$d_{l,k}$), are considered the higher frequency fluctuations and variations to be the small-scale equation (5) are shown. Smooth surface coefficients ($S_{j,\,k}$) take the behavior of process and calculated as equation (6):

$$d_{j,k} = \int \psi_{j,k}(t) f(t) dt \qquad j = 1,\ldots,J \qquad \text{--- (5)}$$

$$s_{j,k} = \int \varphi_{j,k}(t) f(t) dt \qquad \text{-- (6)}$$

Where the $S_{j,k}$ represents the smoothness coefficients or approximation Coefficients and $d_{j,k}$ is a coefficients of details or wavelet.

Wavelet series approximation of the original signal *f(t)*, as the relation (7) is composed sectors of signal detail and smooth signal:

$$f(t) \approx S_J(t) + D_J(t) + D_{J-1}(t) + \ldots + D_l(t) \qquad \text{-- (7)}$$

In the above equations $S_J(t)$ and $D_J(t)$ defines as a (8) and (9) equations.

$$S_J(t) = \sum_k s_{J,K}\varphi_{J,K}(t) \qquad \text{-- (8)}$$

$$D_J(t) = \sum_k d_{J,K}\psi_{J,K}(t) \qquad \text{-- (9)}$$

The terms in equation (7), shows a signal decomposition orthogonal $S_J(t) + D_J(t) + D_{J-1}(t) + \ldots + D_l(t)$ signal components at different scales. Estimating equation (5) is called as a multi-analytic decomposition (MRD). So, each point can be represented as a set of wavelet details and smooth wavelet is decomposed on different time scales, Smooth coefficients mainly affect the behavior of the data, Whereas coefficients of Details, shows the deviation of the behavior of small-scale.

Fernandez (2006) shows that the most commonly used wavelets are the orthogonal wavelets. Therefore, the article will reviewed the Haar wavelets orthogonal and their classification, Daubechies, Symmelets, Coiflets, two orthogonal. Other types of wavelets can also be noted are rbior, Meyr, dmeyr, gaus, mexh, morl, cgau, shan, fbsp, cmor. These wavelets have not been studied yet.

Types of wavelet

Daubechies wavelet

The wavelet that the subset of orthogonal wavelets, briefly shown as dbN. Symbol N represents the degree of the wavelet. If the degree of a wavelet is 1 (db1) it will be equal with the Haar mother wavelet. In the Haar wavelet, father and mother wavelets are defined as follows:

$$\psi(x) = \begin{cases} 1 & if \quad x \in [0,0.5[\\ -1 & if \quad x \in [0.5,1[\\ 0 & if \quad x \notin [0,1[\end{cases} \qquad \text{-- (10)}$$

$$\varphi(x) = \begin{cases} 1 & if \quad x \in [0,1] \\ 0 & if \quad x \notin [0,1[\end{cases} \qquad \text{-- (11)}$$

The general form of the Haar wavelet is as follows:

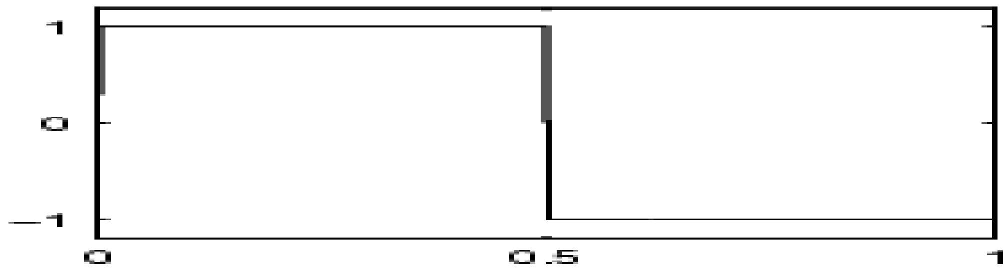

Figure 1: Overview Haar wavelet

Other degree of wavelet doesn't have special definition and have a general definition as follows:

$$P(y) = \sum_{k=0}^{N-1} C_k^{N-1+k_y k} \qquad \text{-- (12)}$$

In this equation, C_k^{N-1+k} represents the coefficients of the binomial distribution.

$$\left|m_0(\omega)\right|^2 = \left[\cos^2(\frac{\omega}{2})\right]^N P\left[\sin^2(\frac{\omega}{2})\right] \qquad \text{--} (13)$$

The relationship is $m_0(\omega) = \frac{1}{\sqrt{2}}\sum_{k=0}^{2N-1} h_k e^{-ik\omega}$. The overall picture of Daubechies wavelet to level 10 is as follows:

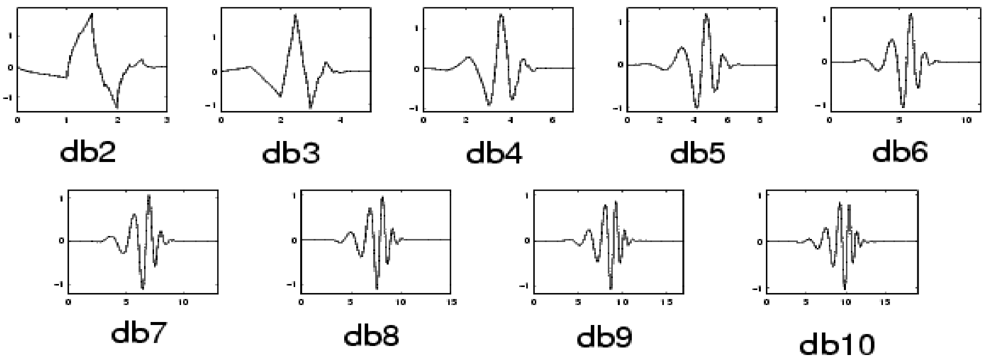

Figure 2: Overview daubechies wavelet

As it is clear on figures, with increasing the degrees of wavelets, the frequency of wavelet would be associated with greater detail.

Symmelets wavelet

The wavelet it is shown by symN, is a special stipulation of the Daubechies wavelet. So that the equation (13) is same and there is other equation is to add which is defined as follows:

$z = e^{i\omega}$ و $W(z) = U(z)U(\frac{1}{z})$ -- (14)

If the root of the above equation is less than 1, then it is equal to the dbN wave. It is also be noted that in this wavelet (sym1) is the same as Haar wavelet either. The wavelet symN's image to level 8 is as follows:

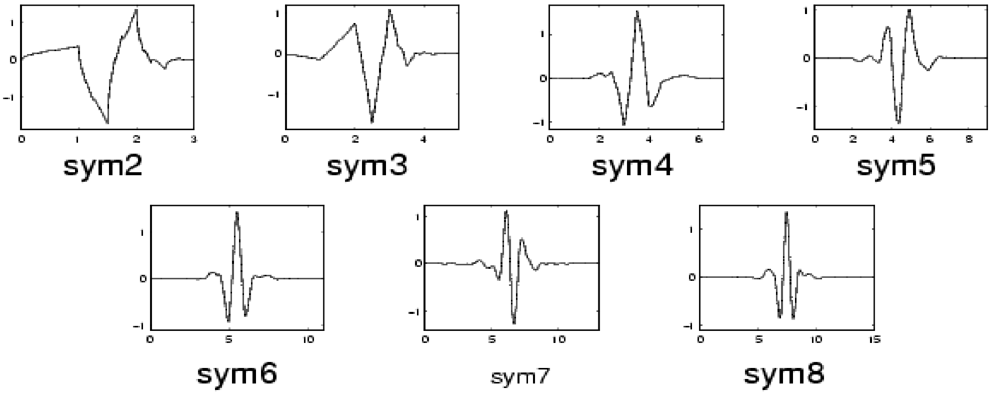

Figure 3: Overview symmelets wavelet

As it is clear from the figures, with increasing degrees of wavelets, wavelet frequency would be associated with greater detail.

Coiflets wavelet

This wavelet (coifN) places according to the definition size of the mother and father wavelets, the wavelets db2, sym2 and db3, sym3 and the overall picture is as follows:

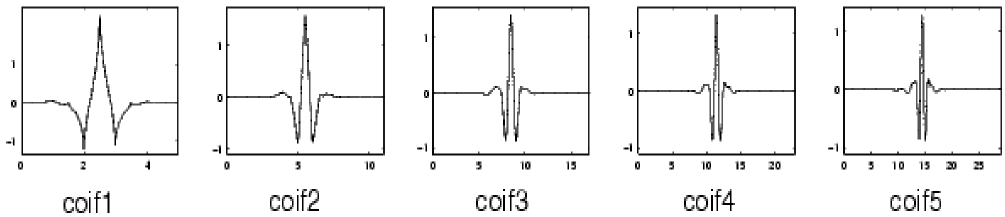

Figure 4: Overview coif lets wavelet

As it is clear from the figures, with increasing degrees of wavelets, wavelet frequency would be associated with greater detail.

Biorthogonal wavelet

The wavelet is briefly shown as biorNr.Nd. Unlike the previous wavelets which were orthogonal and had a single wave, these wavelets are biorthogonal. In this kind of wavelet, symbols Nr refers to the first degree and Nd refers to the second degree of wavelet. The original mother and father's wavelet defines as follows:

First Mother Wavelet) $\tilde{\psi}$ ($\tilde{c}_{j,k} = \int s(x)\tilde{\psi}_{j,k}(x)dx$ ---(15)

Second Mother Wavelet (ψ) ($s = \sum_{j,k} \tilde{c}_{j,k}\psi_{j,k}$ --------------------------------------- (16)

For $j \neq j'$ or $k = k'$, $\int \tilde{\psi}_{j,k}(x)\psi_{j',k'}(x)dx = 0$ and for $k = k'$ there is $\int \tilde{\varphi}_{0,k}(x)\varphi_{0,k'}(x)dx = 0$. Original view of this wavelet is:

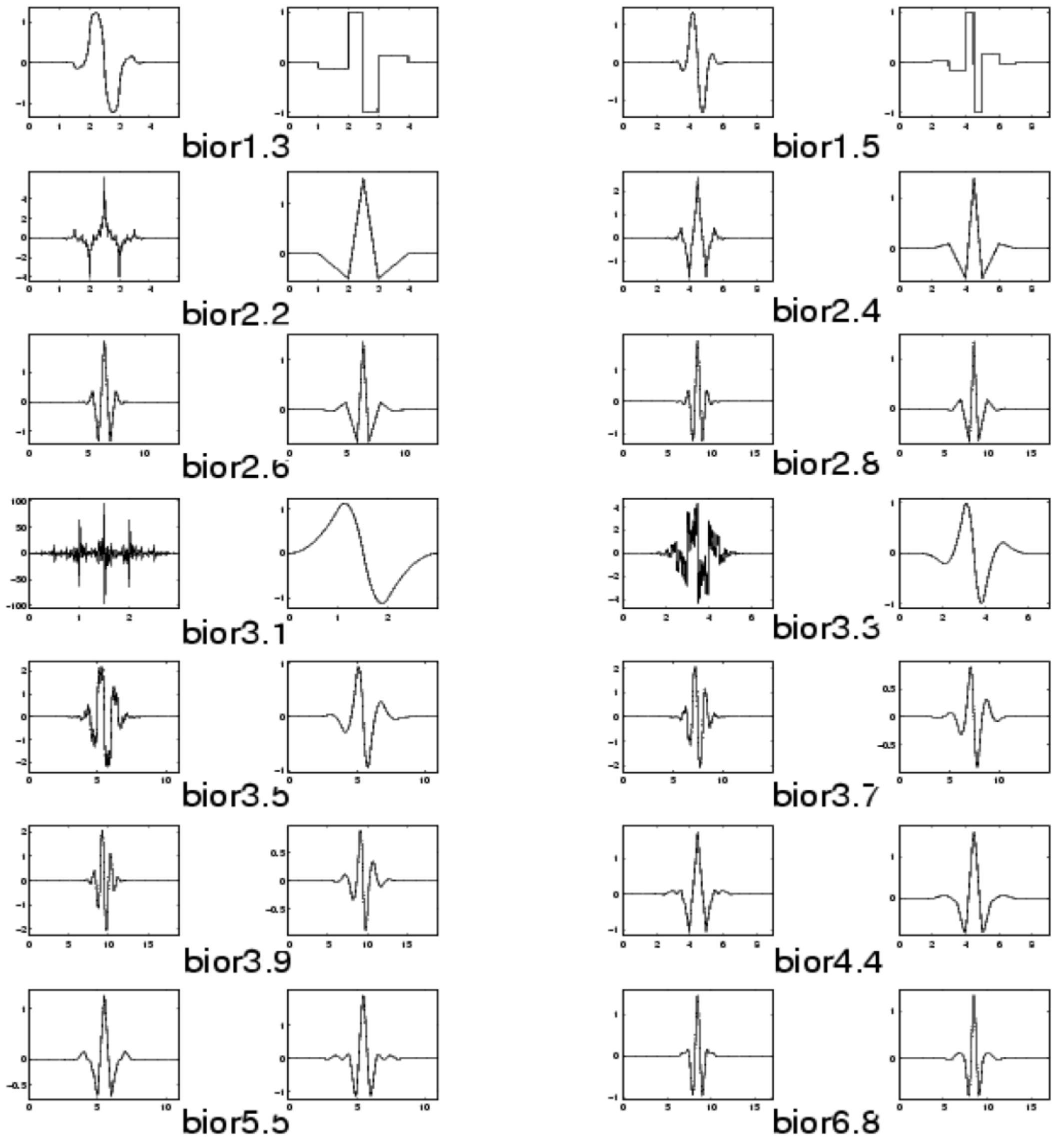

Figure 5: Overview biorthogonal wavelet

Experimental literature

Ramsey and Zhang (1997) have studied the original signal of exchange rate. The results of this study shows that wave analysis of the same data, can be investigated only in the very low frequencies (periods greater than two hours). Ramsey and Lampart (1998a, 1998b) examined the relationship between money supply and income in their first study and for the next study investigated the relationship between income and expenses.

Their results indicate that in the area of time variations, the ability of regression criteria based on wavelet analysis are more than common regression. Yao and partners (2000) using neural networks and wavelet transform for short-term electricity demand forecasts show that the wavelet transform method is the useful to forecast demand cycles.

Alrumaih and partners (2001) use the wavelet method to predict the stock index of time series of Saudi Arabia (SSI) during the period (1999-1994).Their results show that the prediction errors while using the first threshold index for soft noise decreases (assuming white noise). Zhang and Dong (2001) using the wavelet transform technique for short-term forecasts in Australia; have shown that this model gives better results than linear models.

Kim *et al.* (2002) using Wavelet transform and neural networks to predict short-term electricity demand in South Korea show that these models are effective tools for short-term forecasting. Lee (2002) by used the wavelet method, were reviewed the effect of volatility on stock markets (2002-1995). This paper uses wavelet method and analyzed the price and the impact of fluctuations in the stock markets, dynamics and the potential interaction and behavior of international stock markets. Gencay and Partners (2003) used the wavelet analysis method to calculate the systemic risk stocks America. The results of the study show the relationship between stock returns and beta is stronger with increasing scale. Therefore, the prediction of the capital asset pricing model (CAPM) in the medium-term and long-term perspective is more appropriate.

Gerlach (2004) and Assenmacher and Gerlach (2008a, 2008b) were investigated the relationship between money and inflation in consumer prices in different time horizons and found a long-term stable relationship, but the relationship between short-term and mid-term is unstable. Kim and In (2005) studied the relationship between inflation and stock returns in Australia for a period of 128 months (short term, medium term and long term) by using the new approach wavelet.

The results of this study indicate that the relationship between inflation and stock returns in the short term (one month) and long term (128 months) is positive while it is negative in the medium term. Raihan (2005) using a wavelet filter, and have studied the business cycle. This method is able to check the unstable time series. Besides this method, not only check the shocks that cause business cycle, but also identify and review the business cycle frequency conditions. Gallegati and Gallegati (2005) were reviewed wavelet variance of the index of industrial production in the G7 nations between the years 2005 to 1961.

Analysis was carried out using a multi scale. Results showed industrial output variance and covariance of the two countries based on the classic non-orthogonal wavelet transforms (the maximum overlap discrete wavelet transform (MODWT)) and is biodegradable. Fernandez (2006) by using wavelet analysis studied the relationship between stock returns and systematic risk can be assessed at different time scales. According to these results, capital asset pricing model (CAPM) protected the medium term investment.

Conraria and Soares (2006) were used the wavelet analysis and Granger causality test to analyze the effects of time frequency (frequency) of changing oil prices on macroeconomic United States of America (2000-1940). Their results showed that the volatility of inflation and industrial production growth rate were declined in the Fifties and sixties, and then its balance. However, due to the 1970 because of oil crisis, it was temporarily interrupted and has been felt in the mid-1980s.

Yogo (2008) was reviewed America's business cycles by using Wavelet Multi Resolution Analysis (2002-1947). Analysis of economic time series are decomposed into different frequency components of long-term trend, the business cycle and high frequency noise.

This paper shows the method for real GDP and inflation suggests that the business cycle of time series by wavelet filter has a very similarity with the time series is filtered by the approximation filter Bandpass. Dowd and *et al.* (2011) offered wavelet methods for estimating core inflation in the United States of America during the period 2002-1967. Measurement results show that the wavelet method is better than traditional methods.

Data and methodology

This study uses a Haar, Daubechies, Symmelets, Coiflets and Biorthogonal wavelets to level five, analyze and smoothing the logarithmic GDP quarterly data over the period (1389-1357) and

MATLAB software. Therefore, by using the MAM (Moving Average Method), the previous seasonally adjusted data, transforms to the after seasonally adjustment. Since quarterly data are not available for some years, by using the method of Diz (1970), the annual seasonal data have been storage.

In this method, it is assumed that the X_t is value of the variable at time t. Then the seasonal values qi ($i = 1,...,4$) is obtained as follows:

$$q_1 = X_{t-1} + \frac{7.5}{12}(X_t - X_{t-1}) \qquad (17)$$

$$q_2 = X_{t-1} + \frac{10.5}{12}(X_t - X_{t-1}) \qquad (18)$$

$$q_3 = X_t + \frac{1.5}{12}(X_{t+1} - X_t) \qquad (19)$$

$$q_4 = X_t + \frac{4.5}{12}(X_{t+1} - X_t) \qquad (20)$$

$$X_{it} = \frac{4X_t}{q_1 + q_2 + q_3 + q_4} \times q_i \qquad (21)$$

Whereas five levels of the wavelets will be checked, the number of wavelet Daubechies is 50, Symmelets is 35, Coiflets is 25 and biorthogonal is 75.

Thus the logarithm of the GDP quarterly series will break down to 370 series (185 logarithmic series and 185 series of the cyclical business).

Due to the large number of series using correlation analysis, the same series deleted and the different business cycle can be chosen. Initially the wavelet series were arranged based on the biorthogonal, Daubechies, Symmelets and Coiflets.

By use of correlation analysis index, a top of 80 percent wavelet-season correlation series of business cycles as compared to other wavelet series are the ideal choice. For example, in this method, if the seasonal business cycles of the wavelet coefficient time series of a Wavelet bior1.3 are db1 97% and sym3 87; because of these three series are shown very close to the business cycle, so bior1.3 series will be selected as representative. In fact, there will be used a mother wavelet as a representation.

Then choose the best series wavelet based on the simulation is measured. Before evaluating simulations model and compared with the actual value, the three periods are distinguished. The three terms are shown in Table 1.

Table 1: Estimated times of simulation

The historical simulation period	Retrospective simulation period	Simulation of prospective period
T1	T2	T3

The first period (T1 to T2) is considered for the analysis of the series. Second period is (the period between T2 and T3) and T3 represent the present is (the last available observation). In this method, the data variables are available during the second period, but they were not used for series analysis. The duration of the simulation that is famous as retrospective series use for comparing actual and simulated series and evaluating the simulation models, and the closeness of stimulation series is studied by real simulation.

In this paper, we first set of business cycle analysis for the historical period 1978-2004 and then 2005-2010 periods are simulated. Based on Renaud and *et al.* (2002) multiple analysis of signals using a transform redundant wavelet that has the advantage of constant shift is taking place. The resulting signal decomposition method, a range of alternative measures and predictions based on each of these scales are the smallest coefficient.

The simplest form of this method is a linear prediction based on wavelet transform of the signal which is applied in scattered models. However, it's applied for the coefficients that show the attributes a large part of the signal either. Various statistics used for evaluating the performance of the simulation model in the simulation of retrospective.

One of the statistics which traditionally used as an accuracy of measure of the simulation model is error variance simulates. (Pindyck and Rubinfeld, 1998).

According to the statistics of the proximity of simulation parameters to the actual number, is determined. Also, the correlation coefficient is used. Be assumed for the historical period T1 = 1,... ,T and for the retrospective period is T2 = T +1, ..., T + h. In this case, the measure of predictive power is defined as follows:

Where Y is the simulated variable symbol and $\tilde{Y}$ is the symbol of real variable.

Above traditional standards show a significant benefits compared to simulate and real variables. Equation (7) is representing the minimum error of stimulation. Whatever simulation error is much closer to zero, the actual simulate is more closely. And the closer correlation to 1, it is much better. (Gujarati, 2004).

Results

The results of study about correlation of business cycles of 185 indicate that wavelet biorNr.Nd is representative of all wavelets. It was found that just bior wavelet could make smooth with different types of business cycle analysis, and pave. After the decomposition of wavelet, 185 series of 20 series were selected as representative. Bior1.1 wavelets selected at levels 1,2,3,4,5; bior1.3 at 2,3,4; bior1.5 at 3,4,5; bior2.2 levels 1,3,4; bior2. 6 level 3; bior3.1 levels 1, 4, 5; bior3.5 level 4; bior5.5 were selected for level 1. In addition, quantitative results of correlation coefficient and simulation RMSE of the chosen wavelets with real data are shown in Table 2:

Table 2: Correlation coefficient and RMSE simulated series

Rank	Correlation coefficient	Simulated series	RMSE	Simulated series
1	0.93	LGDP11_L2	0.2	LGDP22_L4
2	0.89	LGDP22_L1	0.24	LGDP11_L2
3	0.89	LGDP35_L4	0.25	LGDP31_L4
4	0.89	LGDP22_L3	0.26	LGDP31_L5
5	0.88	LGDP22_L4	0.28	LGDP22_L1
6	0.88	LGDP31_L4	0.29	LGDP11_L1
7	0.88	LGDP31_L5	0.3	LGDP22_L3
8	0.88	LGDP26_L3	0.32	LGDP55_L1
9	0.87	LGDP31_L1	0.34	LGDP26_L3
10	0.86	LGDP11_L1	0.4	LGDP35_L4
11	0.85	LGDP55_L1	0.4	LGDP13_L2
12	0.83	LGDP15_L3	0.41	LGDP31_L1
13	0.81	LGDP11_L3	0.41	LGDP15_L3
14	0.77	LGDP13_L2	0.45	LGDP11_L3
15	0.71	LGDP15_L4	0.65	LGDP15_L4
16	0.71	LGDP15_L5	0.69	LGDP13_L3
17	0.64	LGDP13_L3	0.69	LGDP13_L4
18	0.64	LGDP11_L5	0.75	LGDP11_L4
19	0.52	LGDP11_L4	1.44	LGDP11_L5
20	0.51	LGDP13_L4	1.86	LGDP15_L5

Source: Study results

* The basic Logarithm series of real GDP I indicated by LGDP and symbol L is shown the level of wavelet.

* 11, 13, 15, 22, 26, 31, 36, 55, respectively, which means wavelets bior1.1, bior1.3, bior1.5, bior2.2, bior2.6, bior3.1, bior3.5 and bior5.5. Thus a series of LGDP11_l2 meant to simulate series of log of GDP based on wavelet bior1.1 at level 2.

Table 3: Selected wavelet

Rank	Simulated wavelet	The selected wavelet, regardless to the level of wavelet
1	bior1.1_l2	bior2.2
2	bior2.2_l4	bior3.1
3	bior2.2_l1	bior2.6
4	bior3.1_l4	bior5.5
5	bior2.2_l3	bior1.1
6	bior3.1_l5	bior1.5
7	bior3.5_l4	bior1.3
8	bior1.1_l1	bior2.2
9	bior2.6_l3	bior3.1
10	bior5.5_l1	bior2.6
11	bior3.1_l1	
12	bior1.3_l2	
13	bior1.5_l3	
14	bior1.1_l2	
15	bior1.5_l4	
16	bior1.3_l3	
17	bior1.5_l4	
18	bior1.1_l4	
19	bior1.1_l5	
20	bior1.3_l4	

As you can see in the table above, the results of two series based on two criterions, has shown mixed results. In the left part of the table, that series with the highest correlation and lowest error is selected and it has been rated. To compare the business cycle, business cycles are selected annually based on wavelets to rank sixth is given by in the diagram (1).

As the chart above shows, the quarterly log series of GDP which is decomposition by using bior1.1 wavelet at level 2 has the highest performance among all wavelets. Wavelets bior2.2_l4, bior2.2_l1, bior3.1_l4, bior2.2_l3 and bior3.1_l5 are located in second to sixth. According to the average index of selected wavelets (regardless to the level of surface and just based on the type of wavelet), respectively; wavelets bior2.2, bior3.1, bior2.6, bior5.5, bior1.1, bior1.5 and bior1.3 are selected.

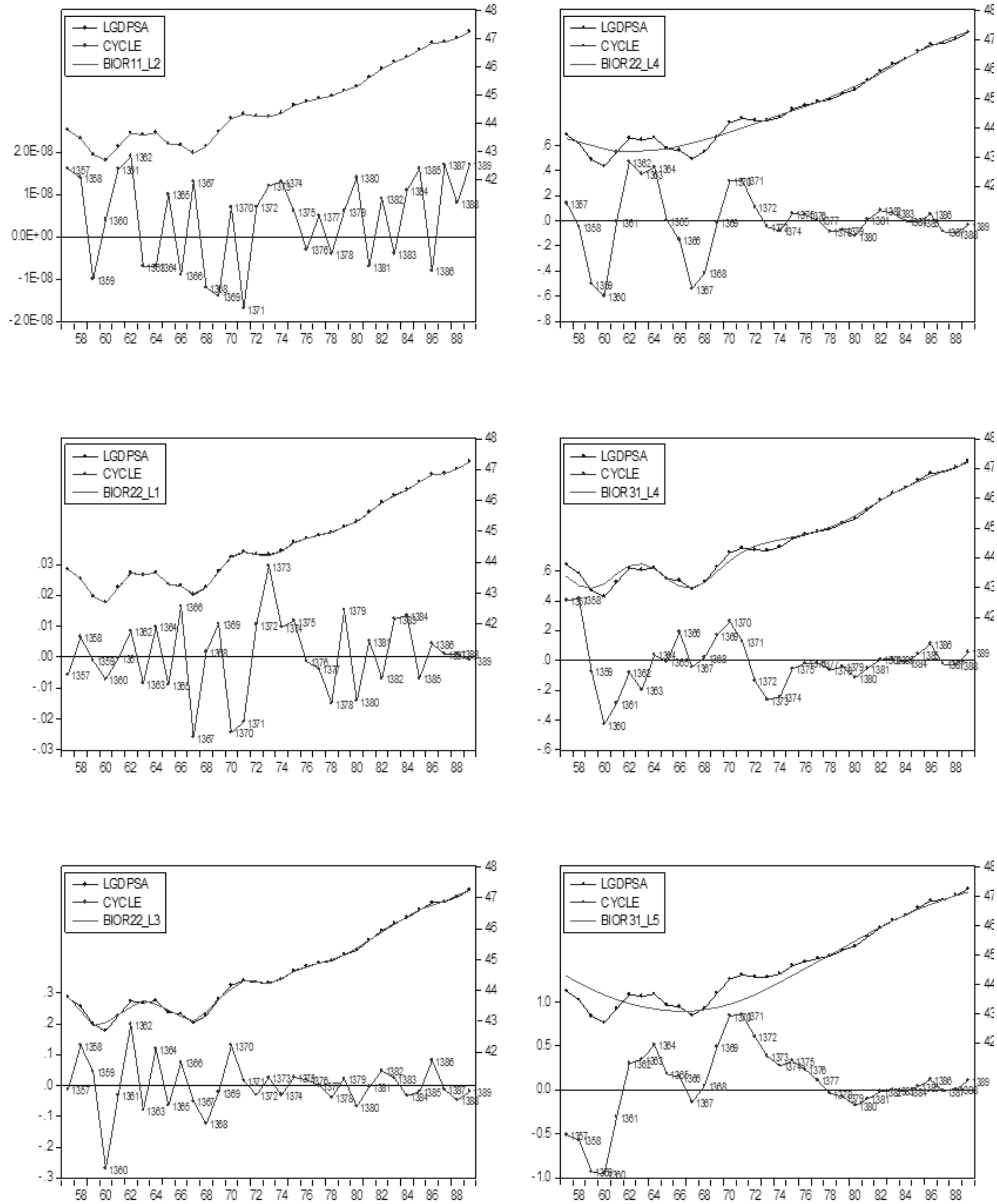

Figure 6: The annual business cycle based on the selected wavelets

* Periods are shown in the figures based on the Iranian calendar. To convert it to the Gregorian calendar should be added 621 years in it.

Business cycles are generally defined in two ways: "Classical cycles" which are refers to ups and downs in the series and "Growth cycle" that refers to the highs and lows in the adjusted series. (John McDermott and Alasdair Scott, 2000). Growth cycles, are very helpful to analyze the business cycle in countries such as Iran that have experienced strong growth rates in recessions and booms. Thus in this paper we are discussed about the measurement of the growth cycle of the cyclic fluctuations which are stated around a trend toward lower and upper. As it is clear from the above charts, based on wavelet is selected there are different business cycles obtained. The result is shown summarized in the table above diagram (3).

Table 4: Business cycles based on the selected wavelets

year	bior1.1_l2	bior2.2_l4	bior2.2_l1	bior3.1_l4	bior2.2_l3	bior3.1_l5
1978	boom	boom	Recessions	boom	recessions	recessions
1979	boom	recessions	Boom	boom	boom	recessions
1980	recessions	recessions	Recessions	recessions	boom	recessions
1981	boom	recessions	Recessions	recessions	recessions	recessions
1982	boom	recessions	Recessions	recessions	recessions	recessions
1983	boom	boom	Boom	recessions	boom	boom
1984	recessions	boom	Recessions	recessions	recessions	boom
1985	recessions	boom	Boom	boom	boom	boom
1986	boom	boom	Recessions	recessions	recessions	boom
1987	recessions	recessions	Boom	boom	boom	boom
1988	boom	recessions	Recessions	recessions	recessions	recessions
1989	recessions	recessions	Boom	boom	recessions	boom
1990	recessions	recessions	Boom	boom	recessions	boom
1991	boom	boom	Recessions	boom	boom	boom
1992	recessions	boom	Recessions	boom	boom	boom
1993	boom	boom	Boom	recessions	recessions	boom
1994	boom	recessions	Boom	recessions	boom	boom
1995	boom	recessions	Boom	recessions	recessions	boom
1996	boom	boom	Boom	recessions	boom	boom
1997	recessions	boom	Recessions	recessions	boom	boom
1998	boom	boom	Recessions	recessions	boom	boom
1999	recessions	recessions	Recessions	recessions	recessions	recessions
2000	boom	recessions	Boom	recessions	boom	recessions
2001	boom	recessions	Recessions	recessions	recessions	recessions
2002	recessions	boom	Boom	recessions	recessions	recessions
2003	boom	boom	Recessions	boom	boom	recessions
2004	recessions	boom	Boom	boom	boom	recessions
2005	boom	recessions	Boom	recessions	recessions	recessions
2006	boom	recessions	Recessions	boom	recessions	boom
2007	recessions	boom	Boom	boom	boom	boom
2008	boom	recessions	Boom	recessions	recessions	recessions
2009	boom	recessions	Boom	recessions	recessions	boom
2010	boom	recessions	Recessions	boom	recessions	boom
Number of Business cycle	21	12	21	13	21	8

It is clear that the business cycle based on the wavelet is determined differently from other types of wavelet. As is clear from the table, however the level of the selected wavelet is lower, determining the business cycle is carried out in detail.

Conclusions

One of the newly methods of economic analysis and data smoothing, is wavelet analysis. Research that has been done in this area recently by wavelet method is considered to the wavelet type. The use of wavelet analysis regardless to the reason of the choice of wavelets, may be useful in some time series analysis, but faces to some skewed. Hence, the method of selecting an appropriate wavelet was investigated for a variable cycle. Therefore, The main purpose of this paper has been determined the best type and length of the wavelet used the case study business cycles of Iran during the period 1978-2010 and on the bases on quarterly data.

Therefore Haar, Daubechies, Symmelets, Coiflets and biorthogonal wavelets was used to level 5, and the quarterly log GDP were decomposed to 370 series of (185 series of quarterly business cycle and 185 series of trend). First by using the correlation index, the same series was removed and then by wavelet simulation, series were simulated for the period 2005-2010. Our findings indicate that while the majority of research conducted have chosen Daubechies wavelet, the biorthogonal wavelet have a higher quality and comprehensiveness than the Haar wavelets, Daubechies, Symmelets, Coiflets.

The study of types of biorthogonal wavelet shows that bior2.2, bior3.1, bior2.6, bior5.5, bior1.1, bior1.5 and bior1.3 respectively, have the highest quality of decomposition and smoothing the business cycle in Iran. In order to provide more accurate results, the business cycle was also examined on an annual basis. The results showed that the business cycle shows high sensitivity and inverse to the level and type of the selected wavelet. So that with increasing the levels of wavelet, the business cycle shrinkage and by the lower of wavelet level, business cycles is more. It is proposed that when annual data are used, the choice of wavelet level is low (maximum 3) and If the data is monthly or quarterly, high-level wavelet (minimum of 4) is selected.

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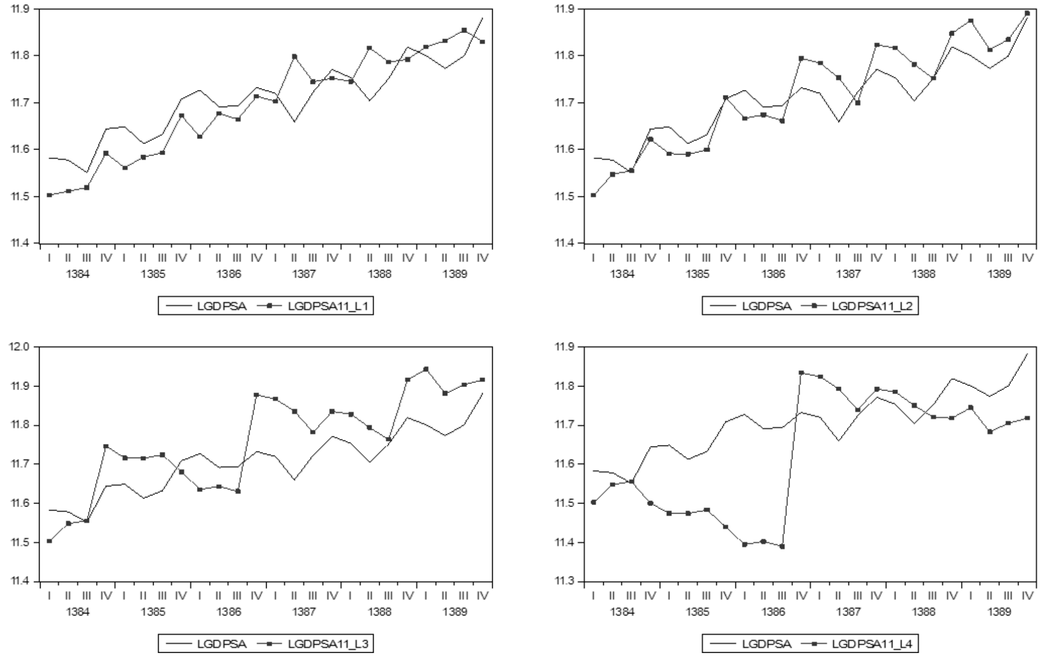
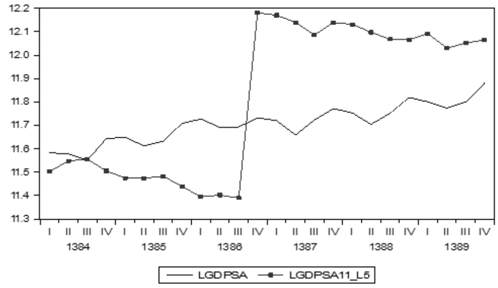
Appendix: Simulation results of GDP logarithm based on wavelets selected in the period of 2005-2010.

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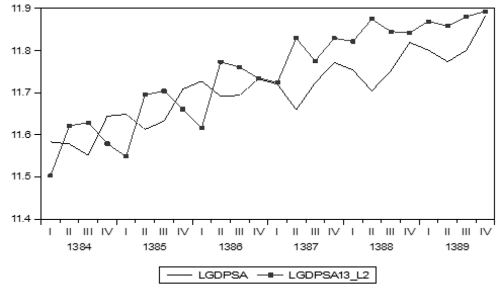
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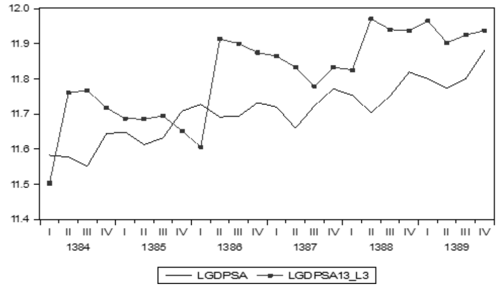
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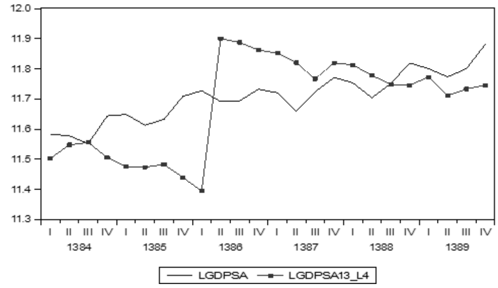
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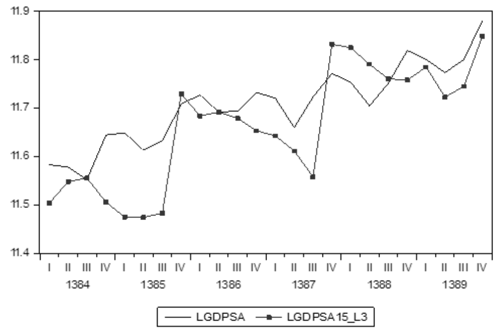
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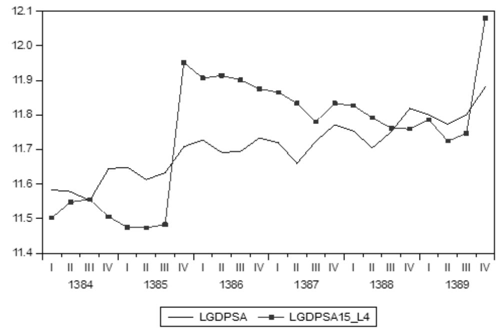
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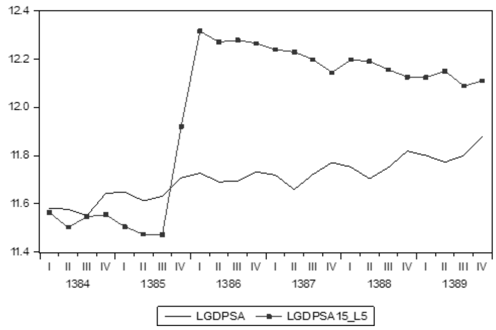
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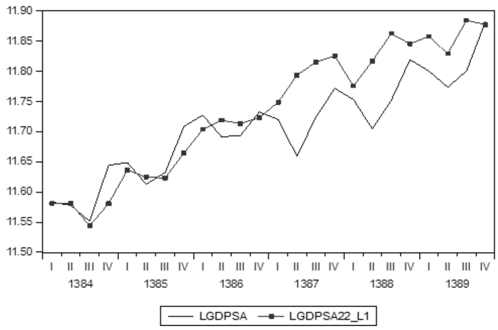
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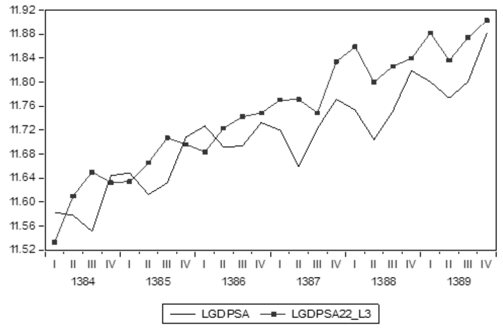
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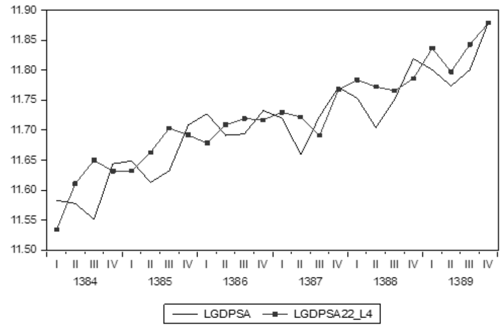
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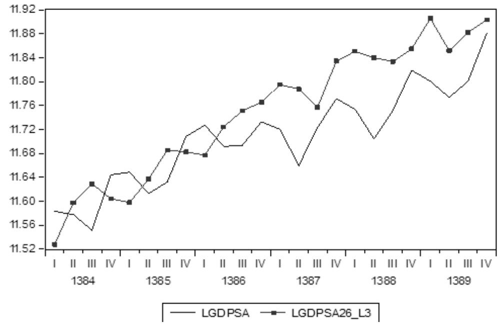
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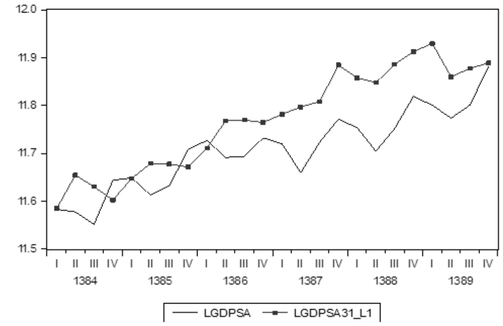
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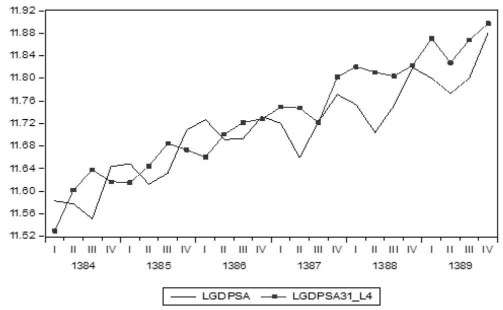
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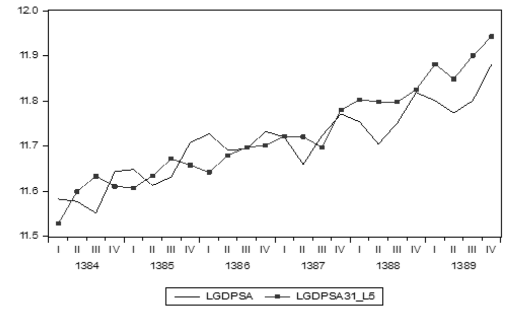
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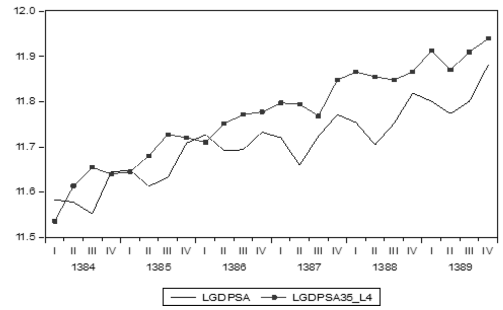
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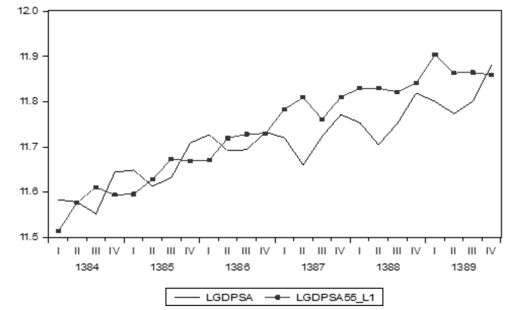
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