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Periodic Cointegration Analysis on the Relationship between the GNP Sectors of the Iran's Economy

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Abstract

This paper analyses the relation between GNP sectors of Iran's economy. The different sectors of the economy directly or indirectly affect each other and can complement or follow each other. Using a number of empirical tests, the paper finds evidence of seasonal or periodic integration in the underlying data. This means that the conventional cointegration tests may not be robust and in result, a more appropriate periodic cointegration test was used. This approach, by recognizing the stochastic nature of the seasonal pattern of the time series involved, avoids inconsistent estimations, errors in statistical inference and also biases in economic policy decisions. Our results find evidence of periodic cointegration between GNP of the industry and service sectors. In addition, we find that the speed of adjustment of misalignments is different depending on the quarter. The adjustment of equilibrium misalignments is faster if they take place in the April-June period than in the rest of the year.

Keywords: Cointegration, GNP Sectors, Iran's Economy, Periodic Behavior, Time-series Data.

JEL Classification: C22, C32, N15.

1. Introduction

Seasonality is an important component of most macroeconomic time series, sometimes tending to dominate other non-trend components (Barsky & Miron, 1989; Miron, 1994). Despite this fact, and until

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recently, most econometricians tended to either completely ignore the issue of seasonality in their applied work, or to filter it away through a host of adjustment techniques, such as the inclusion of deterministic seasonal dummies in their estimated equations or the use of the well-known Census Bureau X-12 and ARIMA X-12 methods. However, in the past three decades, there has been an increasing inclination towards modeling seasonality instead of adjusting it away. This is due to three reasons. One, it was realized that seasonal adjustment distorts inference in dynamic models. An example of this distortion is in the tests for integration and cointegration (seasonal as well as non-seasonal). Two, seasonal cycles are found to have important information, which would be lost if one were to work with seasonally adjusted data. Finally, it has been found that in some cases seasonal and other components are not separable from each other. In such cases, seasonal adjustment gives rise to seasonal and non-seasonal components, which are not orthogonal to each other. On the one hand, it has been shown that seasonality is an independent aspect of economic behavior, thus deserving explanation in its own right (Miron & Zeldes, 1988; Osborn, 1988).

In modeling seasonality, it must be remarked that there are two types of trends, which are commonly associated with macroeconomic data. The first is what is called the deterministic trend, which, in words, entails that the observed trend line will persist in the future. The second is the so-called stochastic trend, which means that the data display a dominant trending pattern, but it seems that the direction of this trend changes once in a while (Franses & Paap, 2004). Econometricians have increasingly tended to model the seasonality component as a stochastic process, to be subjected to stationarity tests. Indeed, it has been shown that if seasonality is ignored, the unit root and cointegration test results are spurious (Franses, 1994; Ghysels, 1994). Consequently, extending the econometrics of unit roots and cointegration to the study of seasonality, Hylleberg et al. (1990), Engle et al. (1993), and Ghysels & Perron (1993), among others, have developed similar seasonal integration and cointegration tests. Since inappropriate seasonal adjustment methods, such as using seasonal dummies to purge stochastic seasonality, can complicate standard unit root and cointegration results, pretesting the data for seasonal unit roots has now become standard practice among many researchers. At the same time, more recent work has come to consider the seasonal unit roots approach, with its assumption of constant autoregressive coefficients for all seasons, too restrictive. By providing evidence to the contrary, this work advocates a more general approach, the so-called periodic integration approach, in which the autoregressive coefficients are allowed to vary across seasons, while at the same time satisfying a newly defined condition for unit root behavior (Osborn, 1991; Franses, 1996; Ghysels & Osborn, 2004). While Seasonal cointegration can apply only for seasonally integrated (*SI*) processes, which are non-stationary processes, periodic cointegration can apply for periodically integrated (*PI*) processes, which are non-stationary but rendered stationary by application of a seasonally varying quasi-difference filter. In an *SI* process, non-stationary unit root behavior exists not only at the long run (or zero) frequency, but also at all the seasonal frequencies. It means periodic cointegration can apply between seasonally integrated, as well as between periodically integrated, processes.

There are a few studies on the periodic cointegration between macroeconomic time series. Lof & Franses (2001) analyze periodic and seasonal cointegration models for quarterly observed time series on consumption and income in six countries. They include both single equation and multiple equations methods. They find that the seasonal cointegration models tend to yield better forecasts and there is no clear indication that multiple equation models improve on single equation methods. Evans (2006) discusses univariate and multivariate methods used to deal with seasonal data of regional ferrous scrap price with special emphasis on periodic models. He found that these scrap prices are shown to be periodically cointegrated in three of the four quarters with rapid speeds of adjustment to these long-run equilibria. Bucacos (2007) estimated periodic cointegration model for REER in Uruguay. She found that the impact of changes in different fundamentals on the long-run target relationships depends on which quarter those changes take place. In addition, she found that reductions in Government size could increase REER in the long run as well as reductions in the net interest rates; changes in nominal exchange rate or in domestic inflation could only affect short-run dynamics. Shirvani et al. (2009)

examined the seasonal properties of the stock prices of the G7 countries. They find both deterministic seasonal dummies and seasonal unit roots to be inadequate to explain the seasonal behavior of these prices and find evidence of periodic integration, but not periodic cointegration, in the underlying data. Shirvani et al. (2011) investigate the present value model of stock price by using of periodic cointegration model. They find evidence of periodic seasonal integration in these variables. That means that the conventional cointegration tests may not be robust. Using a more appropriate periodic cointegration test, their results, nevertheless, fail to support the present value model, thus reinforcing the case against the efficient market hypothesis. Shafiq (2014) examined the static and dynamic causality amongst the sectoral incomes of GDP, and GDPs of agriculture, industry, and services during the period 1972 to 2011. The results show that contribution to GDP forecast error by agriculture sector is highest followed by services and industry.

The object of this paper is to employ some of the above methodological advances to examine the relationship between GNP sectors of Iran, including service, industry, agriculture and oil. The remainder of the paper is organized as follows. Section 2 summarizes the methodology used on the paper. Section 3 introduces the data; Section 4 presents the empirical results. The last section presents some concluding remarks.

2. Methodology

The first objective of this paper is to test the relation between Gross National Production (GNP) components of Iran by explicitly addressing the seasonal properties of the underlying data. Since our data are quarterly, we use only four seasons per annum. As a first step, we consider the following auto regression equation:

$$y_t = \sum_{s=1}^{4} \mu_s D_{s,t} + \sum_{s=1}^{4} \lambda_s D_{s,t} T_t + \sum_{i=1}^{p} \sum_{s=1}^{4} \alpha_{is} D_{s,t} y_{t-i} + \varepsilon_t \qquad (1)$$

where y_t is the Gross National Product of one of the sectors in quarter t, $T_t = [(t-1)/4] + 1$ represents an annual linear deterministic trend, $D_{s,t}$ is a seasonal dummy equal to one for the, i th quarter and zero elsewhere, and ε_t is a white-noise error term.

Then we ascertain that there is indeed a periodic pattern in our data. In Boswijk & Franses (1996) it is proved that the likelihood ratio test for the null hypothesis:

$$H_0: \alpha_{is} = \alpha_i \qquad for \quad s = 1,2,3,4 \qquad and \qquad i = 1,2,\dots,p \quad (2)$$

has an asymptotic X^2(3p) distribution, irrespective of whether the $y_t$series has non-seasonal or seasonal unit roots. The intuition behind this result is that these parameter restrictions do not in any way restrict the possible number of unit roots prior to examining periodicity.

Since the results that were presented later in the paper, do indicate the presence of a seasonal pattern in our data, we need to find an appropriate approach for modeling such seasonal behavior. There is substantial evidence that much of the seasonal variation over time is not constant (Hylleberg, 1994; Canova & Hansen, 1995). Thus, it is considerable interest to determine whether the seasonal pattern in our data follows a stationary stochastic process, and if not, how one could render it stationary. Common assumptions for models of a seasonally observed economic time series are, e.g., (a) the series is seasonally integrated, (b) seasonal patterns can be represented by deterministic dummies, and (c) a variable is periodically integrated (see e.g. Osborn, 1988). The Hylleberg et al. (1990) [HEGY] method is designed to discriminate between models implied by assumptions (a) and (b). Therefore, the HEGY approach considers only a subset of possible models, and, in particular, does not allow for periodically varying coefficients. Therefore, we use HEGY approach, multivariate Franses (1994) test and periodic unit root tests to determine essence of our data.

At first, we perform the HEGY test to determine the number of unit roots, which is based on the following auxiliary regression:

$$\Phi(B)y_{4,t} = \mu_t + \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-2} + \pi_4 y_{3,t-1} + \varepsilon_t \quad (3)$$

where *Φ(B)* is an autoregressive polynomial in *B* with the order *r* chosen to render the error term in the above equation white noise, μ_t is a combination of seasonal dummies and a time trend, and the y variables are defined as follows:

$$y_{1,t} = (1 + B + B^2 + B^3)y_t$$
$$y_{2,t} = -(1 - B)(1 + B^2)y_t$$
$$y_{3,t} = -(1 - B^2)y_t$$
$$y_{4,t} = (1 - B^4)y_t$$

Equation (3) can be estimated by ordinary least squares, possibly with additional lags of *y*, to whiten the errors. HEGY shows that the test in the presence of non-seasonal and seasonal unit roots amounts to testing for the significance of the π terms in the above auxiliary equation. If π_1 equals zero, then the null hypothesis of a non-seasonal unit root 1 cannot be rejected. If π_2 equals 0, the null of a seasonal unit root -1 cannot be rejected. Finally, if $\pi_3 = \pi_4 = 0$, then the null of two seasonal unit roots of $+i$ and $-i$ cannot be rejected. To test the above hypotheses, HEGY shows that we can use *t* tests for π_1 and π_2 and a joint *F-test* for π_3 and π_4, using the nonstandard critical values they provide.

For (c) state i.e. when a variable is periodically integrated, we can use periodic models and investigate for periodic unit roots. In general, the PAR(p) process in (1) can be rewritten as an AR(P) model for the 4×1 vector process $Y_T = (Y_{1T}, Y_{2T}, Y_{3T}, Y_{4T})'$, $T=1,2, \ldots, N$ where Y_{sT} is the observation of y_t in season *s* of year *T*, *s= 1, 2 3 4*. The model is then:

$$A_0 Y_T = \mu + A_1 Y_{T-1} + \cdots + A_p Y_{T-p} + \varepsilon_T \tag{4}$$

the A_0, A_1, …, A_p are 4 × 4 parameter matrices with elements:

$$A_0[i,j] = \begin{cases} 1 & if\ i = j \\ 0 & if\ j > i \\ -\alpha_{i-j,i} & if\ i<j \end{cases} \tag{5}$$

$$A_k[i,j] = \alpha_{i+k-j,i}\ ,$$

for *i= 1, 2, 3, 4* , *j= 1, 2, 3* , *4*, and *k = 1, 2, , ..., P*. For the model order *P* in (4) it holds that *P* = 1 + *[(p* — l)/4*]*, where [.] is again the integer function. Hence, when *p* is less than or equal to 4, the value of *P* is only 1. One way that will sometimes be considered in the analysis of unit roots is described below. The first is given by simply pre-multiplying (4) with A_0^{-1}, that is:

$$Y_T = A_0^{-1}\mu + A_0^{-1}A_1Y_{T-1} + \cdots + A_0^{-1}A_pY_{T-p} + A_0^{-1}\varepsilon_T \qquad (6)$$

The expression in (6) is a vector autoregressive (VAR) model of order *P* for the *YT* process. When $\varepsilon_T \sim N(0, \sigma^2 I_4)$, it follows that:

$$A_0^{-1}\varepsilon_T \sim N(0, \sigma^2 A_0^{-1}(A_0^{-1})') \qquad (7)$$

Note that the vector autoregressive model of (6) can be written in error (or equilibrium) correction form as:

$$\Delta_1 Y_T = A_0^{-1}\mu + A_0^{-1}\tau T + \Pi Y_{T-1} + \Gamma_1\Delta_1 Y_{T-1} + \cdots +$$
$$\Gamma_{P-1}\Delta_1 Y_{T-(P-1)} + A_0^{-1}\varepsilon_T$$
$$\Gamma_i = A_0^{-1}\textstyle\sum_{j=i+1}^{P} A_j \quad for \quad i = 1, 2, \ldots, P-1 \quad \Pi = A_0^{-1}\sum_{j=i}^{P} A_j - I_4 \qquad (8)$$

it is the matrix *Π* which is relevant to the analysis of cointegration relations. When there are *r* cointegration relations between the $Y_{s,T}$ elements, the matrix *Π* has rank *r*, with 0 < *r* < 4. In this condition, there are 4 — *r* unit roots in the Y_T (and y_t) process. The vector process Y_T is stationary if the root of the characteristic equation:

$$|A_0 - A_1 z| = (1 - (\alpha_1\alpha_2\alpha_3\alpha_4)z) = 0) \qquad (9)$$

lies outside the unit circle, i.e. if $\alpha_1\alpha_2\alpha_3\alpha_4 < 1$. On the other hand, the process Y_T can be said to be integrated if Equation (9) has a unit root, i.e., if it is the case that:

$$H_0 : \alpha_1\alpha_2\alpha_3\alpha_4 = 1 \qquad (10)$$

To test the above restriction, we first estimate the unrestricted equation (1). Next, by imposing the above restriction, we have the following restricted equation:

$$y_t = \sum_{s=1}^{4} \mu_s D_{s,t} + \sum_{s=1}^{4} \lambda_s D_{s,t} T_t + \alpha_1 D_{1t} y_{t-1} + \alpha_2 D_{2t} y_{t-1} + \alpha_3 D_{3t} y_{t-1} + (\alpha_1 \alpha_2 \alpha_3)^{-1} D_{4t} y_{t-1} + \sum_{i=1}^{p-1} \sum_{s=1}^{4} \beta_{is} D_{s,t} (y_{t-i} - \alpha_{s-i} y_{t-i-1}) + \varepsilon_t \tag{11}$$

which can be estimated using Non-Linear Squares (NLS). The validity of this differencing filter; that is, the presence of single unit roots, can be tested using a likelihood ratio test defined as:

$$LR = n \times \ln(RSS_0 / RSS_1) \tag{12}$$

where RSS_0 and RSS_1 denote the residual sums of squares from (11) and (1) respectively and *n* is the number of observation. The series y_t contains more than a single unit root if the rank of the matrix Π is smaller than 3. If the rank of Π equals 2, there are two unit roots in the time series Y_T (and y_t) and two cointegration relations between the elements of Y_T. In this case, the restricted model is estimated with imposing the restrictions (13) in equation (11) as follows:

$$\begin{aligned} \alpha_{11} &= -\alpha_{13}/\alpha_{23}\alpha_{24} \\ \alpha_{21} &= (1/\alpha_{23}) - \alpha_{13}\alpha_{14}/\alpha_{23}\alpha_{24} \\ \alpha_{12} &= -\alpha_{14}\alpha_{23}/(\alpha_{13}\alpha_{14} + \alpha_{24}) \\ \alpha_{22} &= 1/(\alpha_{13}\alpha_{14} + \alpha_{24}) \end{aligned} \tag{13}$$

$$y_t = \sum_{S=1}^{4} \mu_s D_{s,t} + \sum_{S=1}^{4} \tau_s D_{s,t} T_t + \sum_{S=1}^{4} \alpha_{1s} D_{s,t} y_{t-1} + \sum_{S=1}^{4} \alpha_{2s} D_{s,t} y_{t-2} + \sum_{i=1}^{p-2} \sum_{S=1}^{4} \beta_{is} D_{s,t} (y_{t-i} - \alpha_{1,s-i} y_{t-i-1} - \alpha_{2,s-i} y_{t-2-i}) + \varepsilon_t \tag{14}$$

The validity of this differencing filter; that is, the presence of two unit roots, can be tested using a likelihood ratio test defined as:

$$LR = n \times \ln(RSS_{01} / RSS_1) \tag{15}$$

where RSS_{01} denotes the residual sum of squares of (14). The parameters of this model can be estimated with NLS.

Having established seasonal or periodic integration for our underlying variables, it is of interest to also test for the presence of periodic cointegration among them. Boswijk & Franses (1995) extend the standard cointegration definition to periodically integrated series and formulate the periodic cointegration test as a Wald test of joint significance of the 4-quarter lagged variables. Indeed, as we will show later in the paper, an application of the HEGY and Franses & Paap (2004) approaches to our data indicates seasonal and periodic unit roots, we consider according to the Boswijk & Franses (1995) approach, the following single equation periodic cointegration model (PCM):

$$\Delta_4 w_t = \sum_{s=1}^{4} \mu_s D_{s,t} + \sum_{s=1}^{4} \gamma_{1s}(w_{t-4} - k_s x_{t-4}) + \sum_{j=1}^{p-4} \beta_j \Delta_4 w_{t-j} + \sum_{i=0}^{p-4} \tau_i' \Delta_4 x_{t-i} + \varepsilon_t \qquad (16)$$

where w_t is the variable of specific interest and where x_t is a vector of explanatory variables. The ε_t is a standard white noise process and $\Delta_4 w_t$ is defined by $\Delta_4 w_t = (1 - B^4) w_t = w_t - w_{t-4}$. It is assumed that x_t is weakly exogenous. The parameter γ_{1s} and k_s in equation (16) are seasonally varying adjustment and long-run parameters, respectively. Adjustment can be easier to achieve in some quarters, or economic agents may want to correct disequilibria faster in some seasons. In a production model context, the target relations may reflect seasonally varying availability of production inputs and facilities or seasonally varying demand for produced goods and services. Periodic cointegration requires that the γ_{1s} parameters are negative. Full periodic cointegration in (16) implies that there is adjustment a long-run relationship in all four quarters, whereas partial periodic cointegration implies that there is no adjustment in some quarters. The Boswijk & Franses (1995) propose a Wald test for cointegration in the PCM. Consider the following, slightly rewritten form of (16):

$$\Delta_4 w_t = \sum_{s=1}^{4} \mu_s D_{s,t} + \sum_{s=1}^{4} \left(\delta_{1s} D_{s,t} w_{t-4} + \delta_{2s} D_{s,t} x_{t-4}\right) + \sum_{j=1}^{p} \beta_i \Delta_4 w_{t-j} + \sum_{j=0}^{p} \tau_i' \Delta_4 x_{t-j} + \varepsilon_t \qquad (17)$$

where $\delta_{1s} = \gamma_{1s}$ and $\delta_{2s} = -\gamma_{1s}k_s$ in (16), Writing $\delta_s = (\delta_{1s}, \delta_{2s})$, the null hypothesis of no cointegration in season s, and the alternative hypothesis of the Wald$_s$ test are $H_{0s}: \delta_s = 0$ and $H_{1s}: \delta_s \neq 0$ for some s, respectively. Now writing $\delta = (\delta_1, \delta_2, \delta_3, \delta_4)$ the null hypothesis of no cointegration in any season and the alternative hypothesis of the joint Wald test are $H_0: \delta = 0$ and $H_1: \delta \neq 0$ for some respectively. The two Wald statistics are calculated as:

$$Wald_s = (n-k)\left(\frac{RSS_{0s} - RSS_1}{RSS_1}\right) \quad Wald = (n-k)\left(\frac{RSS_0 - RSS_1}{RSS_1}\right) \qquad (18)$$

where k is the number of estimated parameters in equation (17), and where RSS_1 is the OLS residual sum of squares from the unrestricted model and RSS_{0s} and RSS_0 are the residual sums of squares under H_{0s} and H_0. The relevant critical values for the Wald test statistic are given in Franses & Paap (2004).

When one obtains evidence for the presence of cointegration in all or some seasons, it is of particular interest to test for the following parameter restrictions:

$$\begin{aligned} &H_0: \gamma_{1s} = \gamma \quad for\ all\ s = 1, 2, 3, 4. \\ &H_0: k_s = k \quad for\ all\ s = 1, 2, 3, 4. \\ &H_0: \delta_s = \delta \quad for\ all\ s = 1, 2, 3, 4. \end{aligned} \qquad (19)$$

These restrictions test whether the estimated parameters for all seasons are statistically equal. Each of these hypotheses may be tested using an F-type test statistic. For the hypotheses $\gamma_{1s} = \gamma$ and $\delta_s = \delta$ these F- tests are the classical F- tests since the model is linear under the null and alternative hypotheses. These F-tests are denoted by F_γ and F_δ. For the hypothesis $k_s = k$ one may use the likelihood ratio-based test statistic:

$$F_k = \frac{n-l}{h} \times \frac{RSS_1 - RSS_0}{RSS_0} \qquad (20)$$

where n, l and h are the number of observations, the number of restricted model parameters and the number of linear constraints respectively and where RSS_0 and RSS_1 are the residual sums of squares under $k_s = k$ and an NLS regression under the alternative, respectively. Under weak exogeneity and given co-integration, these three F-test statistics are all asymptotically F distributed. Similar to the discussion above, a test for weak exogeneity can be performed by adding the cointegrating variables $D_{s,t}(w_{t-4} - \hat{k}_s x_{t-4})$ to a model for $\Delta_4 x_t$ that is, by estimating:

$$\Delta_4 x_t = \sum_{s=1}^{4} \mu_s D_{s,t} + \sum_{s=1}^{4} \gamma_{2s}\left(w_{t-4} - \hat{k}_s x_{t-4}\right) + \sum_{j=1}^{p-4} \beta_j \Delta_4 w_{t-j} + \sum_{i=0}^{p-4} \tau_i' \Delta_4 x_{t-i} + \varepsilon_{2,t} \quad (21)$$

Boswijk (1994) shows that, given cointegration, the LR-test for $\gamma_{2s} = 0$ for all s is asymptotically $x^2(4)$ distributed in the case of full periodic cointegration. When the null hypothesis of weak exogeneity is rejected, one may turn to alternative estimators or models.

3. Data

Iran is the second largest economy in the Middle East and North Africa regions and in a general classification, Iran's economy divided into oil, agriculture, industry and service sectors. The different sectors of the economy directly or indirectly affect each other and can complement or follow each other. In this article, we investigate the relation between GNP sectors of Iran's economy. We use the real Gross National Product (GNP) of Iran for service, industry, oil and agriculture sectors. The base year for evaluating the data is 1997/98 because the quarterly data are presented only for this base year. The required data come from Central Bank of the Islamic Republic of Iran's database over 1988:2 to 2015:1.

Average share of four main sectors of GNP -service, industry, agriculture and oil - were 52%, 23%, 14% and 11%, respectively. The real GNP is nearly 3 times over during the period of study. In this period, shares of agriculture, service and industry sectors have increased from 15.93%, 50.93% and 15/67% (in 1989) to 16.76%, 51/26% and 26/09% (in 2014) respectively. During the study period, the service sector has the largest contribution in Iran's economy, accounting over half of GNP, and the industry sector has the highest growth, so that the share of industry in GNP has increased from 15/67 per cent in 1989 to 26/09 per cent in 2014 and these findings show that the Iran’s economy has industrial development in recent years while the share of agriculture and service sector have been relatively consistent. On the other hand, share of the oil sector strongly has decreased from 17.46% (in 1989) to 5.88% (in 2014). Tough sanctions on Iran and reduction of world price of crude oil, hammered Iran’s oil exports and decrease GNP of this sector. Overall, Iran's economy shrank in 2012 and 2013 after the tightened sanctions. However, its economy was growing again by 2014.

Before offering our quantitative results concerning the seasonal characteristics of Iran's real GNP for its sectors, we present a visual impression of these characteristics in Figures 1 to 4. Each graph contains four curves corresponding to each of the underlying variables for the four quarters of the year, where all the variables cover the period 1988:2 to 2015:1 are measured by billion Rial. Figures 1 and 2 show clearly that there is considerable seasonal variation for GNP of service and industry sectors, as evidenced by the frequent crossings of the quarterly curves in the figures. Figure 3 shows substantial seasonality for agricultural production, while GNP of Oil sector has rather erratic seasonal fluctuations.

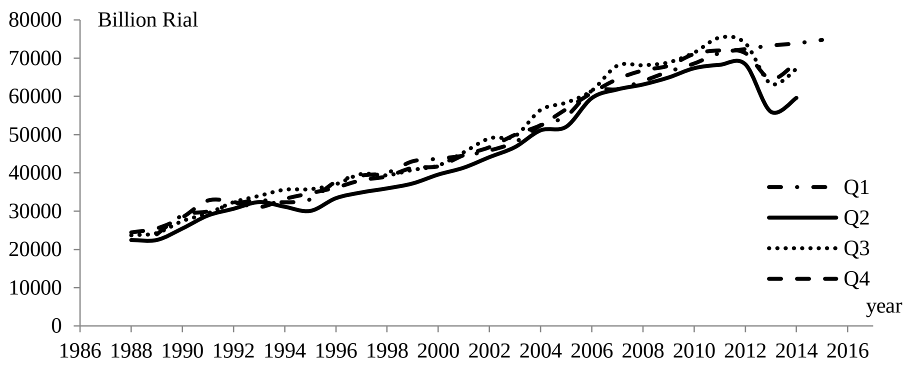

Figure 1: GNP of the Service Sector by the Quarter

Source: own research and Central bank of the Islamic republic of Iran database

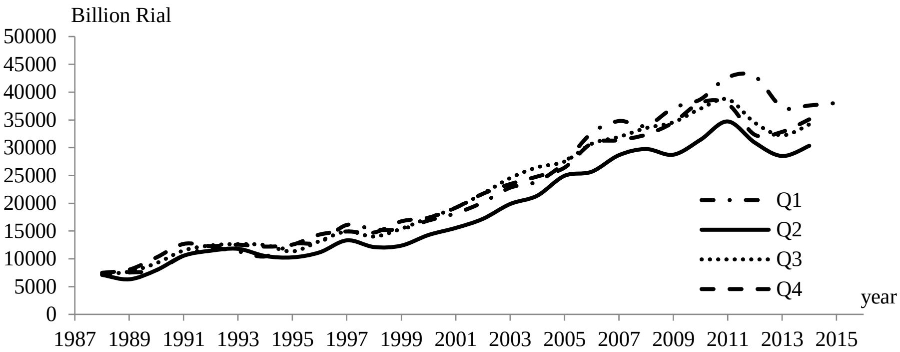

Figure 2: GNP of the industry sector by the Quarter

Source: own research and Central bank of the Islamic republic of Iran database

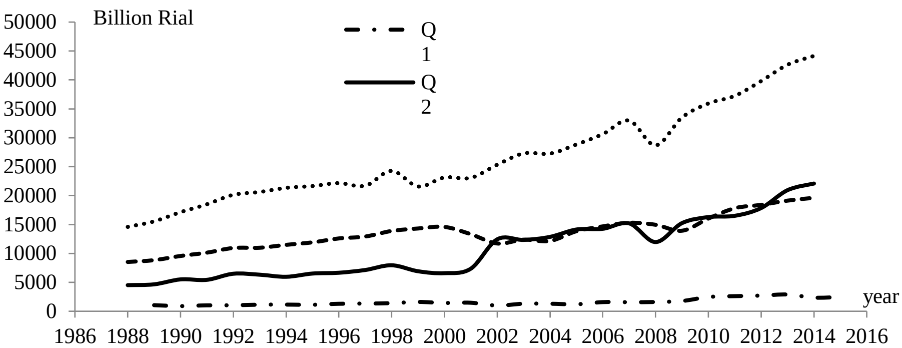

Figure 3: GNP of the agriculture sector by the Quarter

Source: own research and Central bank of the Islamic republic of Iran database

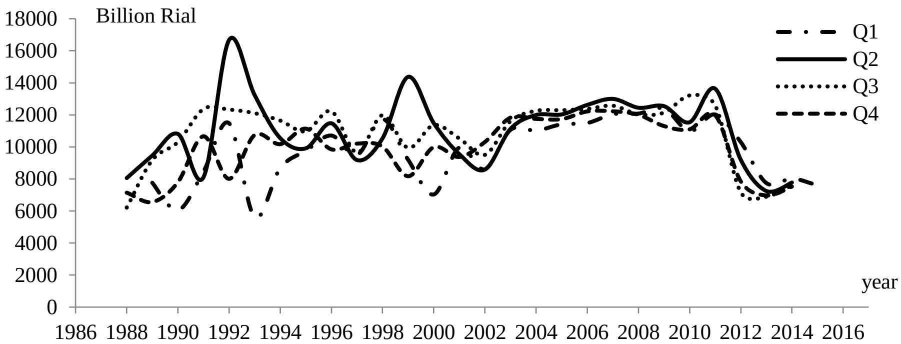

Figure 4: GNP of the Oil sector by the Quarter

Source: own research and Central bank of the Islamic republic of Iran database

4. Empirical Results

To support this visual impression (Figure 1-4), we conduct the Wald test of joint significance of the dummied seasonal variables in Equation 1, presented earlier. The *F –test* version values of the Wald test, which range from 2.58 to 17.65, are all significant at the 5 % level, indicating the presence of seasonality for all the variables. Then we carried up HEGY tests for seasonal unit roots in our time series. Results of these tests appear in Table (1). The auxiliary regressions include an intercept and a deterministic trend in each case.

Table 1: HEGY Seasonal Unit Roots Test

Variable	$t_{\pi 1}$	$t_{\pi 2}$	$F_{\pi 3-\pi 4}$	Lags
Service	-2.01	0.10	2.24	1, 3-5
Industry	-1.48	1.58	0.41	1-4
Agriculture	-1.22	0.42	3.42	1-5
Oil	-2.38	-4.64***	16.73***	0

(*** Significant at the 1% level)

Source: own research

Table 2: Diagnostic Tests for Periodicity

Variable	LM(1)	LM(4)	ARCH(1)	ARCH(4)	Fpser	order	Fper
Service	0.014 (0.9065)	1.012 (0. 704)	0.007 (0.9355)	0.91 (0.9229)	1.22 (0.3102)	2	3.36 (0.0052)
Industry	1.690 (0.1935)	1.476 (0. 595)	0.002 (0.9624)	2.814 (0.5894)	1.15 (0.3375)	2	3.53 (0.0037)
Agriculture	0.081 (0.7757)	1.959 (0.7433)	0.091 (0.7641)	3.917 (0.4174)	1.34 (0.2643)	2	17.65 (0.0000)
Oil	0.900 (0.3428)	4.619 (0.328)	2.178 (0.1400)	1.122 (0.318)	0.61 (0.6558)	2	2.81 (0.0154)

Note: LM (1) and LM (4) are LM-tests for first and fourth-order residual serial correlation, ARCH (1) and ARCH (4) are ARCH-test for first-order and fourth residual heteroscedasticity, Fpser is F-type versions of LM-tests for first-order periodic serial correlation and Fper is F-test for periodicity in the AR parameters. (p values in parentheses)

Source: Authors' finding

Clearly all variables except GNP of the oil sector seem to contain unit roots at zero and seasonal frequency. Altogether, there is substantial evidence of changing seasonal patterns. It is important to obtain independent verification of the HEGY test results through the Franses & Paap (2004) test of periodic unit roots for our variable. The appropriate lag length is selected by using of Schwarz's criterion and diagnostic tests. The results of diagnostic tests appear in Table (2).

Tests for periodic unit roots that described already are shown in Table (3). The auxiliary regressions include an intercept, seasonal dummies and a deterministic trend in each case.

Table 3: Testing for Periodic Unit Roots

Variable	Two periodic unit root	Single periodic unit root
Service	20.93***	0.012
Industry	12.028	2.62
Agriculture	58.94***	12.41***
Oil	29.03***	162.06***

(*** Significant at the 1% level)
Source: Authors' finding

Based on our estimation results for unrestricted model in Equation 1 and restricted models in equations 11 and 14, we compute the likelihood ratio statistics defined by Equations 12 and 15 respectively. The critical values for the LR-test are given in Franses & Paap (2004). A non-significant value for this statistic is indicative that the null hypothesis of the periodic unit root cannot be rejected. The test results are presented in Table (3), which shows clearly that the likelihood ratio statistics for GNP of service and industry sectors are not significant at the 10% level. Thus, we cannot reject the null hypothesis of a single periodic unit root for these variables.

Given our finding that the GNP's sectors except GNP of the oil sector are periodically or seasonally integrated, it is of considerable interest to determine whether these GNP's sectors are periodically cointegrated, that is, whether there are linear combinations of these GNPs which lack periodic or seasonal unit roots. For the reasons mentioned above, our cointegration tests are based on the Boswijk & Franses (1995) test (equation 17). Before doing the periodic cointegration test, we enforce a Toda-Yamamoto causality test for VAR relation in the four- order difference of service, industry and agriculture and first-order difference of oil data to determine the dependent variable for periodic cointegration relation. The results are presented in Table (4). GNP of the oil sector was not imported as a dependent variable because it did not have periodic or seasonal unit root and was I (1).

Table 4: Toda-Yamamoto Causality Test

dependent variable	Service	Industry	Agriculture	Oil
Service	-	11.10 (0.0254)	28.74 (0.0000)	9.65 (0.0468)
Industry	3.32 (0.5061)	-	1.74 (0.7838)	0.23 (0.9941)
Agriculture	1.81 (0.7714)	4.62 (0.3288)	-	2.14 (0.7099)

(p values in parentheses)
Source: Authors' finding

The null hypothesis of Toda-Yamamoto causality test states that there is not causality relation between two sectors. Therefore, Toda-Yamamoto non-causality test for GNP of the service sector to GNP of industry, agriculture and oil sectors fails to reject in the long-run relationships. It is foreseeable, because the growth of the service sector requires the development of other sectors of the economy and in Iran as a developing country, the growth of the agriculture, industry and oil sectors provides the fields of service sector growth. After determining the dependent variable, we use Boswijk- Franses test for periodic cointegration and results appear in Table (5). The result of this table shows that there is not any periodic cointegration relation between these variables.

Table 5: Testing for Periodic Cointegration

w_t	x_t	Wald statistic	Lags	
			$\Delta_4 w_t$	$\Delta_4 x_t$
Service	Agriculture	16.81963	1-6	2
Service	Industry	19.014	1,5	0
Service	Oil	18.44	1,5	0

Source: Authors' finding

We also test periodic cointegration between industry and service sectors because their graphs in Figures 1 and 2 indicate same similar pattern. The model includes an intercept and seasonal dummies in each case. We first estimate (17), where w_t corresponds to the GNP of the industry sector and x_t to the GNP of the service sector. The lag order is chosen by using of LM-tests for first-order (χ^2 statistic= 0.064) first-to-fourth-order (χ^2 statistic = 6.0955) serial correlation in the residuals that are not significant, For this target the lag order is selected 1, 3, 4 for GNP of the industrial sector and 1 for GNP of the service sector. The Wald statistic for the joint restriction $\delta_{1s} = \delta_{2s} = 0$ is tested; the critical values for the Wald test are given in Franses & Paap (2004). Significant value for this statistic is indicative that the null hypothesis of the no-periodic cointegration can be rejected. As the Table (6) shows, the Wald-statistics is significant at the 5 percent level, indicating periodic cointegration for the variables in our sample.

Table 6: Testing for Periodic Cointegration (Wald Test)

w_t	x_t	Wald statistic	Lags	
			$\Delta_4 w_t$	$\Delta_4 x_t$
Industry	Service	33.96518**	1,3,4	1

(**Significant at the 5% level)

Source: Authors' finding

Table 7: Estimate of the Periodic Error Correction Model for Industry Sector GNP

Quarter	Seasonal dummies$^{\Psi}$	$\hat{\gamma}_s^{\Gamma}$	$\hat{k}_s^{\Gamma}$	F_{γ}^{Ψ}	F_{δ}^{Ψ}	F_k^{Ψ}
2	-6312.946 (0.000)	-0.86528 (18.59**)	0.5572 (961.66**)	4.23 (0.2373)	31.69 (0.0000)	1.836 (0.10)
3	-3695.637 (0.0525)	-0.428513 (4.95)	0.602196 (315.40**)			
4	-6311.363 (0.0096)	-0.7765 (8.60)	0.60748 (866.45**)			
1	-6761.558 (0.0065)	-0.4495 (8.387)	0.7759 (505.011**)			

Ψ. Probability level in parentheses. Γ. Wald-statistic in parentheses. (**Significant at the 5% level)

Source: Authors' finding

Now we obtain evidence of the presence of cointegration in all or some seasons; it is of particular interest to test for the parameter restrictions that stated in formula (19). To estimate these restrictions and cointegration relations, we estimate the parameters of (16) with seasonal dummies. The main results are given in Table (7).

Seasonally varying adjustment parameter or error correction terms ($\hat{\gamma}_s$) for spring and long-run parameter ($\hat{k}_s$) for all seasons are statistically significant. The F_γ statistic is insignificant at the 10 % level; therefore, the null hypothesis of equality adjustment parameters can be accepted. The F_δ statistic is statistically significant that indicated the adjustment and long-run parameters are statistically different. Calculating the F_k statistic shows that long run parameters are statistically unequal.

Adjustment coefficients reflect variable cost adjustments according to the quarter, calculating the F_γ indicates that they are the same for all quarters, but the speed of adjustment of misalignments is significant only for second quarter. The effects of any shock that occurs in Q2 dissipate faster than if it took place in Q1, Q3 and Q4. Therefore, it seems that April-June period (Q2) is the “high speed time” for disequilibrium adjustments. The final periodic cointegration model has four long-run target relationships:

$$\Delta_4 ind = -5851.73Q_1 - 0.8728Q1(ind_{t-4} - 0.5516serv_{t-4}) + 0.1912(\Delta_4 serv_t) + 0.6683(\Delta_4 ind_{t-1}) + 0.06025(\Delta_4 ind_{t-3})$$

for Q2 (April-June period)

Finally, we test whether the error correction terms in the model for x_t are significant in equation (21), where the lag order is 1 and 3 (such that no serial correlation is present). The LR statistic for the four restrictions is 17.39 that is insignificant at the 1% level. Therefore, the assumption of weak exogeneity is valid.

5. Concluding Remarks

The different sectors of the economy directly or indirectly affected each other and may have the cointegration relationships. On the other hand, we must consider that many macroeconomic time series like

GNP contain important seasonal or periodic components, and it is a common belief that researchers need to pay specific attention to the nature of seasonality or periodically rather than essentially to ignore it. In this paper, using recent advances in the econometric analysis of seasonal and periodic time series**,** it is aimed at finding and analyzing the periodic cointegration relation between GNP sectors of Iran's economy. The periodic cointegration approach, by recognizing the stochastic nature of the seasonal pattern of the time series involved, avoids inconsistent estimations, errors in statistical inference and also biases in economic policy decisions.

This study finds evidence of seasonal and periodic unit roots in the time series involved. To obtain more robust results, we test for periodic cointegration among the relevant variables. Our result success to detect periodic cointegration, indicating that same seasonal patterns drive the industry and service sectors. The service sector is an important component of any country's economy. It makes a direct and significant contribution to GNP and provides crucial inputs for the rest of the economy. The service sector of Iran has the largest contribution (over half of GNP) in the economy of this country during the study period. Service sector provides the key inputs to the industry sector e.g. infrastructure services such as transportation and financial services which facilitate transactions and provide access to finance for investment, health and education services which contribute to a healthy, well-trained workforce. The service sector is thus a key part of the investment climate, and can have a much wider impact on overall business performance and the level of investment, and hence industrial growth in the country's economy. It is therefore expected that GNP of the industry sector follows the GNP of the service sector during the time.

The periodic cointegration model that finally estimated, shows that GNP of the industry sector in Iran for 1988: 2 to 2015: 1 can be treated as a stationary time series in fourth differences, that is to say, shocks that affect the annual change of GNP of the industry sector have only transitory effects and in the long run GNP of the industry sector would achieve the value given by its fundamentals. Besides, it seems as if GNP of industry sector has different fundamentals, depending on the quarter (season). In addition, the impact of changes in those fundamentals on the long-run target relationships depends on which quarter those changes take place. The adjustment of equilibrium misalignments is faster if they take place in the April-June period than in the rest of the year. Therefore, these periodic long-run dynamics should be taken into account to analyze and forecast behavior of GNP sectors.

Some outcomes of this investigation are useful for economic policy. Industry development strategy must be provided according to the link between the service and industry sectors because it increased value added of each sector and leading to overall economic growth. Furthermore, the results show that seasonally varying adjustment parameter for spring and long-run parameter for all seasons are statistically significant, so there are long run relationship between GNP of the industry and service sectors and the speed of adjustment toward this equilibrium is faster in spring. These findings could be of use in future policy economic decision for these sectors and the timing of their implementation.

This article can be extended in several directions, for example, the cointegration equation can be taken into account to analyze and forecast the GNP of the industry sector. Also, other different approaches like as conventional and seasonal cointegration methods can be used to evaluate the relation between GNP sectors, and the results can be used for selecting the best approach for analyzing and forecasting the GNP or other macroeconomics time series.

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