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THE EFFECT OF CYCLICAL AND SEASONAL VARIATION IN INDUSTRIAL PRODUCTION ON OIL IMPORTS: A STRUCTURAL TIME SERIES STUDY OF THE JAPANESE CASE

IMAD A. MOOSA*

Abstract

This paper examines the cyclical and seasonal relationships between Japanese industrial production and oil imports using structural time series analysis. The time series are decomposed into trend, cyclical, seasonal and irregular components. Results of causality testing reveal that there is causal influence from the seasonal component of industrial production to the seasonal component of oil imports, but no such relationship between the cyclical components. These results are compared and reconciled with those obtained from seasonal error correction modelling.

I. *Introduction*

It has been demonstrated by Moosa (1995) that Japanese oil imports can be modelled, using industrial production as an explanatory variable, as a stable function specified as a seasonal error correction model. One finding of this study is that for the period 1976-1991, oil imports and industrial production, as a proxy for economic activity, were not driven by a common stochastic trend since they turned out not to be cointegrated at the zero frequency. Another finding is that the two variables are cointegrated at the seasonal frequencies of two (seasonal) cycles and one cycle per year, implying the significant role played by the seasonal variation in economic activity in determining oil imports.

Harvey and Scott (1994) have criticised seasonal error correction models on the grounds that the autoregressive representation of these models lacks the ability to handle slowly changing seasonal patterns. Since the autoregressive representation may require the incorporation of long lags, the resulting dynamics may confound seasonal effects with the dynamic responses of prime interest. They, instead, recommend a procedure whereby seasonality is modelled explicitly as an unobserved component. The advantage of this procedure, according to the argument put forward by Harvey and Scott, is that it simplifies the dynamic modelling and removes the risk of misspecification as well as providing useful insights into seasonal integration and cointegration.

The objective of this paper is to reconsider the results of Moosa (1995) using the

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structural time series modelling approach suggested by Harvey (1985, 1989). More specifically, observed time series on oil imports and industrial production are decomposed into trend, cyclical, seasonal and irregular components, and then tests are conducted to reveal the relationship between the various components of oil imports and the corresponding components of industrial production. One clear advantage of this approach is that it allows for an explicit treatment of cycles in the two variables, a facility that is not provided by error correction models, at least not explicitly.

II. *Methodology*

The structural time series model of Harvey (1985, 1989) is used to decompose the observed output and exports series into unobserved trend, cyclical and seasonal components. This model arguably represents the main features of a time series by considering its various constituent components. The model may be written as

$$z_t = \mu_t + \phi_t + \gamma_t + \varepsilon_t \tag{1}$$

where z_t is the logarithm of the observed value of the series, μ_t is the trend component, ϕ_t is the (additive) cyclical component, γ_t is the seasonal component and ε_t is the irregular component. The trend, cyclical and seasonal components are assumed to be uncorrelated while ε_t is assumed to be white noise.

The trend component, which represents the long-term movement in a series, is assumed to be stochastic and linear. This component can be represented by

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{2}$$

$$\beta_t = \beta_{t-1} + \zeta_t \tag{3}$$

where $\eta_t \sim NID\ (0, \sigma_\eta^2)$, and $\zeta_t \sim NID\ (0, \sigma_\zeta^2)$. μ_t is a random walk with a drift factor, β_t, which follows a first order autoregressive process as represented by equation (3). This process collapses to a simple random walk with drift if $\sigma_\zeta^2 = 0$, and to a deterministic linear trend if $\sigma_\eta^2 = 0$ as well. If, on the other hand, $\sigma_\eta^2 = 0$ while $\sigma_\zeta^2 \neq 0$, the process will have a trend which changes relatively smoothly.

The cyclical component, which is assumed to be a stationary linear process, may be represented by

$$\phi_t = a \cos \theta_t + b \sin \theta_t \tag{4}$$

where t is time and the amplitude of the cycle is given by $(a^2 + b^2)^{\frac{1}{2}}$. In order to make the cycle stochastic, the parameters a and b are allowed to evolve over time, while preserving continuity is achieved by writing down a recursion for constructing ϕ before introducing the stochastic elements. By introducing disturbances and a damping factor we obtain

$$\phi_t = \rho\ (\phi_{t-1} \cos \theta + \phi^*_{t-1} \sin \theta) + \omega_t \tag{5}$$

$$\phi_t^* = \rho\,(-\phi_{t-1} \sin\theta + \phi_{t-1}^* \cos\theta) + \omega_t^* \tag{6}$$

where ϕ_t^* appears by construction such that ω_t and ω_t^* are uncorrelated white noise disturbances with variances σ_ω^2 and $\sigma_{\omega*}^2$ respectively. The parameters $0 \leq \theta \leq \pi$ and $0 \leq \rho \leq 1$ are the frequency of the cycle and the damping factor on the amplitude respectively.[1] In order to make numerical optimisation easier, the constraint $\sigma_\omega^2 = \sigma_{\omega*}^2$ is imposed.

The seasonal component, γ_t, is stationary when multiplied by the seasonal summation operator, $S(L)$, which is given by

$$S(L) = \sum_{j=0}^{s-1} L^j \tag{7}$$

where s is the number of seasons per year (four for quarterly data), and L is the lag operator such that $L^j\gamma_t = \gamma_{t-j}$. While there are a number of different specifications for seasonality (see Harvey, 1989, chapter 2), we use the trigonometric specification which, for an even s, is written as

$$\gamma_t = \sum_{j=1}^{s/2} \gamma_{j,t} \tag{8}$$

$\gamma_{j,t}$ is given by

$$\gamma_{j,t} = \gamma_{j,t-1} \cos\lambda_j + \gamma_{j,t-1}^* \sin\lambda_j + \kappa_{j,t} \tag{9}$$

$$\gamma_{j,t}^* = \gamma_{j,t-1} \sin\lambda_j + \gamma_{j,t-1}^* \cos\lambda_j + \kappa_{j,t}^* \tag{10}$$

where $j = 1, \ldots, s/2-1$, $\lambda_j = 2\pi j/s$ and

$$\gamma_{j,t} = -\gamma_{j,t-1} + \kappa_{j,t} \quad j = s/2 \tag{11}$$

where $\kappa_{j,t} \sim NID\,(0, \sigma_\kappa^2)$ and $\kappa_{j,t}^* \sim NID\,(0, \sigma_{\kappa*}^2)$. Again, the assumption $\sigma_\kappa^2 = \sigma_{\kappa*}^2$ is imposed. One advantage of this specification is that it allows for smoother changes in the seasonals (Harvey and Scott, 1994, p1328).

The extent to which the trend, seasonal and cyclical components evolve over time depends on the values of σ_η^2, σ_ζ^2, σ_κ^2, σ_ω^2, θ and ρ which are known as the hyperparameters. These parameters can be estimated by maximum likelihood in the time or frequency domain once the model has been written in a state space form (Harvey, 1989, chapter 4). The frequency domain estimation is much faster but it provides slightly different results because the procedure is based on an approximation to the frequency domain likelihood function. When these parameters have been estimated via the Kalman filter and prediction error decomposition, it is possible to obtain estimates of the unobserved components.

[1] The period of the cycle, which is the time taken by the cycle to go through its complete sequence of values is $2\pi/\theta$ (Harvey, 1990, 38). The stochastic cycle in equations (5) and (6) collapses to AR (1) process when $\theta = 0$ or π.

III. *Data and Empirical Results*

The data sample used in this study is the same as the sample used by Moosa (1995). The sample consists of quarterly observations covering the period 1976:1–1991:4 on oil imports, (in 1000 barrels per day) and industrial production, both of which are seasonally unadjusted. The data were obtained from *Datastream* (OECD series).

Figures 1–8 plot the observed (logarithmic) time series as well as their estimated unobserved components. Figure 1, which plots the observed oil imports series, shows that while oil imports were declining secularly until the second quarter of 1986 (due to measures of conservation following the price rises of the 1970s), the trend was reversed, perhaps due to the collapse of oil prices in 1986. Moreover, Figure 1 shows a very strong seasonal behaviour in oil imports. On the other hand, Figure 2 plots the observed series of industrial production, showing a strong upward trend, some seasonal variation, and what appears to be some cyclical dips. Figures 3 and 4, which plot the trend components, show clearly the reversal of trend in oil imports (following the collapse of oil prices in 1986) without any major change in the trend

FIGURE 1. OIL IMPORTS (LOGARITHM)

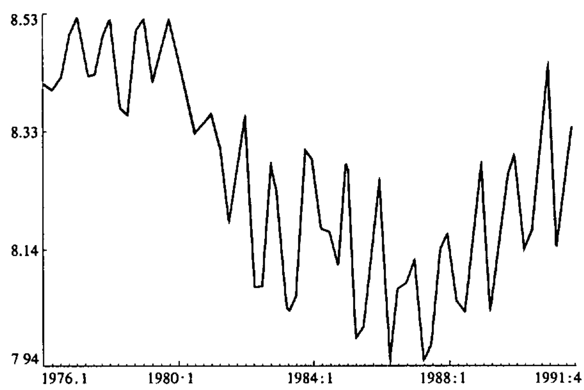

FIGURE 2. INDUSTRIAL PRODUCTION (LOGARITHM)

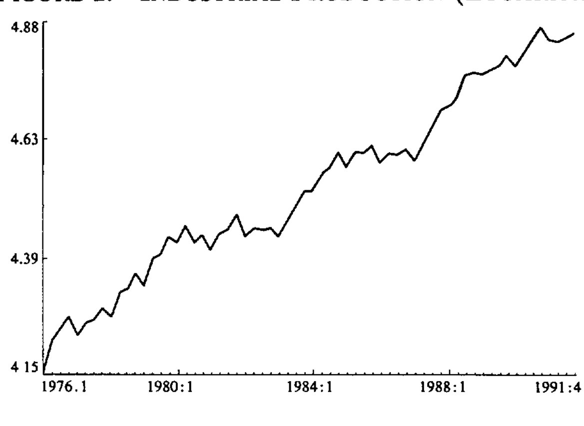

FIGURE 3. OIL IMPORTS (TREND)

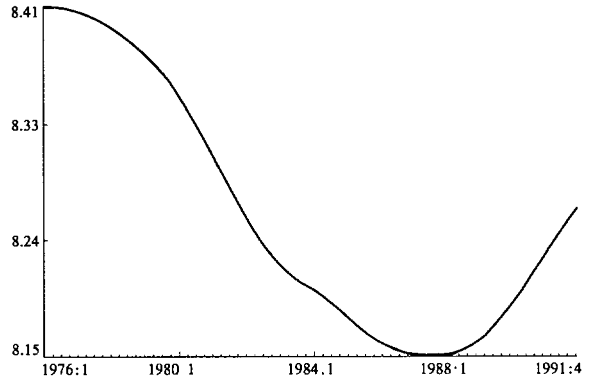

FIGURE 4. INDUSTRIAL PRODUCTION (TREND)

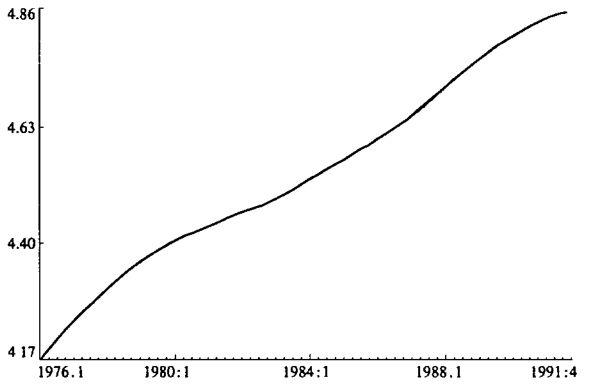

FIGURE 5. OIL IMPORTS (CYCLE)

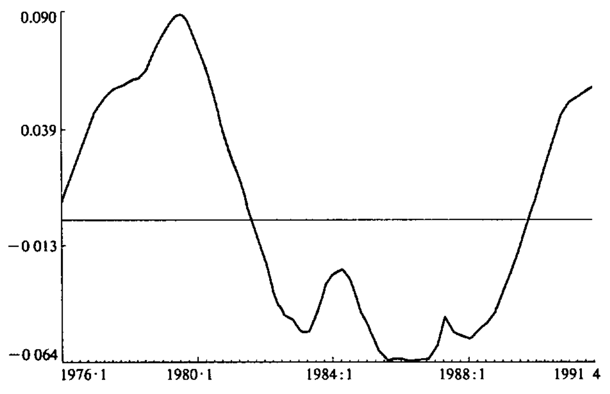

FIGURE 6. INDUSTRIAL PRODUCTION (CYCLE)

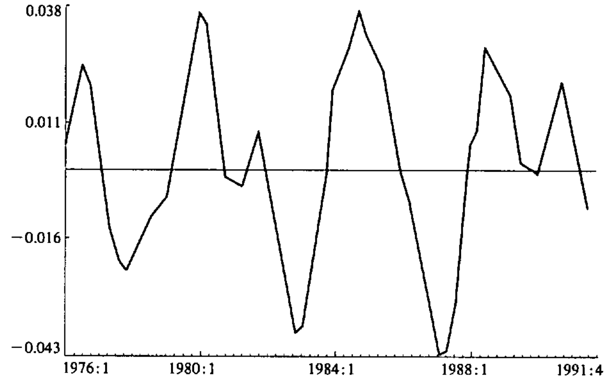

FIGURE 7. OIL IMPORTS (SEASONAL)

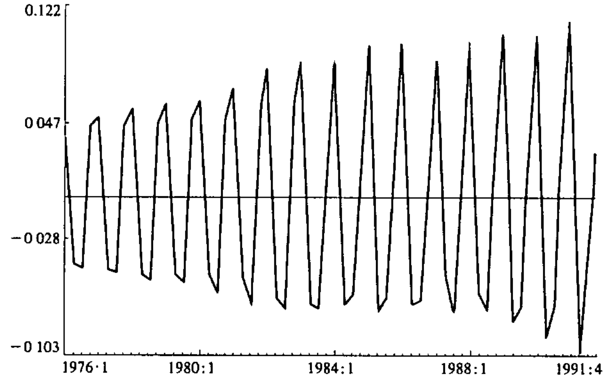

FIGURE 8. INDUSTRIAL PRODUCTION (SEASONAL)

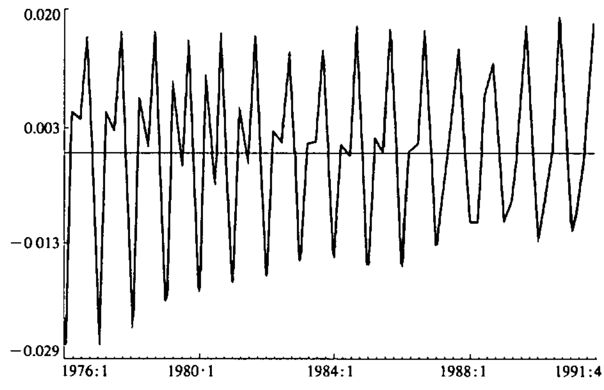

TABLE 1. FREQUENCY DOMAIN ESTIMATES OF THE HYPERPARAMETERS*

Parameter	Oil Imports	Industrial Production
σ_η^2	0.00	0.00
	(1.00)	(1.00)
σ_ζ^2	16.3×10^{-6}	9.3×10^{-6}
	(9.5×10^{-6})	(4.4×10^{-6})
σ_κ^2	5.4×10^{-5}	2.3×10^{-6}
	(2.3×10^{-5})	(1.3×10^{-6})
σ_ω^2	33.1×10^{-5}	7.3×10^{-5}
	(6.7×10^{-4})	(2.5×10^{-5})
θ	0.98	0.94
	(0.07)	(0.04)
ρ	0.11	0.36
	(0.16)	(0.05)

*Figures in parentheses are standard errors.

of industrial production. Figures 5 and 6 show different cyclical behaviour in the two series, in the sense that oil imports do not exhibit strong or frequent cyclical variation, possibly reflecting the practice of stock piling when economic activity is slack. Finally, Figures 7 and 8 show some difference in the behaviour of the seasonal components, and also that the seasonal behaviour of industrial production changed in the latter part of the sample period.

Table 1 reports the frequency domain estimates of the hyperparameters of oil imports and industrial production. The difference in the cyclical behaviour of oil imports and industrial production is confirmed by the values of the damping factor, ρ, and the frequency, θ. These parameters also imply that while the period of the oil imports cycle is nearly 56 quarters, that of industrial production is less than 18 quarters.

Obviously, one cannot infer much about the causal relationships between the cyclical and seasonal components, and so formal econometric testing is warranted. For this purpose causality testing is employed to find out if there is a causal link between the cyclical and seasonal components of oil imports and the corresponding components of industrial production. Testing for causality from industrial production to oil imports is based on the unrestricted VAR

$$m_t = \sum_{i=1}^{k} \alpha_i m_{t-i} + \sum_{i=0}^{k} \beta_i y_{t-i} + \xi_t \tag{12}$$

where m is the cyclical (seasonal) component of oil imports and y is the cyclical (seasonal) component of industrial production. The order of the VAR (the value of k) is determined by the general-to-specific methodology, and once the parsimonious specification is established, we examine causality in terms of three statistics: (i) the t statistic for $\beta_0 = 0$, (ii) the F statistic for $\beta_i = 0 \forall i$, and (iii) the F statistic for $\beta i = 0 \forall i > 0$. The difference between the two F statistics is that the first takes into account contemporaneous causality as well.

The results of causality testing are reported in Table 2. The results show that the cyclical component of industrial production has no contemporaneous or lagged causal effect on the cyclical component of oil imports. On the other hand, the seasonal component of industrial production seems to have both contemporaneous and lagged (positive) causal effect on the

TABLE 2. TESTING FOR CAUSALITY FROM INDUSTRIAL PRODUCTION TO OIL IMPORTS*

	Seasonal Components	Cyclical Components
k	1	2
$t(\beta_0 = 0)$	5.53	−1.54
$F(\beta_i = 0)\forall i$	61.75(2,60)	1.19(3,57)
$F(\beta_i = 0)\forall i>0$	109.01(1,60)	1.78(1,60)

*Figures in parentheses are degrees of freedom.

seasonal component of oil imports. These results can be reconciled with the findings of Moosa (1995) as follows. The finding of no cointegration at the zero frequency (the long run) is due to the different behaviour of the trend components which seem to be driven by different factors. Cointegration at the seasonal frequencies despite the apparent difference in the behaviour of the seasonal components is implied by Moosa's finding of a negative cointegrating parameter at the seasonal frequency of two (seasonal) cycles per year. The absence of any cyclical relationship seems to be due to the weakness of cyclical behaviour and the dominance of seasonal behaviour in oil imports, which may be explained in terms of the role of factors other than economic activity such as climatic conditions.

IV. *Conclusion*

In this paper, an attempt has been made to explain the results of modelling the relationship between Japanese oil imports and industrial production using two different techniques. The results obtained in Moosa (1995) using a seasonal error correction model were compared with those obtained in this paper by using time series decomposition. The findings of this paper, which can be readily reconciled with the findings of Moosa (1995), are that: (i) the trends of the two variables are rather different, (ii) there is an absence of strong cyclical behaviour in oil imports, and (iii) there is causal influence from the seasonal component of industrial production to that of oil imports.

Moreover, it seems that the approach used in this paper is rather appealing because it provided more insight into the time series behaviour of the two variables. First, it revealed a changing seasonal pattern in industrial production and to a lesser extent in oil imports. Second, it distinguished between seasonal and business cycles. Both of these aspects cannot be handled adequately by seasonal error correction modelling.

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