Dynamic Relationship between Business Fluctuation and Capacity Utilization in the Japanese Manufacturing Industry

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***Abstract*—This study presents a Bayesian regression method for estimating the dynamic dependence of the stationary component of Gross Domestic Product (GDP) on that of capacity utilization. First, stationary components from original GDP and capacity utilization time series are extracted using a set of state space models. Then, a set of Bayesian regression models with a time-varying coefficient is constructed. As an application of our proposed method, we analyze the dynamic relationship between GDP and capacity utilization using Japanese economy data from 1980 to 2005. The results imply that capacity utilization has had a larger influence on GDP in the expansion phase than in the recession phase of the Japanese business cycle since the 1990s.**

***Index Terms*—Bayesian modeling, dynamic relationship analysis, time-varying coefficient, gross domestic product, capacity utilization rate, Japanese economy.**

I. Introduction

Macroeconomic performance is closely related to manufacturing capacity utilization. Therefore, from the perspective of macroeconomic policies, considering the mechanism by which capacity utilization has an influence on economic fluctuations is an important issue. The objective of this study is to understand the dynamic relationship between capacity utilization and real Gross Domestic Product (GDP).

Many empirical studies exist regarding the relationship between capacity utilization and macroeconomic performance. For example, [1] examined the determinants of capacity utilization in 40 chemical product industries. As a result, they found that capacity utilization was positively related to capital intensity and the rate of demand growth. [2] attempted to identify the channels through which economic reforms enhanced productivity growth in the total manufacturing sector in India. Because one possible channel is better utilization of plant capacity, they estimated the capacity utilization rate in Indian manufacturing, and showed that there was evidence of a favorable impact of economic reforms on productivity growth in total manufacturing beyond the positive impact of improved capacity utilization. [1] investigated the relationship between inflation and capacity utilization in the US. An interesting finding is that in the long run, a one-percent increase in the rate of inflation leads to approximately a 0.0046-percent increase in capacity utilization.

However, existing empirical studies do not tackle some important questions. For example, regarding the lead-lag relationship between capacity utilization and GDP, is there a difference between expansion and recession periods of business cycles? What kinds of things can be learned about the effect of capacity utilization on GDP during expansion and recession periods? How does the effect of capacity utilization on GDP change over time?

In particular, understanding the time-varying effect of capacity utilization on GDP is crucial for the following reason. Regression analysis models are often used for relationship analysis with constant regression coefficients, the implication being that no structural changes occur. However, when the study period spans several decades, it is clearly unrealistic to assume constant coefficient parameters. Thus, conventional approaches are considered inadequate for the analysis of business cycles with long-term time series. [3] developed a Bayesian approach based on vector autoregressive models with time-varying coefficients for analyzing time series that are nonstationary in covariance. [4] introduced a Bayesian time-varying regression model for dynamic relationship analysis. [5] More recently, these approaches have been used by [6], [7], and [8]. To manage the above difficulties, in this study, we propose an approach to analyzing the relationship between a quarterly economic indicator and a monthly economic indicator, and then apply the proposed approach to analyzing the relationship between capacity utilization and GDP in Japan from 1980 to 2005.

In this study, as the first step in analyzing the dynamic relationship between capacity utilization and GDP, we extract the stationary components from each original time series. Then, we present a method to analyze the dynamic

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relationship between the stationary components of capacity utilization and GDP using Bayesian dynamic modeling. There are two aspects to the relationship between capacity utilization and GDP, i.e., the lead-lag relationship and the time-varying dependence between these two indicators. These are considered by introducing a lag parameter and time-varying coefficients into a set of Bayesian dynamic models. In our recent studies, we analyzed the dynamic dependence of GDP on the unemployment rate, and examined the dynamic relationship between economic growth and inflation in Japan using a similar method (see, [9] and [10]).

Main results obtained from an empirical study are as follows. In both the expansion and recession phases of the Japanese business cycle, a movement in capacity utilization has preceded a movement in GDP by several months. Capacity utilization had a larger influence on GDP in the recession phase than in the expansion phase during the 1980s. However, the reverse has been the case since the 1990s. That is, capacity utilization has had a larger influence on GDP in the expansion phase than in the recession phase since the 1990s.

The rest of this paper is organized as follows. In Section II, we introduce a method for estimating a stationary component from quarterly or monthly time series data. In Section III, we present our models and parameter estimation methods for the proposed approach.
An empirical study based on the proposed approach is presented in Section IV. Some conclusions are presented in Section V.

II. Stationary Component Estimation

As mentioned above, the first step in analyzing the relationship between GDP and capacity utilization is the estimation of the stationary components of GDP and capacity utilization. Thus, we introduce a method for estimating the stationary components from the original time series of these indicators.

For quarterly GDP time series y_m, we consider a set of statistical models as follows:

$$y_m = t_m^y + s_m^y + r_m^y + w_m^y, \tag{1}$$

$$t_m^y = 2t_{m-1}^y - t_{m-2}^y + v_{m1}^y, \tag{2}$$

$$s_m^y = -s_{m-1}^y - s_{m-2}^y - s_{m-3}^y + v_{m2}^y, \tag{3}$$

$$r_m^y = \sum_{j=1}^{p} \alpha_j r_{m-j}^y + v_{m3}^y \ (m = 1,2,\cdots,M), \tag{4}$$

where t_m^y, s_m^y, and r_m^y are the trend component, the seasonal component, and the stationary component, respectively, of the time series y_m. In addition, p represents the order of an autoregressive model for the stationary components and α_1, $\cdots$, α_p are the AR coefficients. $w_m^y \sim \mathrm{N}(0, \sigma^2)$ is the observation noise, while $v_{m1}^y \sim \mathrm{N}(0, \tau_1^2)$, $v_{m2}^y \sim \mathrm{N}(0, \tau_2^2)$, and $v_{m3}^y \sim \mathrm{N}(0, \tau_3^2)$ are system noises for each component model. It is assumed that w_m^y, v_{m1}^y, v_{m2}^y and v_{m3}^y are independent of one another.

When the model order p and the hyperparameters $\alpha_1, \cdots, \alpha_p, \sigma^2, \tau_1^2, \tau_2^2$ and τ_3^2 are given, we can express the models in (1) - (4) by a state space representation. A likelihood function for the hyperparameters is defined by the Kalman filter algorithm, so we can estimate the model order and the hyperparameters using a maximum likelihood method. Then, we can estimate each component in the time series y_m, using the Kalman filter algorithm so that the estimate for the stationary component r_m^y of GDP can be obtained (see [11] for details).

Further, to estimate a stationary component in a monthly capacity utilization time series x_n, we use a set of models similar to that in (1) - (4) as follows:

$$x_n = t_n^x + s_n^x + r_n^x + w_n^x, \tag{5}$$

$$t_n^x = 2t_{n-1}^x - t_{n-2}^x + v_{n1}^x, \tag{6}$$

$$s_n^x = -s_{n-1}^x - \cdots - s_{n-11}^x + v_{n2}^x, \tag{7}$$

$$r_n^y = \sum_{j=1}^{q} \beta_j r_{n-j}^x + v_{n3}^x \ (m = 1,2,\cdots,N), \tag{8}$$

where q represents the order of an AR model for the stationary component and β_1, $\cdots$, β_q are the AR coefficients. $w_n^x \sim \mathrm{N}(0, \psi^2)$ is the observation noise, while $v_{n1}^x \sim \mathrm{N}(0, \eta_1^2)$, $v_{n2}^x \sim \mathrm{N}(0, \eta_2^2)$ and $v_{n3}^x \sim \mathrm{N}(0, \eta_3^2)$ are system noises. The other quantities correspond to each term in the models in (1) - (4). Thus, the model order q and the hyperparameters $\beta_1, \cdots, \beta_q, \psi^2, \eta_1^2, \eta_2^2$ and η_3^2 are estimated using the same algorithm. As a result, the estimate of the stationary component r_m^y in the time series x_n can be obtained.

III. Proposition

A. Model Construction

To analyze the dynamic relationship between quarterly GDP and monthly capacity utilization, we propose an approach based on a set of two-mode regression with time-varying coefficient (TMR-TVC) models.

We classify GDP growth into two states, the upside mode corresponding to the situation in which the stationary component of GDP continues to increase, and the downside mode corresponding to the situation in which it continues to decrease. We consider that the relationship between GDP and capacity utilization may differ according to the situation. Thus, we use different models for the two modes.

For the upside mode, the TMR-TVC models are given in the form of a regression model with time-varying coefficients as follows:

$$r_m^y = \sum_{i=1}^{3} a_{3(m-1)+i} r_{3(m-1)+i+L_1}^x + \varepsilon_m^{(1)}, \tag{9}$$

$$a_{3(m-1)+3} = 2a_{3(m-1)+2} - a_{3(m-1)+1} + e_{3(m-1)+3,}^{(1)} \tag{10}$$

$$a_{3(m-1)+2} = 2a_{3(m-1)+1} - a_{3(m-1)} + e_{3(m-1)+2,}^{(1)} \tag{11}$$

$$a_{3(m-1)+1} = 2a_{3(m-1)} - a_{3(m-1)-1}$$

$$+e^{(1)}_{3(m-1)+1}, \qquad (12)$$

$$(m = 1,2,\cdots,M),$$

where r^y_m denotes the estimate of the stationary component in the quarterly time series of GDP, which is obtained from the estimation of models in (1) - (4), and r^x_n denotes that for the monthly capacity utilization time series, which is obtained from theestimation of models in (5) - (8). a_n is the time-varying coefficient that comprises a monthly time series, and L_1 denotes a lag. $\varepsilon^{(1)}_m \sim \mathrm{N}(0,\lambda^2_1)$ is the observation noise and $e^{(1)}_n \sim \mathrm{N}(0,\phi^2_1)$ is the system noise with λ^2_1 and ϕ^2_1 being hyperparameters. We assume that $\varepsilon^{(1)}_m$ and $e^{(1)}_n$ are independent of each other for any values of m and n.

The lag L_1 and the time-varying coefficient a_n are two important parameters. From the value of L_1 we can see the lead-lag relationship between GDP and capacity utilization in which the case where $L_1 > 0$ implies that capacity utilization lags GDP and the case where $L_1 < 0$ implies that capacity utilization precedes GDP. Moreover, from the estimate of a_n we can examine the dynamic relationship between GDP and capacity utilization.

The models in (9) - (12) are essentially Bayesian linear models in which the model in (9) defines the likelihood and the models in (10) - (12) form a second-order smoothness prior for the time-varying coefficient. Thus, we can estimate the time-varying coefficient with optimal smoothness on a_n by controlling the value of ϕ^2_1.

Similar to the upside mode, the TMR-TVC models for the downside mode are given as

$$r^y_m = \sum_{i=1}^{3} b_{3(m-1)+i} r^x_{3(m-1)+i+L_2} + \varepsilon^{(2)}_m, \qquad (13)$$

$$b_{3(m-1)+3} = 2b_{3(m-1)+2} - b_{3(m-1)+1} + e^{(2)}_{3(m-1)+3}, \qquad (14)$$

$$b_{3(m-1)+2} = 2b_{3(m-1)+1} - b_{3(m-1)} + e^{(2)}_{3(m-1)+2}, \qquad (15)$$

$$b_{3(m-1)+1} = 2b_{3(m-1)} - b_{3(m-1)-1} + e^{(2)}_{3(m-1)+1}, \qquad (16)$$

$$(m = 1,2,\cdots,M),$$

with L_2, b_n being the lag and the time-varying coefficient, respectively. In addition, $\varepsilon^{(2)}_m \sim \mathrm{N}(0,\lambda^2_2)$ is the observation noise and $e^{(2)}_n \sim \mathrm{N}(0,\phi^2_2)$ is the system noise for the case where λ^2_2 and ϕ^2_2 are hyperparameters. As in the models in (9) - (12), we assume that $\varepsilon^{(2)}_m$ and $e^{(2)}_n$ are independent of each other for any values of m and n.

Below we only show the methods for estimating the hyperparameters in the TMR-TVC models for the upside mode because those for the downside mode are similar.

B. Time-Varying Coefficient Estimation

Now, we set

$$\boldsymbol{z}_m = \begin{bmatrix} a_{3(m-1)+3} \\ a_{3(m-1)+2} \\ a_{3(m-1)+1} \end{bmatrix}, \ \boldsymbol{H}^T_m = \begin{bmatrix} r^{(x)}_{3(m-1)+3+L_1} \\ r^{(x)}_{3(m-1)+2+L_1} \\ r^{(x)}_{3(m-1)+1+L_1} \end{bmatrix},$$

$$\boldsymbol{G} = \begin{bmatrix} 1 & -2 & 1 \\ 0 & 1 & -2 \\ 0 & 0 & 1 \end{bmatrix}^{-1} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 1 & 2 \\ 0 & 0 & 1 \end{bmatrix},$$

$$\boldsymbol{F} = -\boldsymbol{G} \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ -2 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 1 & 2 \\ 0 & 0 & 1 \end{bmatrix},$$

$$\boldsymbol{e}_m = \begin{bmatrix} e^{(x)}_{3(m-1)+3} \\ e^{(x)}_{3(m-1)+2} \\ e^{(x)}_{3(m-1)+1} \end{bmatrix}, \boldsymbol{Q} = \mathrm{E}\{\boldsymbol{e}_m \boldsymbol{e}^T_m\} = \phi^2_1 \boldsymbol{I}_3$$

with $\boldsymbol{I}_3$ denoting a 3-th identity matrix. Thus, the models in (9) - (12) can be expressed by a state space representation as

$$\boldsymbol{z}_m = \boldsymbol{F}\boldsymbol{z}_{m-1} + \boldsymbol{G}\boldsymbol{e}_m, \qquad (17)$$

$$r^y_m = \boldsymbol{H}_m \boldsymbol{z}_m + \varepsilon^{(1)}_m. \qquad (18)$$

In the state space representation comprising (17) and (18), the time-varying coefficient a_n is included in the state vector $\boldsymbol{z}_m$. So, the estimate for a_n can be obtained from the estimate of $\boldsymbol{z}_m$. Moreover, the parameters, λ^2_1 and ϕ^2_1, which are called hyperparameters, can be estimated using the maximum likelihood method.

Let $\boldsymbol{z}_0$ denote the initial value of the state and let $Y^{(k)}_1$ denote a set of estimates for r^y_m up to time point k, where k denotes a quarter. Assume that $\boldsymbol{z}_0 \sim \mathrm{N}(\boldsymbol{z}_{0|0}, \boldsymbol{C}_{0|0})$. Because the distribution $f(\boldsymbol{z}_m | Y^{(k)}_1)$ for the state $\boldsymbol{z}_m$ conditional on $Y^{(k)}_1$ is Gaussian, it is only necessary to obtain the mean $\boldsymbol{z}_{m|k}$ and the covariance matrix $\boldsymbol{C}_{m|k}$ of $\boldsymbol{z}_m$ with respect to $f(\boldsymbol{z}_m | Y^{(k)}_1)$.

Given the values of L_1, λ^2_1 and ϕ^2_1, the initial distribution $\mathrm{N}(\boldsymbol{z}_{0|0}, \boldsymbol{C}_{0|0})$, and a set of estimates for r^y_m up to time point M, the means and covariance matrices in the predictive distribution and filter distribution for the state $\boldsymbol{z}_m$ can be obtained using the Kalman filter for $m = 1,2,\cdots,M$ (see for example, [11]):

[**Prediction**]

$$\boldsymbol{z}_{m|m-1} = \boldsymbol{F}\boldsymbol{z}_{m-1|m-1},$$
$$\boldsymbol{C}_{m|m-1} = \boldsymbol{F}\boldsymbol{C}_{m-1|m-1}\boldsymbol{F}^{\mathrm{t}} + \boldsymbol{G}\boldsymbol{Q}\boldsymbol{G}^{\mathrm{t}}.$$

[**Filter-1**]

$$\boldsymbol{K}_m = \boldsymbol{C}_{m-1|m-1}\boldsymbol{H}^{\mathrm{t}}_m\left(\boldsymbol{H}_m\boldsymbol{C}_{m-1|m-1}\boldsymbol{H}^{\mathrm{t}}_m + \lambda^2_1\right)^{-1},$$
$$\boldsymbol{z}_{m|m} = \boldsymbol{z}_{m|m-1} + \boldsymbol{K}_m\left(r^y_m - \boldsymbol{H}_m\boldsymbol{z}_{m|m-1}\right),$$
$$\boldsymbol{C}_{m|m} = (\boldsymbol{I}_3 - \boldsymbol{K}_m\boldsymbol{H}_m)\boldsymbol{C}_{m|m-1}.$$

[**Filter-2**]

$$\boldsymbol{z}_{m|m} = \boldsymbol{z}_{m|m-1},$$

$$\boldsymbol{C}_{m|m} = \boldsymbol{C}_{m|m-1}.$$

Note that for EACH value of m, when the time point m is in an upside period we use Filter-1; otherwise Filter-2 is applied.

Based on the results of the Kalman filter, we can obtain an estimate for $\boldsymbol{z}_m$ using the fixed-interval smoothing for $m = M-1, M-2, \cdots, 1$ as follows:

[**Fixed-Interval Smoothing**]

$$\boldsymbol{A}_m = \boldsymbol{C}_{m|m}\boldsymbol{F}^{\mathrm{t}}\boldsymbol{C}_{m+1|m}^{-1},$$

$$\boldsymbol{z}_{m|M} = \boldsymbol{z}_{m|m} + \boldsymbol{A}_m\left(\boldsymbol{z}_{m+1|M} - \boldsymbol{z}_{m+1|m}\right),$$

$$\boldsymbol{C}_{m|M} = \boldsymbol{C}_{m|m} + \boldsymbol{A}_m\left(\boldsymbol{C}_{m+1|M} - \boldsymbol{C}_{m+1|m}\right)\boldsymbol{A}_m^{\mathrm{t}}.$$

Then, the posterior distribution of $\boldsymbol{z}_m$ is given by $\boldsymbol{z}_{m|M}$ and $\boldsymbol{C}_{m|M}$. Subsequently, the estimate for the time-varying coefficient a_n can be obtained because the state space representation described by (17) and (18) incorporates a_n in the state vector $\boldsymbol{z}_m$.

C. Constant Parameters Estimation

Given the time series data $Y_1^{(M)} = \{r_1^y, r_2^y, \cdots, r_M^y\}$ and the corresponding time series data $\{r_1^x, r_2^x, \cdots, r_{3M}^x\}$, a likelihood function for the hyperparameters λ_1^2 and ϕ_1^2 and the parameter L_1 is given by:

$$f\left(Y_1^{(M)}\middle|\lambda_1^2, \phi_1^2, L_1\right) = \prod_{m=1}^{M} f_m\left(r_m^y|\lambda_1^2, \phi_1^2, L_1\right),$$

where $f_m\left(r_m^y|\lambda_1^2, \phi_1^2, L_1\right)$ is the density function of r_m^y. By taking the logarithm of $f\left(Y_1^{(M)}\middle|\lambda_1^2, \phi_1^2, L_1\right)$, the log-likelihood is obtained as

$$l(\lambda_1^2, \phi_1^2, L_1) = \log f\left(Y_1^{(M)}\middle|\lambda_1^2, \phi_1^2, L_1\right)$$
$$= \sum_{m=1}^{M} \log f_m\left(r_m^y|\lambda_1^2, \phi_1^2, L_1\right). \quad (19)$$

Following [11], using the Kalman filter, the density function $f_m\left(r_m^y|\lambda_1^2, \phi_1^2, L_1\right)$ is a normal density given by:

$$f_m\left(r_m^y|\lambda_1^2, \phi_1^2, L_1\right) = \frac{1}{\sqrt{2\pi w_{m|m-1}}}$$
$$\times \exp\left\{-\frac{\left(r_m^y - \hat{r}_{m|m-1}^y\right)^2}{2w_{m|m-1}}\right\} \quad (20)$$

where $\hat{r}_{m|m-1}^y$ is the one-step-ahead prediction for r_m^y and $w_{m|m-1}$ is the variance of the predictive error, respectively given by

$$\hat{r}_{m|m-1}^y = \boldsymbol{H}_m\boldsymbol{z}_{m|m-1},$$

$$w_{m|m-1} = \boldsymbol{H}_m\boldsymbol{C}_{m-1|m-1}\boldsymbol{H}_{\boldsymbol{m}}^{\mathrm{t}} + \lambda_1^2.$$

Moreover, for a fixed value of L_1, the estimates of the hyperparameters can be obtained using the maximum likelihood method, i.e., we can estimate the hyperparameters by maximizing the log-likelihood $l(\lambda_1^2, \phi_1^2, L_1)$ in (19) together with (20). In practice, when we substitute the new $\lambda_1^2 = 1$ into the Kalman filter algorithm outlined above, the estimate $\hat{\lambda}_1^2$ for λ_1^2 is obtained analytically by

$$\hat{\lambda}_1^2 = \frac{1}{M}\sum_{m=1}^{M}\frac{\left(r_m^y - \hat{r}_{m|m-1}^y\right)^2}{w_{m|m-1}}. \quad (21)$$

Thus, an estimate $\hat{\phi}_1^2$ for ϕ_1^2 can be obtained by maximizing the log-likelihood $l(\hat{\lambda}_1^2, \phi_1^2, L_1)$ using (21).

Information about the value of lag L_1 is important for analyzing the lead-lag relationship between GDP and capacity utilization, and can be obtained from the maximum value of the likelihood function. For a given value of the lag L_1, the maximum likelihood is given as $f\left(Y_1^{(M)}\middle|\hat{\lambda}_1^2, \hat{\phi}_1^2, L_1\right)$. Then, for a set $\left\{L_1^{(1)}, L_1^{(1)}+1, \cdots, L_1^{(2)}-1, L_1^{(2)}\right\}$ of values for L_1 we can calculate the relative likelihood by

$$R(L_1) = \frac{f\left(Y_1^{(M)}\middle|\hat{\lambda}_1^2, \hat{\phi}_1^2, L_1\right)}{\sum_{j=L_1^{(1)}}^{L_1^{(2)}} f\left(Y_1^{(M)}\middle|\hat{\lambda}_1^2, \hat{\phi}_1^2, j\right)}$$

$$\left(L_1 = L_1^{(1)}, L_1^{(1)}+1, \cdots, L_1^{(2)}-1, L_1^{(2)}\right)$$

with $L_1^{(1)}$ and $L_1^{(2)}$ denoting an negative integer and a positive integer respectively. Thus, we can analyze the lead-lag relationship between GDP and capacity utilization from the distribution of the relative likelihood on L_1. The same is used to analyze the lag L_2 in the downside-mode models.

IV. Empirical Analysis

Here, we present an empirical study analyzing the relationship between real GDP and capacity utilization (especially that for the manufacturing industry) in Japan for the period between 1980 and 2005. The real GDP data are obtained from the Cabinet Office, Government of Japan, while the capacity utilization data are obtained from the website of the Ministry of Economy, Trade and Industry, Japan.

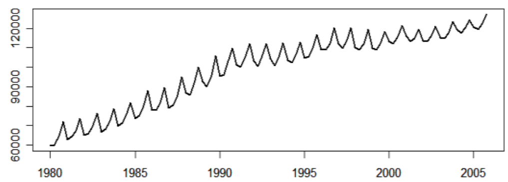

Figure 1. Real GDP time series data for Japan (1980Q1 - 2005Q4).

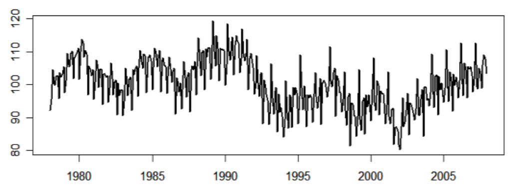

Figure 2. Capacity utilization time series data for Japan (1978.1 - 2007.12).

Figs 1 and 2 show the quarterly real GDP time series for the period 1980Q1 - 2005Q4 and the monthly capacity utilization time series for the period 1978.1 - 2007.12, respectively. Note that GDP is measured in billions of Japanese Yen.

For simplicity of parameter estimation, we adjust the scale for the GDP time series. Specifically, letting y_m^* denote the original GDP data, we adjust the associated scale by

$$y_m = 100 \times \frac{y_m^*}{y_1^*} \quad (m = 1,2,\cdots).$$

In addition, because time series x_n^* for capacity utilization is an index, we transform it as follows:

$$x_n = \log(x_n^*) \quad (n = 1,2,\cdots).$$

In the analysis below, we use the scale-adjusted time series y_m as the GDP data and the logarithmically transformed time series x_n as the capacity utilization data.

To estimate the stationary component in GDP, we compute the log-likelihoods of the models in (1) - (4) for $p = 1, 2, 3, 4$. Table I shows the values of the log-likelihood for each value of p. From Table I, we can see that the maximum log-likelihood is obtained for models with $p = 1$. Thus, we use models with $p = 1$ as a set of the best models for data analysis.

TABLE I. LOG-LIKELIHOOD OF MODEL IN (1) - (4)

p = 1	p = 2	p = 3	p = 4
-230.63	-231.46	-231.82	-231.21

Similarly, to estimate the stationary components of capacity utilization, we compute the log-likelihoods of the models in (5) - (8) for $q = 1, 2, \ldots, 12$. Table 2 shows the values of the log-likelihood for each value of q. From Table 2, it can be seen that the values of the log-likelihoods are almost monotonously increasing with the value of q. However, when the value of q is made even larger, it runs the risk of unstable estimates for parameters in the models, hence we take the models with $q = 12$ as a set of reasonable models. Thus, in the data analysis, we use the models for capacity utilization with $q = 12$.

TABLE II. LOG-LIKELIHOOD OF MODEL IN (5) – (8)

q = 1	q = 2	q = 3	q = 4	q = 5	q = 6
889.02	888.54	889.85	904.57	904.25	907.61
q = 7	q = 8	q = 9	q = 10	q = 11	q = 12
913.47	915.48	914.13	922.27	922.13	926.20

Fig. 3 shows the estimate for the stationary component of GDP. The thin line shows the original estimate and the thick line shows the seven-quarter moving average. The vertical lines indicate inflections of the business cycle (the solid and broken lines indicate peaks and troughs, respectively). It can be seen from Fig. 3 that fluctuations in the stationary component of GDP correlate closely with business cycles in Japan.

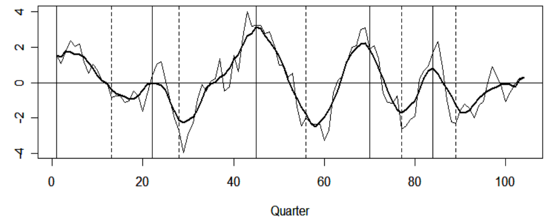

Figure 3. Time series for the estimation of the stationary components of real GDP. The vertical lines indicate turning points in the business cycle (the solid and broken lines indicate peaks and troughs, respectively).

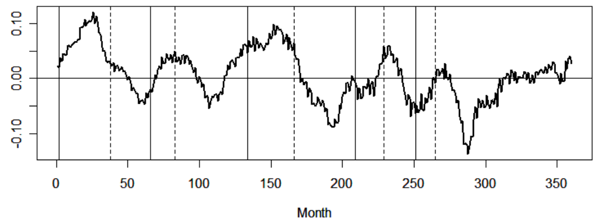

Figure 4. Time series for the estimation of the stationary component of the capacity utilization. The vertical lines indicate inflections of the business cycle (the solid and broken lines indicate peaks and troughs, respectively).

The estimate for the stationary component of capacity utilization is shown in Fig. 4. Similar to Fig. 3, the vertical lines indicate inflections in the business cycle (the solid and broken lines indicate peaks and troughs, respectively). From Fig. 4, we can see that fluctuations in the stationary component of capacity utilization are almost in harmony with business cycles in Japan.

Fig. 5 shows the relative likelihood distribution of the lags between -24 and 24 in the capacity utilization models, with the horizontal axis representing time in months. It can be seen from Fig. 5 that in panel (a), the relative likelihood for the upside-mode model shows a peak corresponding to a two-month lead. Moreover, the result for the downside-mode model, which is shown in panel (b), shows that a peak in relative likelihood is observed at a three-month lead. The above results imply that in both the expansion and recession phases, capacity utilization leads GDP with a short lead time. However, looking at Fig. 5 in detail, it can be seen that the relative likelihood for the upside-mode model is distributed over a wider range than that for the downside-mode model. This suggests that the estimated lags for the upside-mode model may show greater fluctuations.

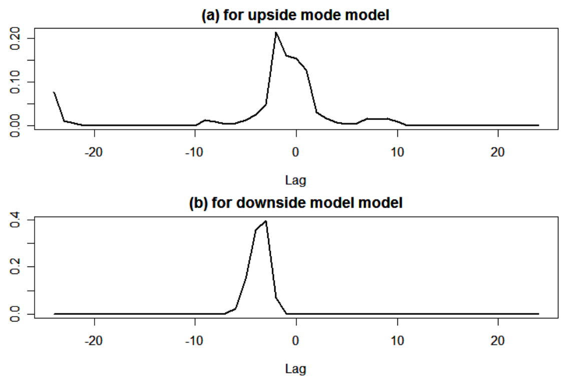

Figure 5. Relative likelihood distribution on the lag.

We show time series of the estimates for the time-varying coefficient in Fig. 6, in which panel (a) is the time-varying coefficient for the upside-mode models with $L_1 = -2$ and panel (b) is that for the downside-mode models with $L_2 = -3$. It can be seen that the time-varying coefficients take positive values in both cases. However, for the upside-mode models, the estimate for the time-varying coefficient has continued to rise, while for the downside-mode model it shows significantly larger values during the bubble economy period since the 1990s in Japan.

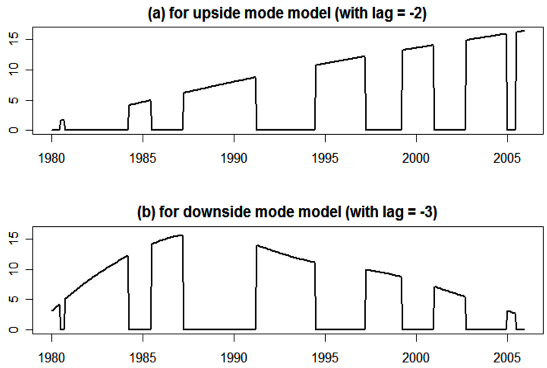

Figure 6. Time series of the time-varying coefficient.

V. Conclusions

We analyzed the dynamic relationship between the stationary components of GDP and capacity utilization in Japan from 1980 to 2005. The main results can be summarized as follows: In both the expansion and recession phases of the business cycle, a movement in capacity utilization has preceded a movement in GDP by several months. This implies that capacity utilization can be used to predict the monthly value of GDP, and can also be regarded as a leading indicator of the business cycle. Therefore, information from movements in capacity utilization provide telling clues for forecasting trends in the Japanese economy and business conditions.

We obtained the following key findings. Capacity utilization had a larger influence on GDP in the recession phase than in the expansion phase during the 1980s. However, the reverse has applied since the 1990s, i.e., the influence of capacity utilization on GDP has been larger in the expansion phase than in the recession phase. In addition, the time-varying coefficients in the expansion and recession phases show very different patterns since the 1990s. For the expansion phase, the positive effect of capacity utilization on GDP has exhibited an upward trend since the 1990s. In contrast, for the recession phase, the positive effect of capacity utilization on GDP has exhibited a downward trend since the 1990s.

Therefore, in terms of policies aimed at promoting economic growth, an increase in capacity utilization is expected to have a relatively large impact on economic growth during periods of expansion. This implies that investment in equipment by the Japanese manufacturing industry during periods of expansion is becoming increasingly important.

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