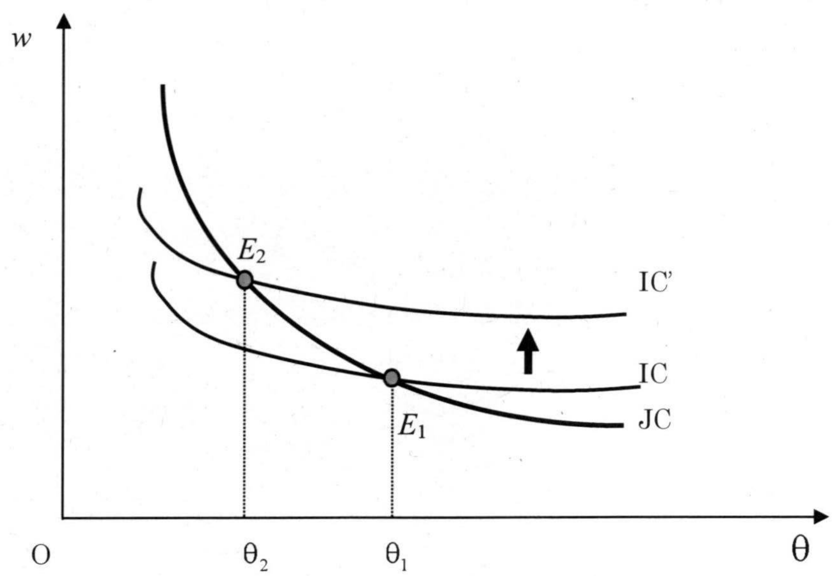

Figure 3a

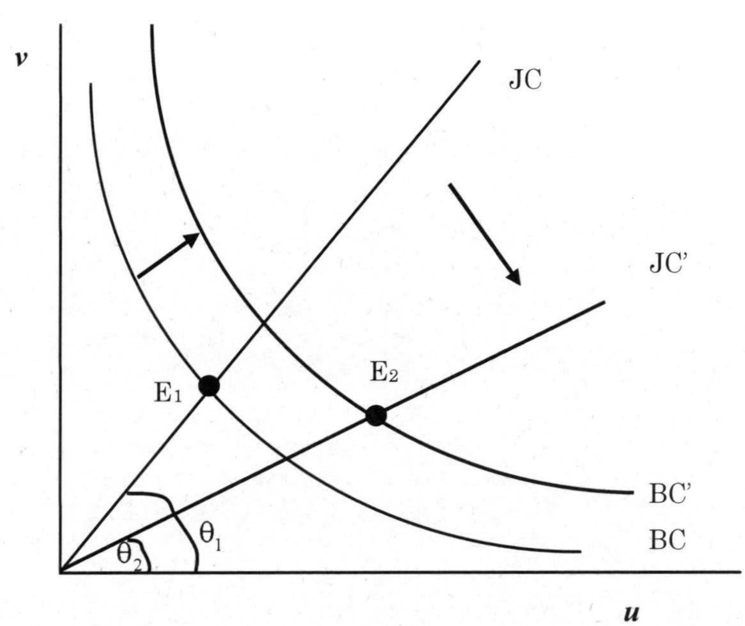

Figure 3b

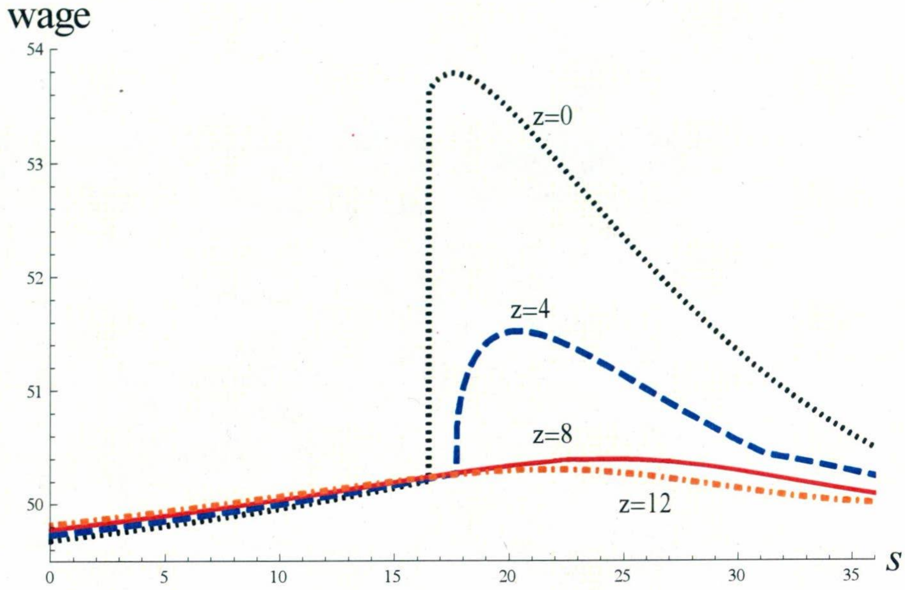

Figure 4: wage

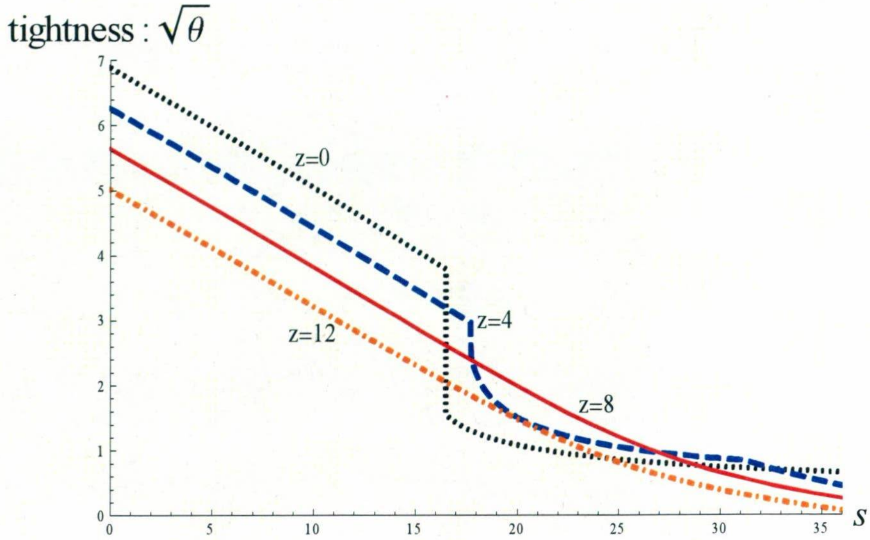

Figure 5: market tightness

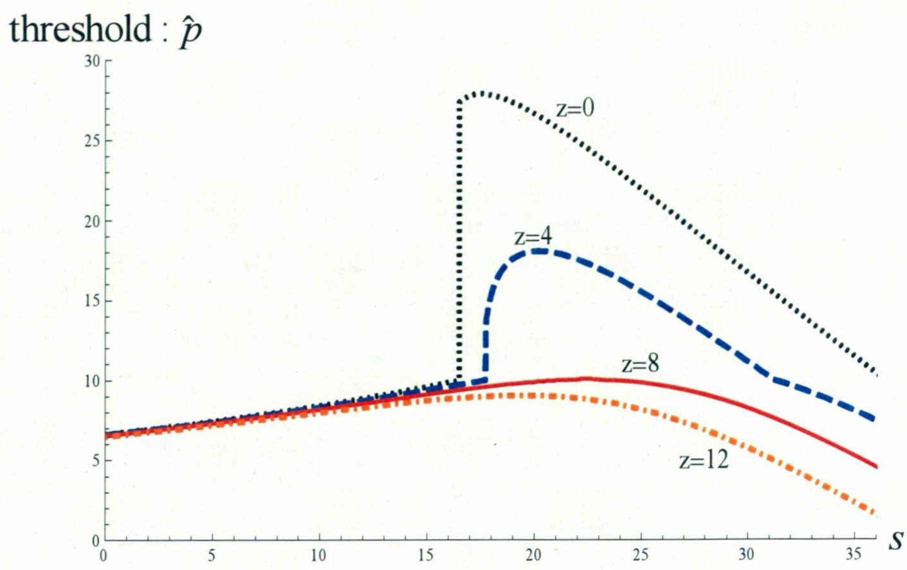

Figure 6: the threshold

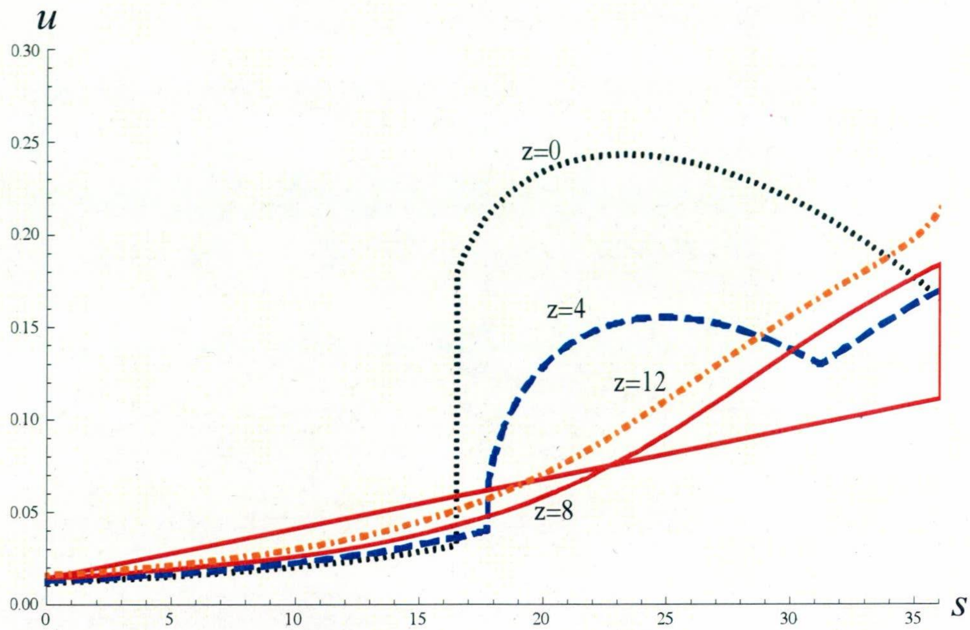

Figure 7: unemployment rate

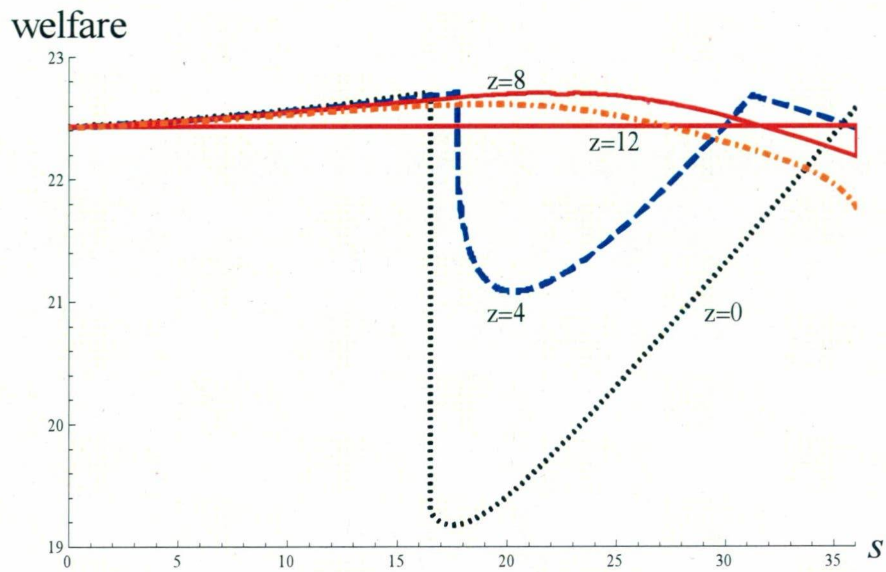

Figure 8: welfare

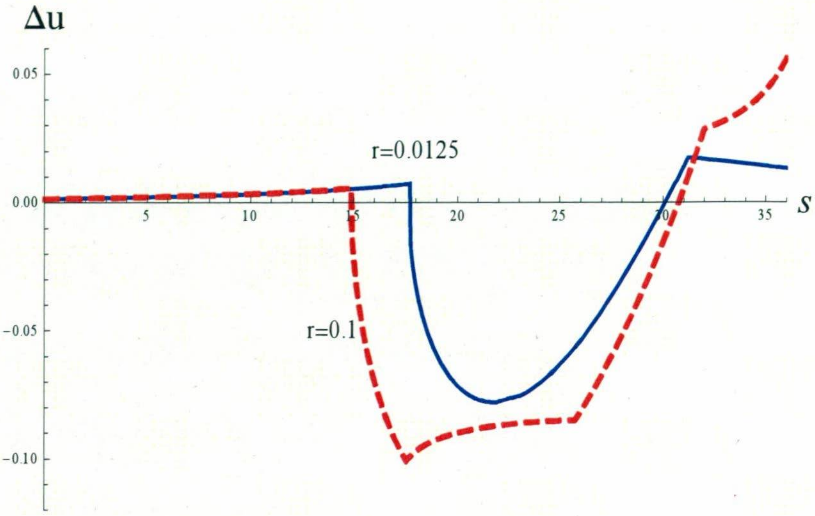

Figure 9a

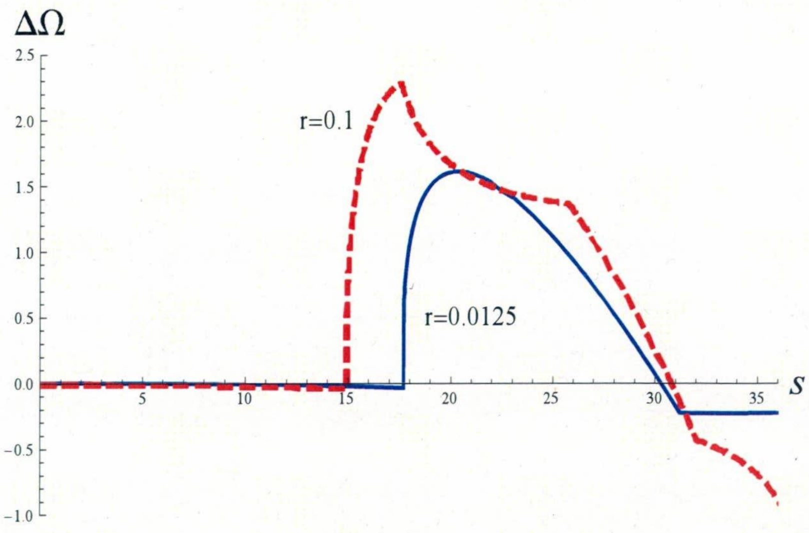

Figure 9b

Table 1

Values of Parameters

Parameters	***Values***
range of state	$p \in [0, 100]$
density function of diligent workers	$\phi(p) = \frac{1}{100} \quad for \quad p \in [0, 100]$
density function of shirking workers	$\phi^S(p) = \begin{cases} \frac{1}{10} & for \quad p \in [0, 10] \\ 0 & for \quad p \in [10, 100] \end{cases}$
reservation wage	$\overline{w} = 10$
interest rate	$r = 0.0125$
effort cost	$c = 25$
vacancy cost	$k = 5$
matching function	$m = 0.8(uv)^{0.5}$

BAYESIAN ESTIMATION OF AN ASYMMETRIC EMPLOYMENT ADJUSTMENT MODEL

Akikuni Matsumoto* , Hisayuki Hara** and Kazumitsu Nawata***

In this paper, we analyze the dynamic labor demand structure of large Japanese firms. We propose a new dynamic model which explicitly considers the asymmetric behavior of the firms between decreasing and increasing regimes. The model modifies the ordinary partial adjustment and the switching cost models. The model is a Tobit-type model; that is, the employment strategies and desired levels of labor are determined by latent variables. We estimate the model using the data augmentation algorithm, which is a Bayesian simulation method. We apply the model to the panel data constructed from financial reports of large Japanese manufacturing firms. When asymmetric adjustment costs are included in the model, we find that: i) a hiring cost does not become lower even if lay-off and dismissal are easier, and ii) employment strategies differ among the industrial sectors even if their cost structures are similar.

Key words and phrases: Asymmetric labor adjustment, Bayesian estimation, Dynamic panel data, Markov chain Monte Carlo method.

1. Introduction

The partial adjustment model is widely used in many empirical works employing dynamic factor demand analyses because it allows easy interpretation and estimation. This model is obtained from the quadratic adjustment cost function without a fixed cost. In this model, the adjustment occurs continuously and the adjustment cost depends on the adjustment speed. (We refer to this type of the adjustment cost as the variable cost.) However, Hamermesh (1989) points out that the aggregation of data makes the adjustment continuous even if the adjustment occurs in a lumpy fashion at the micro unit level. In a study using data on U.S. manufacturing plants, Hamermesh (1989) shows the lumpy adjustment model fits better than the partial adjustment model. He suggests that the continuous adjustment can be observed by aggregating data. Hildreth and Ohtake (1998) apply both the partial adjustment and lumpy adjustment models to Japanese motor vehicle plants data using the method proposed by Hamermesh (1989). They find that the adjustment is continuous for short-term adjustments. Although they analyze the firms' cost structures for the adjustment, they do not consider the structures of firing and hiring costs.

These two models include either the fixed or the variable adjustment costs. The fixed cost of firing includes the costs of bargaining with the labor unions and damage to workers' morale. The cost of hiring includes the costs of recruiting and training. Therefore, when the labor inputs are measured as the number of employees, the fixed adjustment costs can not be ignored. On the other hand, it is reasonable

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to assume that the adjustment speed affects the adjustment costs. Therefore, the variable cost should also be included in the model.

Hamermesh (1992) proposes a model including both the fixed and the variable adjustment costs. This model assumes that the fixed cost occurs at every period when the adjustment is implemented. However, the fixed cost mentioned above can be considered a sunk cost; that is, it rises just once, when a firm decides to adjust the labor input, and does not occur again until the adjustment is completed. Although his model also assumes that the cost structures are the same in both firing and hiring regimes, the adjustment cost structures may depend on the regimes.

In this paper, we modify the generalized model of Hamermesh (1992) and propose a new model where the fixed cost arises only when a firm begins to implement the adjustment. The model also allows different adjustment cost structures in firing and hiring regimes. Park et al. (2005) propose a method of testing asymmetry in the framework of the threshold autoregression (TAR) model. The TAR model is based on the threshold regression model, where the parameters can differ depending on whether a threshold variable is less than a threshold value (Hansen, 1999; Caner and Hansen, 2001). In the TAR model, the threshold variable is an observabale lagged dependent variable which is observable. In our model, following Hamermesh (1992), the threshold variable is assumed to be unobservable. The unobservable threshold variable model is available in the framework of profit maximization. However, we cannot use the conventional estimation method for this model.

Our model is a Tobit-type model; that is, the employment strategies and desired levels of labor are determined by latent variables. The model is comprised of two parts. One is the regime switching part. A firm chooses one of three strategies; that is, firing, no adjustment, or hiring. The other determines the actual size of the adjustment. This type of model is also referred to as a friction, hidden Markov, state-space or dynamic mixture distribution model. The estimation proceeds by the data augmentation algorithm by Tanner and Wong (1987), which is a Bayesian simulation method widely used in financial econometric analyses (e.g., Jacquier et al., 1994; Oga, 2005). The model is estimated by the Markov Chain Monte Carlo (MCMC) method, which is a modification of Albert and Chib (1993).

We construct panel data for the large Japanese manufacturing firms using the annual data of these firms and analyze the behavior of the Japanese firms using the newly developed model. We call the model an *asymmetric factor adjustment model.* In this model, i) a firm chooses one of three (firing, no adjustment, or hiring) regimes, ii) the regimes are determined by threshold values and iii) the speeds of adjustment are different between the firing and hiring regimes. The threshold values reflect the sizes of fixed cost and the adjustment speeds reflect the sizes of variable cost. The variable cost is not the same in firing and hiring regimes in some sectors of the industry. The lower cost of the lay-off (and dismissals) does not necessarily make hiring easier. Similar adjustment speeds do not necessarily mean similar employment behaviors. The labor adjustment behaviors may differ among firms depending on the business conditions. Unlike previous models, our model can handle these problems.

This paper proceeds as follows. In Section 2, we first give a brief review of the conventional models and introduce the asymmetric factor adjustment model. We also illustrate the estimation scheme using the MCMC method. In Section 3, we explain the construction of the panel data of the large Japanese manufacturing firms used in this paper. In Section 4, we provide estimates of the parameters for each sector of the manufacturing industry. The economic implications of the results are also evaluated in this section. Concluding remarks are given in Section 5.

2. Models and an Estimation Method

2.1. Conventional Adjustment Models

In this section we first provide a brief review of the conventional adjustment models. Then, we explain the asymmetric factor adjustment model we used in the present analysis. The ordinary partial adjustment model is expressed as

$$L_t - L_{t-1} = \lambda(L_t^* - L_{t-1}) + u_t, \tag{2.1}$$

where L_t is the logarithm of the labor input at period t, L_t^* is that of the desired level derived from the firm's static optimization problem and u_t is the disturbance term. It is known that (2.1) can be derived as the solution of the dynamic optimization such that a firm maximizes the discounted total profit on an infinite time horizon by assuming a quadratic structure for the adjustment cost given by

$$C(\dot{L}) = b\dot{L}^2, \tag{2.2}$$

where $\dot{L}$ is the rate of the labor input change and $b > 0$ (e.g., Gould, 1968; Nickell, 1986). We can interpret λ as the speed of adjustment in (2.1). Because the interpretation is easy, the model has been widely used in empirical analyses.

Hamermesh (1989) proposes the following cost structure with the fixed adjustment cost k which includes (2.2) as a special case:

$$C(\dot{L}) = \begin{cases} b\dot{L}^2 + k & \text{if } |\dot{L}| > 0, \\ b\dot{L}^2 & \text{if } |\dot{L}| = 0. \end{cases} \tag{2.3}$$

When $b > 0$ and $k = 0$, (2.3) is identical to (2.2). When $b = 0$ and $k > 0$, the dynamic optimization gives the following lumpy adjustment strategy with the fixed cost,

$$L_t = \begin{cases} L_{t-1} + u_{1t} & \text{if } |L_t^* - L_{t-1}| \le \gamma, \\ L_t^* + u_{2t} & \text{if } |L_t^* - L_{t-1}| > \gamma, \end{cases} \tag{2.4}$$

where the threshold γ is an increasing function of the fixed cost k. This type of model is often called the model of friction (Maddala, 1983, pp. 162–165). In this case, the desired level L_t^* is immediately achieved when the firm decides to adjust the labor input. We note that (2.2) is the case where only the variable cost is considered, and (2.3) with $b = 0$ and $k > 0$ is the case where only the fixed cost is considered. Hamermesh (1989) analyzes the plant level data of one U.S. manufacturing firm with these two models. He shows that the lumpy adjustment model given by (2.4) explains the employment adjustment better than the the partial adjustment model of (2.1). Koike (1983) also suggests that two consecutive years of losses or one year of large losses causes a large amount of lay-offs in large Japanese manufacturing firms. However, he did not perform any quantitative analysis. Suruga (1998) confirms Koike's conclusion using the partial adjustment model. Hildreth and Ohtake (1998) analyze the data of a large Japanese company in the motor vehicles sector. They evaluate the short-term transfers of employees among plants of the company and among group companies using the model of Hamermesh (1989). They show that the partial adjustment model fits better. However, they mainly analyze the fixed cost of short term transfers, and do not consider the firing and hiring costs. Therefore, their conclusion may not necessarily be true when both firing and hiring are considered. The fixed cost may be considerably large when a firm plans employment adjustments by firing or hiring.

Clearly, neither the fixed nor the variable cost should be ignored: a successful model includes both. Hamermesh (1992) proposes such a model by allowing b and k to be positive in the cost function (2.3) and shows that the following model fits well for data on airline mechanics:

$$
(2.5) \qquad L_t - L_{t-1} = \begin{cases} \lambda(L_t^* - L_{t-1}) + u_{1t} & \text{if } |L_t^* - L_{t-1}| > \gamma, \\ u_{2t} & \text{if } |L_t^* - L_{t-1}| \leq \gamma, \end{cases}
$$

where u_{1t} and u_{2t} are disturbance terms. The model in (2.5) indicates that even if the firm takes action — that is, the present value of the total profit of adjusting exceeds that of not adjusting — the adjustment is only done gradually depending on the value of adjustment coefficient λ.

In the model (2.5), the fixed cost k is assumed to arise at every period. However, as mentioned in the previous section, the fixed cost consists of the costs of recruiting and training for new employees, bargaining with the unions and damage to the workers' morale. Hence it may be reasonable to assume that it is a sunk cost; that is, it arises only when the firm decides to adjust the employment and does not occur again until the adjustment is completed. The firm can continue to change the employment without the fixed cost. In the model (2.5), the adjustment is also assumed to be symmetric between the firing and hiring regimes.

2.2. Theoretical Basis of the Asymmetric Factor Adjustment Model

In this subsection, we explain the theoretical basis of the asymmetric factor adjustment model which is introduced in the next subsection. We assume the Cobb-Douglas production function

$$
Y = AL_S^{\alpha} L_U^{\beta} K^{\gamma},
$$

where A, α, β, γ are constant, Y is the production level, L_S and L_U are the skilled and unskilled labor inputs, and K is the capital input.

In the Japanese labor market, the primary method of labor adjustment is not lay-off (and dismissal) but adjustment of overtime working hours, as pointed out by Hildreth and Ohtake (1998) and many other researchers. However, this method requires excess payments for hoarding excess employees and overtime working hours. Therefore, we make the following assumptions.

(i) A firm can hire two types of employees, regular (permanent or full-time) and non-regular (temporary and part-time) employees.

(ii) The regular employees can provide both skilled and unskilled labor. On the other hand, the non-regular employees can only provide unskilled work.

(iii) Although the firm can adjust the non-regular employment without any adjustment costs, it must pay adjustment costs in the case of regular employment.

(iv) The firm can increase the skilled labor input through over-time working hours without increasing the regular employment. However, the wage rate is increased by the extra payment.

Table 1 summarizes these assumptions. We denote the price level of production as P, the wage rates for regular and non-regular employees as W_R and W_N, and the price level of capital as R at the static equilibrium.

When the firm increases its production level, it has two choices. One is paying hiring costs to increase the regular employment, and the other is keeping the number of regular employees and making them work overtime. Whether the firm increases the regular employment or not is determined by dynamic profit maximization. The firm changes the number of regular employees if and only if the present value of the profit with adjustment exceeds that without adjustment.

Table 1. The summary of assumptions

	Regular employees	Non-regular employees
Sort of labor	Skilled Unskilled	Unskilled
Adjustment costs	yes	No

We define the wage rate of regular employees as

(2.6) $$W_R^* = W_R \left(\frac{L_S}{N_R}\right)^{1+a},$$

where N_R is the number of regular employees, L_S is the quantity of skilled labor including overtime working, and $a > 0$.

When the firm adjusts the regular employments, the present value of the total profit is given by

(2.7) $$\mathrm{Pr}_{ev} = -\mathrm{Fc}_e + \max \int_0^\infty e^{-rt}\Big\{PAL_S^\alpha(t)N_N^\beta(t)K^\gamma(t) - W_R\left(\frac{L_S(t)}{N_R(t)}\right)^{1+a} N_R(t) - W_N N_N(t) - RK(t) - b_e B^2(t)\Big\}dt,$$

where Fc_e is the fixed adjustment cost, N_N is the number of non-regular employees and

(2.8) $$B(t) = \dot{N}_R(t) = \frac{d}{dt}N_R(t).$$

$N_R(t)$ is the state variable and $L_S(t)$, $N_N(t)$, $K(t)$ and $B(t)$ are control variables. The maximization of (2.7) constrained by $B(t) = \dot{N}_R(t)$ is solved by the Maximum Principle. Solving the differential equation obtained from the first order conditions under terminal conditions gives the continuous analogue of the usual partial adjustment model.

The present value of the total profit without adjustment of the regular employment is given by

(2.9) $$\mathrm{Pr}_{ef} = \max \int_0^\infty e^{-rt}\Big\{PAL_S^\alpha(t)N_N^\beta(t)K^\gamma(t) - W_R\left(\frac{L_S(t)}{N_R(t)}\right)^{1+a} N_R(t) - W_N N_N(t) - RK(t)\Big\}dt,$$

(2.10) $$\text{s.t. } N_R(t) = \bar{N}_R,$$

where $\bar{N}_R$ is constant. In this case, instantaneous maximization of the terms in the braces will give the solution. The firm increases the number of regular employees if and only if $\mathrm{Pr}_{ev} > \mathrm{Pr}_{ef}$ in the expanding phase.

When the firm decreases its production level, it has two choices. One is paying firing costs to decrease the regular employment, and the other is keeping the number of regular employees and making them do unskilled jobs. When fixed costs of employment adjustment exists, the firm changes the number of regular employees if and only if the present value of the profit with adjustment exceeds that without adjustment.

Substitution of regular employees for non-regular employees is expressed as the production function:

(2.11) $$Y = A(N_R(t) - N_1(t))^\alpha (N_N(t) + N_1(t))^\beta K^\gamma(t),$$

where N_1 is the number of regular employees used as the unskilled labor input.

When the firm adjusts the regular employment, the present value of the total profit is given by

$$\Pr_{cv} = -\mathrm{Fc}_c + \max \int_0^\infty e^{-rt}\{PA(N_R(t) - N_1(t))^\alpha (N_N + N_1(t))^\beta K^\gamma(t) - W_R N_R(t) - W_N N_N(t) - RK(t) - b_c B^2(t)\}dt, \tag{2.12}$$

$$\text{s.t. } N_N(t) \geq 0. \tag{2.13}$$

$N_R(t)$ is the state variable and $N_1(t)$, $N_N(t)$, $K(t)$ and $B(t)$ are control variables. The maximization of (2.12) constrained by $B(t) = \dot{N}_R(t)$ and $N_N(t) \geq 0$ is solved by the maximum principle.

The present value of the total profit without adjustment of the regular employment is given by

$$\Pr_{cf} = \max \int_0^\infty e^{-rt}\{PA(N_R(t) - N_1(t))^\alpha (N_N + N_1(t))^\beta K^\gamma(t) - W_R N_R(t) - W_N N_N(t) - RK(t)\}dt, \tag{2.14}$$

$$\text{s.t. } N_N(t) \geq 0. \tag{2.15}$$

The firm adjusts the number of regular employees if and only if $\Pr_{cv} > \Pr_{cf}$ in contracting phase, as before.

The firm increases its employment if $\Pr_{ev} - \Pr_{ef} > 0$ in the expanding phase, and decreases if $\Pr_{cv} - \Pr_{cf} > 0$ in the contracting phase. Since these values are generally different in two phases, the thresholds and adjustment speeds should be asymmetric in expanding and contracting phases.

2.3. Asymmetric Factor Adjustment Model

In this paper, we consider three regimes, hiring, no adjustment, and firing. We cannot directly observe the regimes of firms. We propose a model where the adjustment costs are asymmetric and the regime at period t depends on the regime at the previous period $(t-1)$. We change the index t to it for panel analysis where i indicates the firm, $i = 1, \dots, I$ and $t = 1, \dots, T$. The model is a Tobit-type model as follows:

$$L_{it} = \begin{cases} \lambda_1 L_{it}^* + (1-\lambda_1)L_{i,t-1} + u_{1it} & \text{if} \quad y_{it} = 1, \\ L_{i,t-1} + u_{2it} & \text{if} \quad y_{it} = 2, \\ \lambda_2 L_{it}^* + (1-\lambda_2)L_{i,t-1} + u_{3it} & \text{if} \quad y_{it} = 3, \end{cases} \tag{2.16}$$

where $y_{it} = 1, 2,$ and 3 indicate the firing, no adjustment, and hiring regimes, respectively. $\{u_{kit}\}$ are independently and identically distributed and follow the normal distribution with mean 0 and variance τ_u^{-1}. We measure L_{it} as the logarithm of the regular employment measured by the number of regular employees. As shown in Subsection 2.2., the non-regular employment does not change our model. y_{it} is determined by

$$y_{it} = \begin{cases} 1 \text{ if } \; L_{it}^* - L_{i,t-1} \leq \gamma_1 \quad \text{or} \quad (L_{it}^* - L_{i,t-1} \leq 0 \text{ and } y_{i,t-1} = 1), \\ 3 \text{ if } \; L_{it}^* - L_{i,t-1} > \gamma_2 \quad \text{or} \quad (L_{it}^* - L_{i,t-1} > 0 \text{ and } y_{i,t-1} = 3), \\ 2 \text{ otherwise.} \end{cases} \tag{2.17}$$

γ_1 and γ_2 satisfy $\gamma_1 < 0 < \gamma_2$.

L_{it}^* represents the logarithm of the desired regular employment for the firm i at period t estimated by the firm at $t-1$. According to previous studies about factor adjustment (Hamermesh, 1989, 1992; Hildreth and Ohtake, 1998; Suruga, 1998), we model L_{it}^* in a linear function of covariates, which is derived by solving the static profit maximization problem with the Cobb-Douglas production function.

We represent L^*_{it} by the following random effect model:

$$L^*_{it} = \boldsymbol{x}'_{it}\boldsymbol{\beta} + \alpha_i + \nu_{it}, \tag{2.18}$$
$$\alpha_i \overset{\text{i.i.d.}}{\sim} N(0, \tau_\alpha^{-1}) \quad \text{and} \quad \nu_{it} \overset{\text{i.i.d.}}{\sim} N(0, \tau_\nu^{-1}),$$

where $\boldsymbol{x}_{it} = (1, x_{1it}, x_{2it}, t)'$, x_{1it} is the logarithm of the sales of the firm i expected at $t-1$, x_{2it} is the logarithm of the ratio of the wage rate to the interest rate expected at $t-1$, and N denotes a normal distribution. We assume that firms in period $t-1$ have perfect foresight on the prices and its own sales of the next period, t. Define $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2, \beta_3)'$ and $\boldsymbol{\theta} = (\lambda_1, \lambda_2, \boldsymbol{\beta}, \gamma_1, \gamma_2, \tau_u, \tau_\alpha, \tau_\nu)$. $\boldsymbol{\theta}$ is the vector of unknown parameters in Equations (2.16), (2.17) and (2.18).

2.4. Bayesian Estimation of the Model with Latent Variables

In this paper, we consider the Bayesian estimation of $\boldsymbol{\theta}$. In this section, we introduce the following prior distributions:

$$\begin{gathered} \lambda_1, \lambda_2 \sim N(0.5, 1/16), \quad \boldsymbol{\beta} \sim N(\boldsymbol{0}, 10000 \cdot \boldsymbol{I}_4), \\ \tau_u \sim G(0.0001, 0.0001), \quad \tau_\alpha \sim G(0.0001, 0.0001), \quad \tau_\nu \sim G(10, 1), \\ \gamma_1 \sim TN_{[-\infty, 0]}(\ln(1/2), (\ln(100))^2) \quad \text{and} \quad \gamma_2 \sim TN_{[0,\infty]}(\ln(2), (\ln(100))^2), \end{gathered} \tag{2.19}$$

where G is a gamma distribution, $TN_{[r_1,r_2]}$ is a truncated normal distribution defined within the range $[r_1, r_2]$, and $\boldsymbol{I}_4$ is the identity matrix of dimension 4. For the priors for λ_i, τ_ν and γ_i, we imposed some ex ante restrictions derived from economic implications or the estimates of previous studies. γ_1 and γ_2 are the thresholds such that a firm decides to adjust the labor input or not according to

$$y_{it} = 1: \; L^*_{it} - L_{i,t-1} \leq \gamma_1 \;\Leftrightarrow\; \ln \frac{N^*_{it}}{N_{i,t-1}} \leq \gamma_1 \;\Leftrightarrow\; \frac{N^*_{it}}{N_{i,t-1}} \leq e^{\gamma_1}, \tag{2.20}$$

$$y_{it} = 3: \; L^*_{it} - L_{i,t-1} > \gamma_2 \;\Leftrightarrow\; \ln \frac{N^*_{it}}{N_{i,t-1}} > \gamma_2 \;\Leftrightarrow\; \frac{N^*_{it}}{N_{i,t-1}} > e^{\gamma_2}, \tag{2.21}$$

where N_{it} is the number of employees and N^*_{it} is the desired level of that. It is unlikely that the ratio of N^*_{it} to $N_{i,t-1}$ becomes either very large or very small; e.g. 10,000% or 0.01%. In fact, previous studies using TAR models search the threshold value from the realized lag $y_{i,t-1} - y_{i,t-m}$ (Caner and Hansen, 2001; Park et al., 2005). So we set the means of γ_1 and γ_2 as $\ln(1/2)$ and $\ln(2)$, respectively, and both variances $(\ln(100))^2$. Since we have assumed that firms have perfect foresight, ν_{it}, the error term of (2.18), is assumed to be small. Hamermesh (1989) and Hildreth and Ohtake (1998) reported the error terms of the logarithm of desired employment to be about 0.2. Therefore, we set the prior distribution of τ_ν as the gamma distribution with mean 10 and variance 10.

As mentioned in the previous section, λ_1 and λ_2 represent the adjustment speeds and are expected to satisfy $0 \leq \lambda_j \leq 1$ for $j = 1, 2$. Since estimated adjustment coefficients were about 0.2–0.3 for the partial adjustment model (Hamermesh, 1989; Hildreth and Ohtake, 1998) and about 0.9 for the model with threshold, we set the prior of λ_i with mean 0.5 and variance 1/16. Note that if the true λ_j is close to 0, a locally unidentified problem arises, as seen in AR models (Lancaster, 2004). In other words, the model is unidentifiable between the two cases; one case where adjustment coefficients are zero and the other case where all samples are in regime 2.

The model used here consists of two parts. One is the non-linear regression model on L_{it} and the other is the trinomial probit model on the latent variable y_{it}. Both parts are related to the latent variable L^*_{it}. In order to calculate the Bayes estimator of $\boldsymbol{\theta}$, we can use the data augmentation algorithm in Albert and Chib (1993). The conditional posterior density of (L^*_{it}, y_{it}) can be obtained explicitly when the values of other latent variables and the parameters are given. The posterior densities of parameters for the random effect model are obtained using the method of Chib and Carlin (1999). The global Markov property (see, e.g., Lauritzen, 1996) is used in derivations of conditional posterior distributions. The conditional posteriors become the gamma, normal, truncated normal distributions. (Details are available from the authors upon request.)

The conditional posteriors of the latent variables are as follows.

$$f(L_{it}^*, y_{it} \mid \boldsymbol{L}_{i,-t}^*, \boldsymbol{y}_{i,-t}, \boldsymbol{L}_i, \boldsymbol{\alpha}, \boldsymbol{\theta}) = f(L_{it}^* \mid y_{i,t-1}, y_{it}, L_{i,t-1}, L_{it}, \alpha_i, \boldsymbol{\theta}) \times f(y_{it} \mid L_{i,t+1}^*, y_{i,t-1}, y_{i,t+1}, L_{i,t-1}, L_{it}, \alpha_i, \boldsymbol{\theta}). \tag{2.22}$$

We denote

$$\tau_1^* = \lambda_1^2\tau_u + \tau_\nu, \quad \tau_2^* = \tau_\nu, \quad \tau_3^* = \lambda_2^2\tau_u + \tau_\nu, \quad \mu_{it}^{2*} = \boldsymbol{x}_{it}'\boldsymbol{\beta} + \alpha_i,$$

$$\mu_{it}^{1*} = \frac{\tau_u\lambda_1(L_{it} - (1-\lambda_1)L_{i,t-1}) + \tau_\nu(\boldsymbol{x}_{it}'\boldsymbol{\beta} + \alpha_i)}{\tau_1^*}, \quad \text{and}$$

$$\mu_{it}^{3*} = \frac{\tau_u\lambda_2(L_{it} - (1-\lambda_2)L_{i,t-1}) + \tau_\nu(\boldsymbol{x}_{it}'\boldsymbol{\beta} + \alpha_i)}{\tau_3^*}.$$

The posterior distributions of L_{it}^* for each pairs of $(y_{i,t-1}, y_{it})$ are truncated normal distributions, as shown in Table 2. For $y_{it} = 1, 2, 3$,

Table 2. The posterior distributions of L_{it}^*

$(y_{i,t-1}, y_{it})$	posterior distributions
(1,1)	$TN_{[-\infty, L_{i,t-1}]}(\mu_{it}^{1*}, \tau_1^*)$
(1,2)	$TN_{[L_{i,t-1}, L_{i,t-1}+\gamma_2]}(\mu_{it}^{2*}, \tau_2^*)$
(1,3)	$TN_{[L_{i,t-1}+\gamma_2, \infty]}(\mu_{it}^{3*}, \tau_3^*)$
(2,1)	$TN_{[-\infty, L_{i,t-1}+\gamma_1]}(\mu_{it}^{1*}, \tau_1^*)$
(2,2)	$TN_{[L_{i,t-1}+\gamma_1, L_{i,t-1}+\gamma_2]}(\mu_{it}^{2*}, \tau_2^*)$
(2,3)	$TN_{[L_{i,t-1}+\gamma_2, \infty]}(\mu_{it}^{3*}, \tau_3^*)$
(3,1)	$TN_{[-\infty, L_{i,t-1}+\gamma_1]}(\mu_{it}^{1*}, \tau_1^*)$
(3,2)	$TN_{[L_{i,t-1}+\gamma_1, L_{i,t-1}]}(\mu_{it}^{2*}, \tau_2^*)$
(3,3)	$TN_{[L_{i,t-1}, \infty]}(\mu_{it}^{3*}, \tau_3^*)$

$$f(y_{it} \mid L_{i,t+1}^*, y_{i,t-1}, y_{i,t+1}, L_{i,t-1}, L_{it}, \alpha_i, \boldsymbol{\theta}) = \frac{q(y_{it})}{\sum_{y_{it}=1}^{3} q(y_{it})}.$$

where

$$q(y_{it}) = f(L_{i,t+1}^* \mid y_{it}, y_{i,t+1}, L_{it}, \alpha_i, \boldsymbol{\theta}) f(y_{i,t+1} \mid y_{it}, L_{it}, \alpha_i, \boldsymbol{\theta}) \times f(L_{it}, y_{it} \mid y_{i,t-1}, L_{i,t-1}, \alpha_i, \boldsymbol{\theta}),$$

$f(L_{i,t+1}^* \mid y_{it}, y_{i,t+1}, L_{it}, \alpha_i, \boldsymbol{\theta})$ is the density function of the truncated normal distribution $TN_{[r_1, r_2]}(\boldsymbol{x}_{i,t+1}\boldsymbol{\beta} + \alpha_i, \tau_\nu^{-1})$ for some r_1 and r_2. Table 3 presents r_1 and r_2 for each $(y_{i,t-1}, y_{it})$. $f(y_{i,t+1} \mid y_{it}, L_{it}, \alpha_i, \boldsymbol{\theta})$ can be expressed as in Table 4. $f(L_{it}, y_{it} \mid y_{i,t-1}, L_{i,t-1}, \alpha_i, \boldsymbol{\theta})$ for other pairs of $(y_{i,t-1}, y_{it})$ can be obtained as in Table 5.

Table 3. r_1 and r_2

$(y_{i,t-1}, y_{it})$	r_1	r_2
$(1,1)$	$-\infty$	$L_{i,t-1}$
$(1,2)$	$L_{i,t-1}$	$L_{i,t-1}+\gamma_2$
$(1,3)$	$L_{i,t-1}+\gamma_2$	∞
$(2,1)$	$-\infty$	$L_{i,t-1}+\gamma_1$
$(2,2)$	$L_{i,t-1}+\gamma_1$	$L_{i,t-1}+\gamma_2$
$(2,3)$	$L_{i,t-1}+\gamma_2$	∞
$(3,1)$	$-\infty$	$L_{i,t-1}+\gamma_1$
$(3,2)$	$L_{i,t-1}+\gamma_1$	$L_{i,t-1}$
$(3,3)$	$L_{i,t-1}$	∞

Table 4. $f(y_{i,t+1} \mid y_{it}, L_{it}, \alpha_i, \boldsymbol{\theta})$ for each $(y_{it}, y_{i,t+1})$

$(y_{it}, y_{i,t+1})$	$f(y_{i,t+1} \mid y_{it}, L_{it}, \alpha_i, \boldsymbol{\theta})$
$(1,1)$	$\Pr(L^*_{i,t+1} - L_{it} \leq 0) = \Phi(\sqrt{\tau_\nu} L^0_{it})$
$(1,2)$	$\Pr(0 < L^*_{i,t+1} - L_{it} \leq \gamma_2) = \Phi(\sqrt{\tau_\nu}(L^0_{it}+\gamma_2)) - \Phi(\sqrt{\tau_\nu} L^0_{it})$
$(1,3)$	$\Pr(L^*_{i,t+1} - L_{it} > \gamma_2) = 1 - \Phi(\sqrt{\tau_\nu}(L^0_{it}+\gamma_2))$
$(2,1)$	$\Pr(L^*_{i,t+1} - L_{it} \leq \gamma_1) = \Phi(\sqrt{\tau_\nu}(L^0_{it}+\gamma_1))$
$(2,2)$	$\Pr(\gamma_1 < L^*_{i,t+1} - L_{it} \leq \gamma_2) = \Phi(\sqrt{\tau_\nu}(L^0_{it}+\gamma_2)) - \Phi(\sqrt{\tau_\nu}(L^0_{it}+\gamma_1))$
$(2,3)$	$\Pr(L^*_{i,t+1} - L_{it} > \gamma_2) = 1 - \Phi(\sqrt{\tau_\nu}(L^0_{it}+\gamma_2))$
$(3,1)$	$\Pr(L^*_{i,t+1} - L_{it} \leq \gamma_1) = \Phi(\sqrt{\tau_\nu}(L^0_{it}+\gamma_1))$
$(3,2)$	$\Pr(\gamma_1 < L^*_{i,t+1} - L_{it} \leq 0) = \Phi(\sqrt{\tau_\nu} L^0_{it}) - \Phi(\sqrt{\tau_\nu}(L^0_{it}+\gamma_1))$
$(3,3)$	$\Pr(L^*_{i,t+1} - L_{it} > 0) = 1 - \Phi(\sqrt{\tau_\nu} L^0_{it})$

$\Phi(\cdot)$: distribution function of the standard normal distribution

Table 5. $f(L_{it}, y_{it} \mid y_{i,t-1}, L_{i,t-1}, \alpha_i, \boldsymbol{\theta})$ for each $(y_{it}, y_{i,t-1})$

$(y_{i,t-1}, y_{it})$	$f(L_{it}, y_{it} \mid y_{i,t-1}, L_{i,t-1}, \alpha_i, \boldsymbol{\theta})$
$(1,1)$	$\sqrt{\tau_1}\phi(\sqrt{\tau_1}(L_{it}-\mu_{it}^1)) \cdot \Phi(\sqrt{\tau_1^*}(L_{i,t-1}-\mu_{it}^{1*}))$
$(1,2)$	$\sqrt{\tau_2}\phi(\sqrt{\tau_2}(L_{it}-\mu_{it}^2)) \times \left(\Phi(\sqrt{\tau_2^*}(L_{i,t-1}+\gamma_2-\mu_{it}^{2*})) - \Phi(\sqrt{\tau_2^*}(L_{i,t-1}-\mu_{it}^{2*}))\right)$
$(1,3)$	$\sqrt{\tau_3}\phi(\sqrt{\tau_3}(L_{it}-\mu_{it}^3)) \cdot \left(1-\Phi(\sqrt{\tau_3^*}(L_{i,t-1}+\gamma_2-\mu_{it}^{3*}))\right)$
$(2,1)$	$\sqrt{\tau_1}\phi(\sqrt{\tau_1}(L_{it}-\mu_{it}^1)) \cdot \Phi(\sqrt{\tau_2^*}(L_{i,t-1}+\gamma_1-\mu_{it}^{2*}))$
$(2,2)$	$\sqrt{\tau_2}\phi(\sqrt{\tau_2}(L_{it}-\mu_{it}^2)) \times \left(\Phi(\sqrt{\tau_2^*}(L_{i,t-1}+\gamma_2-\mu_{it}^{2*})) - \Phi(\sqrt{\tau_2^*}(L_{i,t-1}+\gamma_1-\mu_{it}^{2*}))\right)$
$(2,3)$	$\sqrt{\tau_3}\phi(\sqrt{\tau_3}(L_{it}-\mu_{it}^3)) \cdot \left(1-\Phi(\sqrt{\tau_3^*}(L_{i,t-1}+\gamma_2-\mu_{it}^{3*}))\right)$
$(3,1)$	$\sqrt{\tau_1}\phi(\sqrt{\tau_1}(L_{it}-\mu_{it}^1)) \cdot \Phi(\sqrt{\tau_1^*}(L_{i,t-1}+\gamma_1-\mu_{it}^{1*}))$
$(3,2)$	$\sqrt{\tau_2}\phi(\sqrt{\tau_2}(L_{it}-\mu_{it}^2)) \times \left(\Phi(\sqrt{\tau_2^*}(L_{i,t-1}-\mu_{it}^{2*})) - \Phi(\sqrt{\tau_2^*}(L_{i,t-1}+\gamma_1-\mu_{it}^{2*}))\right)$
$(3,3)$	$\sqrt{\tau_3}\phi(\sqrt{\tau_3}(L_{it}-\mu_{it}^3)) \cdot \left(1-\Phi(\sqrt{\tau_3^*}(L_{i,t-1}-\mu_{it}^{3*}))\right)$

$\phi(\cdot)$: density function of the standard normal distribution

The Gibbs sampling is used as a sampling scheme. Let $\boldsymbol{L}$ and $\boldsymbol{L}_i$ be

$$\boldsymbol{L} = (L_{10}, \ldots, L_{IT}) \quad \text{and} \quad \boldsymbol{L}_i = (L_{i0}, \ldots, L_{iT}).$$

$\boldsymbol{L}^*$, $\boldsymbol{L}_i^*$, $\boldsymbol{y}$ and $\boldsymbol{y}_i$ are defined in the same way. Define $\boldsymbol{\theta}^{(l)}$ as the estimated vector of $\boldsymbol{\theta}$ at the l-th updating stage. Let $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_I)$. The estimating procedure is as follows:

(i) Set the initial values of $\boldsymbol{\theta}$, $\boldsymbol{\alpha}$ and the latent variables as $\boldsymbol{\theta}^{(0)}$, $\boldsymbol{\alpha}^{(0)}$ and $(\boldsymbol{L}^*, \boldsymbol{y})^{(0)}$.

(ii) Sample a set of the l-th stage latent variables $(\boldsymbol{L}^*, \boldsymbol{y})^{(l)}$ from the posterior distributions given $(\boldsymbol{L}^{*(l-1)}, \boldsymbol{y}^{(l-1)}, \boldsymbol{\alpha}^{(l-1)}, \boldsymbol{\theta}^{(l-1)})$ sequentially for $i = 1, \ldots, I$ and $t = 1, \ldots, T$ as follows:

   (a) Sample $y_{it}^{(l)} \sim y_{it} \mid \boldsymbol{L}_i, \boldsymbol{L}_i^{*(l-1)}, y_{i,t-1}^{(l)}, y_{i,t+1}^{(l-1)}, \boldsymbol{\alpha}^{(l-1)}, \boldsymbol{\theta}^{(l-1)}$.

   (b) Sample ${L_{it}^*}^{(l)} \sim L_{it}^* \mid \boldsymbol{L}_i, {L_{i,t-1}^*}^{(l)}, {L_{i,t+1}^*}^{(l-1)}, {\boldsymbol{y}_i}^{(l)}, \boldsymbol{\alpha}^{(l-1)}, \boldsymbol{\theta}^{(l-1)}$.

(iii) Based on the values of $({\boldsymbol{L}^*}^{(l)}, \boldsymbol{y}^{(l)}, \boldsymbol{\alpha}^{(l-1)}, \boldsymbol{\theta}^{(l-1)})$ calculated by the previous step, sample the l-th stage parameters $\boldsymbol{\theta}^{(l)}$.

(iv) Sample $\boldsymbol{\alpha}^{(l)} \sim \boldsymbol{\alpha} \mid \boldsymbol{L}, {\boldsymbol{L}^*}^{(l)}, \boldsymbol{y}^{(l)}, \boldsymbol{\theta}^{(l)}$.

(v) Repeat Steps (ii)–(iv) until the convergence is achieved.

After a substantial number of samplings, samples of $\boldsymbol{\theta}$ generated by this algorithm can be regarded as samples obtained by the marginal distributions. The mean of those samples is a Bayes estimator of $\boldsymbol{\theta}$. We calculate the sample mean and the standard deviation from 100,000 draws after discarding the first 10,000 trials as the burn-in period.

Table 6. Small sectors in the manufacturing industry

Sector	Main products
1	Food products and beverages
2	Textiles
3	Pulp, paper and paper products
4	Chemicals
5	Medical products
6	Petroleum products
7	Rubber products
8	Non-metallic mineral products
9	Iron and steel
10	Non-ferrous
11	Fabricated metal products
12	Machinery
13	Electrical machinery, equipment and supplies
14	Transport equipment
15	Precision instruments
16	Others

In practice, we fix all values of y_{i0} at 2 for simplicity. It has been pointed out that setting arbitrary initial conditions may cause a problem (Heckman, 1981). However, this was not a critical problem in this study, since the number of periods was large and the obtained portions of regime 1 were significantly different from zero.

3. Data

In this paper, we use panel data constructed from the annual financial data of large Japanese manufacturing firms during fiscal years 1980–2004 from the Nikkei NEEDS-Financial QUEST. This database is based on individual financial reports and Nikkei's original research. Japan experienced a bubble economy in the latter half of the 1980s and a subsequent recession in the 1990s. The labor demand increased during the bubble period and it declined from the mid 90s and still remains low. Hence the observation period is expected to include both increasing and decreasing regimes of labor input. The data is collected from sixteen small sectors defined by their main products, as shown in Table 6.

The summary of the data is given in Table 7. This table shows the sample means and the standard deviations of the number of employees (N_{it}), its fluctuation rate ($N_{it}/N_{i,t-1}$), the sales (Y_{it}), the wage rate (W_{it}), the interest rate (R_{it}) and the number of firms (I) in each sector. For N_{it}, we use the number of *regular* employees at the end of fiscal year. The number of periods, T, is 24. Each monetary value is deflated using the deflator classified by economic activities reported by the Department of National Accounts, Economic and Social Research Institute (ESRI), Cabinet Office of the Japanese government.

Table 7. The summary of the data of the small sectors in manufacturing

Sector	N_{it}	$N_{it}/N_{i,t-1}$	Y_{it}	W_{it}	R_{it}	I
1	1855.1(1994.1)	0.980(0.058)	137275(155612)	7.69(2.06)	1.92(1.50)	25
2	689.9 (440.2)	0.967(0.090)	19491 (14652)	5.12(1.99)	2.76(1.89)	9
3	1460.8(1153.3)	0.983(0.060)	101098 (92089)	7.06(1.22)	3.12(2.03)	7
4	1280.8(1549.3)	0.988(0.065)	81329(129453)	6.82(2.43)	2.29(1.59)	49
5	2084.1(1992.9)	1.013(0.056)	89860(116233)	6.61(2.56)	1.91(1.60)	14
6	404.3 (55.8)	1.003(0.088)	23075 (10173)	8.48(1.59)	2.39(2.18)	2
7	1282.4 (943.5)	0.971(0.090)	40277 (34985)	6.48(2.17)	2.30(1.79)	9
8	1434.9(1498.1)	0.976(0.056)	57096 (67950)	6.26(1.63)	2.71(1.79)	17
9	1502.3(2060.4)	0.976(0.076)	72927 (89438)	6.94(1.40)	2.73(1.93)	22
10	611.1 (131.0)	0.973(0.096)	15575 (3874)	5.53(1.68)	3.47(2.12)	1
11	1231.7(1622.3)	0.988(0.084)	59224 (97790)	6.76(1.76)	2.15(1.69)	26
12	1033.5(1119.4)	0.989(0.076)	38569 (45797)	6.78(1.54)	2.30(1.69)	63
13	1249.7(1203.7)	1.004(0.100)	55524 (99321)	6.23(4.47)	2.14(1.71)	25
14	1930.4(1532.7)	0.991(0.070)	80854(101057)	6.24(1.72)	1.84(1.38)	36
15	1549.2(1478.4)	0.984(0.076)	53500 (66983)	6.60(1.74)	2.02(1.44)	14
16	849.8 (630.7)	0.997(0.124)	50072 (49711)	6.60(1.45)	2.86(1.90)	10

Standard deviations are given in parentheses.

Y_{it}, W_{it}: million yen.

R_{it}: %