Economics Bulletin

Volume 34, Issue 1

# A new test for the Box-Cox transformation model: An analysis of length of hospital stay for diabetes patients in Japan

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## Abstract

The Box-Cox (1964) transformation model (BC model) is widely used to examine various problems. The likelihood function under the normality assumption is misspecified, and the maximum likelihood estimator (BC MLE) cannot in general be consistent. However, under the "small sigma" assumption described in Bickel and Doksum (1981), the BC MLE can be consistent. It is, therefore, necessary to test whether this assumption is satisfied when the BC model is used. In this paper, we propose a new test of whether or not the BC MLE can be used based on the estimator proposed by Nawata (2013). We then analyze length of hospital stay for type 2 diabetes patients hospitalized for educational programs about managing diabetes at home. A dataset of 970 patients collected from 27 general hospitals in Japan is used.

This study was supported by the Grant-in-Aid for Scientific Research "Analyses of the Large Scale Medical Survey Data and the Policy Evaluations in Japan (Grant Number: 24330067)" of the Japan Society of Science. The authors wish to thank an anonymous referee for helpful comments and suggestions.

**Citation:** Kazumitsu Nawata and Koichi Kawabuchi, (2014) "A new test for the Box-Cox transformation model: An analysis of length of hospital stay for diabetes patients in Japan", *Economics Bulletin*, Vol. 34 No. 1 pp. 324-332.

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**Submitted:** October 29, 2013. **Published:** February 28, 2014.

## 1. Introduction

The Box-Cox (1964) transformation model (BC model) is widely used to examine various problems. For details of the model, see Sakia (1992) and Hossain (2011). Generally, the likelihood function under the normality assumption (BC likelihood function) is misspecified, and the maximum likelihood estimator (BC MLE) is not consistent. However, the BC MLE can be a consistent estimator under the "small $\sigma$" assumption described in Bickel and Doksum (1981). It is, therefore, necessary to test whether this assumption is satisfied when the BC model is used.

In this paper, we propose a new test of whether or not the BC MLE can be used based on the estimator proposed by Nawata (2013). Using the newly proposed test, we then analyze the length of stay (LOS) in a hospital for type 2 diabetes patients who were hospitalized to receive educational programs about managing diabetes at home, rather than regular medical treatments. About 30% of patients joined the educational programs. Diabetes has become a very serious medical concern in Japan. In 2007, medical care costs for diabetes reached 11.471 billion yen (Ministry of Health, Labour and Welfare, 2009). A large part of the medical costs of diabetic patients is determined by hospital LOS; LOS for diabetic patients, however, has not been widely studied. Data from 970 patients were included in the dataset.

## 2. Model

### 2.1 A consistent estimator for the BC transformation model

We consider the BC model

$$z_t = x_t'\beta + u_t,\ y_t \geq 0, \qquad t = 1,2,...,T, \tag{1}$$

$$z_t = \begin{cases} \dfrac{y_t^{\lambda}-1}{\lambda}, & \text{if } \lambda \neq 0, \\ \log(y_t), & \text{if } \lambda = 0, \end{cases}$$

where $y_t$ is the LOS, $x_t$ and $\beta$ are k-th dimensional vectors of the explanatory variables and the coefficients, respectively, and $\lambda$ is the transformation parameter. The BC likelihood function is given by

$$\log L(\theta) = \sum_t \left[\log\phi\{(z_t - x_t'\beta)/\sigma\} - \log\sigma\right] + (\lambda-1)\sum_t \log y_t, \tag{2}$$

where $\phi$ is the probability density function of the standard normal assumption and $\sigma^2$ is the variance of $u_t$. The BC MLE is obtained as follows:

$$\frac{\partial \log L}{\partial \lambda} = 0,\ \frac{\partial \log L}{\partial \beta} = \frac{1}{\sigma^2}\sum_t x_t(z_t - x_t'\beta) = 0,\ \text{and}\ \frac{\partial \log L}{\partial \sigma^2} = \sum_t \frac{(z_t - x_t'\beta)^2 - \sigma^2}{2\sigma^4} = 0. \tag{3}$$

Let $\theta_0'=(\lambda_0,\beta_0',\sigma_0^2)$ be the true parameter value of $\theta$. Since $E[\frac{\partial \log L}{\partial \lambda}|_{\theta_0}]\neq 0,$ the BC MLE cannot be consistent generally. Instead of $\partial \log L/\partial\lambda=0$, Nawata (2013) considered the roots of the equations,

$$G_T(\theta)=\sum_t\Big[-\frac{1}{\sigma^2\lambda}[\{\frac{\log(\lambda x_t'\beta+1)}{\lambda}+\frac{z_t-x_t'\beta}{\lambda x_t'\beta+1}\}y_t^{\lambda}-z_t\}](z_t-x_t'\beta) \tag{4}$$

$$+\frac{1}{\lambda}\log(\lambda x_t'\beta+1)+\frac{z-x_t'\beta}{\lambda x_t'\beta+1}\Big]\equiv\sum_t g_t(\theta)=0,$$

$$\frac{\partial \log L}{\partial\beta}=0,\quad \text{and}\ \frac{\partial \log L}{\partial\sigma^2}=0.$$

$G_T(\theta)$ is obtained by the approximation of $\partial \log L/\partial\lambda$. If the first and third moments of $u_t$ are zero, we get $E[G_T(\theta_0)]=0$ and the estimator obtained by Equation (4) is consistent. (For details, see Nawata, 2013.) The asymptotic distribution of this estimator $\hat{\theta}_N'=(\lambda_N,\beta_N',\sigma_N^2)$ is given by

$$\sqrt{T}(\hat{\theta}_N-\theta_0)\to N[0,A^{-1}B(A')^{-1}], \tag{5}$$

where $A=-E[\frac{\partial \ell_t(\theta)}{\partial\theta'}|_{\theta_0}]=-\begin{bmatrix}A_{11}&A_{12}&A_{13}\\A_{21}&A_{22}&A_{23}\\A_{31}&A_{32}&A_{33}\end{bmatrix}$, $A_{11}=E[\frac{\partial g_t}{\partial\lambda}|_{\theta_0}]$, $A_{12}=E[\frac{\partial g_t}{\partial\beta'}|_{\theta_0}]$, $A_{13}=E[\frac{\partial g_t}{\partial\sigma^2}|_{\theta_0}]$,

$A_{21}=E[\frac{\partial \xi_t}{\partial\lambda}|_{\theta_0}]$, $A_{22}=E[\frac{\partial \xi_t}{\partial\beta'}|_{\theta_0}]$, $A_{23}=A_{32}'=E[\frac{\partial \xi_t}{\partial\sigma^2}|_{\theta_0}]=E[\frac{\partial \varsigma_t}{\partial\beta}|_{\theta_0}]$, $A_{31}=E[\frac{\partial \varsigma_t}{\partial\lambda}|_{\theta_0}]$,

$B=E[\ell_t(\theta_0)\ell_t(\theta_o)']=\begin{bmatrix}B_{11}&B_{12}&B_{13}\\B_{21}&B_{22}&B_{23}\\B_{31}&B_{32}&B_{33}\end{bmatrix}$, $B_{11}=E[g_t(\theta_0)^2]$, $B_{12}'=B_{21}=E[g_t(\theta_0)\xi_t(\theta_0)]$,

$B_{13}=B_{31}=E[g_t(\theta_0)\varsigma_t(\theta_0)]n$, $B_{22}=E[\xi_t(\theta_0)\xi_t(\theta_0)']$, $B_{23}=B_{32}'=E[\xi_t(\theta_0)\varsigma_t(\theta_0)]$, $B_{33}=E[\varsigma_t(\theta_0)^2]$,

$\ell_t(\theta)'=[g_t(\theta),\xi_t(\theta)',\varsigma_t(\theta)]$, $\xi_t(\theta)=\frac{1}{\sigma^2}x_t(z_t-x_t'\beta)$, and $\varsigma_t(\theta)=\frac{(z_t-x_t'\beta)-\sigma^2}{2\sigma^2}$.

### 2.2 A test of the "small $\sigma$" assumption

The BC MLE is generally inconsistent. However, if $\lambda_0\sigma_0/(1+\lambda_0 x_t'\beta_0)\to 0$ and $P[y_t<0]\to 0$ (in practice, $P[y_t<0]$ is small enough), the BC MLE performs well, and we can use it. Following Bickel and Doksum (1981), we call this the "small $\sigma$" assumption. (In other words, an enormous number of studies using the BC MLE implicitly assume this condition.) Here,

$$\frac{\partial \log L}{\partial\lambda}|_{\theta_0}=-\frac{1}{\sigma_0^2\lambda_0}\sum_t\{y^{\lambda_0}\log(y_t)-z_t^*\}u_t+\sum_t\log(y_t), \tag{6}$$

where $z_t^*=y_t^{\lambda_0}$. Under the "small $\sigma$" assumption, (i.e. $|\lambda_0 u_t/(\lambda_0 x_t'\beta_0+1)|$ is small) and $\lambda_0\neq 0$, we get

$$\log(y_t) = \frac{1}{\lambda_0}\log(\lambda_0 x_t'\beta_0 + 1 + \lambda_0 u_t) = \frac{1}{\lambda_0}\{\log(\lambda_0 x_t'\beta_0 + 1) + \log(1 + \frac{\lambda_0 u_t}{\lambda_0 x_t'\beta_0 + 1})\}$$

$$\approx \frac{1}{\lambda_0}\log(\lambda_0 x_t'\beta_0 + 1) + \frac{u_t}{\lambda_0 x_t'\beta_0 + 1}. \quad (7)$$

Therefore,

$$\frac{\partial \log L}{\partial \lambda}|_{\theta_0} \approx -\frac{1}{\sigma_0^2\lambda_0}\sum_t[\{\frac{(\lambda_0 x_t'\beta_0 + 1)\log(\lambda_0 x_t'\beta_0 + 1)}{\lambda_0} - x_t'\beta_0\}u_t + \log(\lambda_0 x_t'\beta_0 + 1)u_t^2 + \frac{\lambda_0 u_t^3}{\lambda_0 x_t'\beta_0 + 1}] \quad (8)$$

$$+\sum_t\{\frac{1}{\lambda_0}\log(\lambda_0 x_t'\beta_0 + 1) + \frac{u_t}{\lambda_0 x_t'\beta_0 + 1}\} = G_T(\theta_0).$$

Hence the BC MLE becomes a consistent estimator and "small $\sigma$ asymptotics" of the BC MLE $\hat{\theta}_{BC}' = (\hat{\lambda}_{BC}, \hat{\beta}_{BC}', \hat{\sigma}_{BC}^2)$ are obtained by

$$\sqrt{T}(\hat{\theta}_{BC} - \theta_0) \to N(0, C^{-1}BC^{-1}) \quad (9)$$

where $C = -E[\frac{\partial^2 \log L}{\partial\theta\partial\theta'}|_{\theta_0}] = -\begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{23} & C_{33} \end{bmatrix}$ $C_{11} = E[\frac{\partial^2 \log L}{\partial\lambda^2}|_{\theta_0}]$, $C_{12}' = C_{21} = CE[\frac{\partial^2 \log L}{\partial\lambda\partial\beta}|_{\theta_0}]$,

$C_{13} = C_{31} = E[\frac{\partial^2 \log L}{\partial\lambda\partial\sigma^2}|_{\theta_0}]$, $C_{22} = E[\frac{\partial^2 \log L}{\partial\beta\partial\beta'}|_{\theta_0}]$, $C_{23}' = C_{32} = E[\frac{\partial^2 \log L}{\partial\beta\partial\sigma^2}|_{\theta_0}]$, and $C_{33} = E[\frac{\partial \log L}{\partial(\sigma^2)^2}|_{\theta_0}]$.

$$A^* \equiv A^{-1}, \quad A^* = \begin{bmatrix} A_{11}^* & A_{12}^* & A_{13}^* \\ A_{21}^* & A_{22}^* & A_{23}^* \\ A_{31}^* & A_{32}^* & A_{33}^* \end{bmatrix}, \quad C^* \equiv C^{-1}, \text{ and } C^* = \begin{bmatrix} C_{11}^* & C_{12}^* & C_{13}^* \\ C_{21}^* & C_{22}^* & C_{23}^* \\ C_{31}^* & C_{32}^* & C_{33}^* \end{bmatrix}. \quad (10)$$

$A_{ij}^*$ and $C_{ij}^*$ are submatrices of $A^*$ and $C^*$ whose locations correspond to $A_{ij}$ and $C_{ij}$, respectively. Under the "small $\sigma$" assumption, the asymptotic distributions of $\hat{\theta}_N$ and $\hat{\theta}_{BC}$ are similar. (In fact, the differences are the first rows of $A$ and $C$ only. Moreover, when the values of $\hat{\lambda}_N$ and $\hat{\lambda}_{BC}$ are the same, estimates of other parameters become exactly the same values, and we do not have to consider tests concerning other parameters.) Hence we can perform a more precise test than the Hausman (1978) test. Since $G_T(\theta_0) = \frac{\partial \log L}{\partial\lambda}|_{\theta_0}$ under the "small $\sigma$" assumption, we get

$$\sqrt{T}(\hat{\lambda}_N - \hat{\lambda}_{BC}) \to N(0, d), \quad (11)$$

where

$$d = \lim_{n\to\infty} T \cdot V(\hat{\lambda}_N - \hat{\lambda}_{BC}) = (A_{11}^* - C_{11}^*)^2 B_{11} + (A_{12}^* - C_{12}^*)B_{22}(A_{12}^* - C_{12}^*)' + (A_{13}^* - C_{13}^*)^2 B_{33}$$

$$+ 2(A_{11}^* - C_{11}^*)(A_{12}^* - C_{12}^*)B_{12}' + 2(A_{11}^* - C_{11}^*)(A_{13}^* - C_{13}^*)B_{13}.$$

Using $t = \sqrt{T}(\hat{\lambda}_N - \hat{\lambda}_{BC})/\sqrt{\hat{d}}$ as the test statistic, where $\hat{d}$ is the estimator of $d$, we can test the "small $\sigma$" assumption; that is, we can test whether we can successfully use the BC

MLE or not. When $\lambda_0 = 0$, we replace $\lim_{\lambda_0 \to 0} A$, $\lim_{\lambda_0 \to 0} B$, and $\lim_{\lambda_0 \to 0} C$ for $A$, $B$ and $C$, and the test can be done using the same formula.

## 3. Analysis of hospital LOS for type 2 diabetes patients

### 3.1 Data

In this section, we analyze the LOS of type 2 diabetic patients who were hospitalized to take part in educational programs about managing diabetes at home rather than to receive medical treatments. The dataset was collected by the Section of Health Care Economics, Tokyo Medical and Dental University. The survey period was July-December 2008. For each patient, data collected included: dates of hospitalization and discharge; date of birth; gender; placement after hospitalization; International Classification of Diseases-10 (ICD-10) code for principle disease; reason for hospitalization; presence of secondary disease and treatment, if any; and amount of medical payment. There were a total of 3,229 patients in 67 hospitals, and 1,036 (31.4%) joined the educational programs. We used a dataset of 970 patients in 27 hospitals (Hp1-27) that had 10 or more patients. Generally, it is easier for hospitals to standardize educational programs than regular medical treatments. Moreover, hospitalization can generally be scheduled in advance for patients attending such programs. This means that if the current system works properly, the differences in the LOS should be small among hospitals. Thus, these cases were considered to be the most suitable candidates for evaluating the efficiencies of hospitals. In other words, if the differences in the LOS were large, it might be possible for some hospitals to reduce LOS through standardization of educational programs and proper management of hospitalization schedules for the most effective use of medical resources.

In all 27 hospitals, the average length of stay (ALOS) was 14.67 days; the median was 14.0 days; the standard deviation was 6.53 days; the skewness was 1.33; and the kurtosis was 6.44 (the kurtosis is the value where the normal distribution is 0). The maximum ALOS by hospital was 23.3 days (Hp5), and the minimum ALOS was 6.9 days (Hp12). Thus, there were very large differences in ALOSs among hospitals. The skewness and kurtosis values were large for some hospitals, suggesting that some patients remained in these hospitals for a long period of time.

### 3.2 Results of estimation

We chose the following as explanatory variables. The Female Dummy (0: male, 1: female) was used for gender. The proportions of male and female patients were 58.8% and 41.2%, respectively. Since the LOS tends to increase with patient age, we use Age as an explanatory variable. The average patient age was 61.0 years, with a standard deviation of 13.1. Other explanatory variables representing characteristics of patients included: Secondary Diseases (number of secondary diseases), Complications (number of complications), Acute Hospitalization Dummy (acute hospitalization: 1, otherwise: 0), Introduction Dummy (introduction of another hospital: 1, otherwise 0), Outpatient Dummy (outpatient of the same hospital before hospitalization: 1, otherwise : 0), and Discharge Dummy (discharged to another hospital or facility: 1, otherwise: 0). Among our study subjects, 786 patients had secondary diseases, and the average number per patient was 2.29. A total of 267 patients had complications, and averaged 2.05 complications per patient. The numbers of the acute hospitalizations, outpatients before hospitalization, and patients discharged to another hospital or facility were 379, 919 and 187, respectively.

For principal disease classifications, dummy variables based on the ICD-10 code E111 (type 2 diabetes mellitus with acidosis) were used. In terms of classification, 324 patients had diseases classified under E111, 49 had diseases under E112 (type 2 diabetes mellitus with kidney complications), 36 had diseases under E113 (type 2 diabetes mellitus with ophthalmic complications), 75 had diseases under E114 (type 2 diabetes mellitus with neurological complications), 2 had diseases under E115 (type 2 diabetes mellitus with circulatory complications), 195 had diseases under E116 (type 2 diabetes mellitus with other specified complications), and 296 had diseases under E117 (type 2 diabetes mellitus with multiple complications). We used 27 hospital dummies, hp1, hp2,…,hp27 (1: if hospital *i*, 0: otherwise) to represent the influence of hospitals, and a constant term was not included in $x_{ij}$.

In our model, $x_{ij}'\beta$ of Equation (5) becomes

$$x_{ij}'\beta = \beta_1 \text{Female Dummy} + \beta_2 \text{Age} + \beta_3 \text{ Secondary Diseases} + \beta_4 \text{Complications} \quad (12)$$
$$+ \beta_5 \text{ Acute Hospitalization Dummy} + \beta_6 \text{Introduction Dummy} + \beta_7 \text{ Outpatient Dummy}$$
$$+ \beta_8 \text{ Discharge Dummy} + \sum_{\ell} \beta_{\ell}\ \ell\text{-th Principle Disease Dummy} + \sum_{i} \beta_i \text{ hp}i \text{ Dummy}.$$

Tables I and II present the results of the estimation by the BC MLE and Nawata's estimator. The estimates of the transformation parameters are $\hat{\lambda}_{BC} = 0.3935$ and $\hat{\lambda}_N = 0.3471$, which are significantly smaller than 1.0; that implies that some patients remained in the hospital for a long period of time. To calculate the test statistic, it is possible to use the values of $\hat{\lambda}_{BC}$ and $\hat{\lambda}_N$. We get $\hat{d}/\sqrt{n} = 0.02546$ for $\hat{\lambda}_{BC} = 0.3935$ and 0.02469 for $\hat{\lambda}_N = 0.3471$, respectively. Hence, the values of $t = \sqrt{T}(\hat{\lambda}_N - \hat{\lambda}_{BC})/\hat{d}$ are 1.8225 and 1.8790, respectively. Therefore, the "small $\sigma$" assumption is not rejected at the 5% significant level in either case, which means that the BC MLE can be used in this study. The rest of this paper is thus an analysis of the results of the BC MLE.

The estimates for the Female Dummy and Age were positive, but not significant at the 5% level, so we did not admit the effects of these variables in this study. The estimate of Secondary Diseases was positive and significant at the 1% level; this indicates that the presence of secondary diseases made the LOS longer, as expected. The estimate of Complications was also positive and significant at the 5% level, showing that complications also make the LOS longer. The estimates of the Acute Hospitalization, Introduction, Outpatient and Discharge Dummies were not significant at the 5% level, and we could not find any evidence that the LOS depended on these variables. With respect to the principal disease classifications, E117 was significant at the 1% level, and the other estimates were significant at the 5% level.

For the estimates of the hospital dummies, the maximum and minimum values are 4.8031(hp5) and 1.7504 (hp12), respectively. The difference between these two is much larger than the estimates of the other variables. Thus, despite the exclusion of the effects of patient characteristics, surprisingly large differences remain among hospitals. For the effective use of medical resources, it may be necessary for some hospitals to revise their current educational programs by efficiently managing hospitalization schedules (Vissers, Van Der Bij and Kusters, 2001) and adopting proper educational methods to reduce LOS.

## 4. Conclusion

The BC model is widely used to examine various problems. The BC MLE, however, cannot in general be consistent. However, under the "small $\sigma$" assumption described in Bickel and Doksum (1981), the BC MLE can be consistent. It is, therefore, necessary to test whether this assumption is satisfied when the BC model is used. In this paper, we proposed a new test of whether or not the BC MLE could be used. With the proposed test, we then analyzed the length of stay (LOS) in a hospital for type 2 diabetes patients hospitalized to attend educational programs. There were 970 patients in the dataset. The "small $\sigma$" assumption was not rejected, indicating that the BC MLE could be used in this analysis. The variables found to affect the LOS were number of secondary diseases, complications, and the principal disease classifications E117. We found large differences in the LOS among hospitals, even after eliminating the influence of patient characteristics and principal disease classifications.

Medical information is computerized in many hospitals in Japan. To evaluate and improve the medical payment system in Japan more precisely, it is necessary to analyze datasets using a proper model. It is also necessary to analyze information about care for other important diseases such as cancer, cardiac infarction, and stroke. These subjects will be analyzed in future studies.

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Table I. Results of estimation (BC MLE)

| Variable | Estimate | Standard Error | t-value | Variable | Estimate | Standard Error | t-value |
|---|---|---|---|---|---|---|---|
| Female Dummy | 0.0074 | 0.0676 | 0.1095 | Hospital Dummies | | | |
| Age | 0.0051 | 0.0036 | 1.4224 | hp7 | 3.3136 | 0.6517 | 5.0846** |
| Secondary Diseases | 0.1949 | 0.0385 | 5.0598** | hp8 | 2.9387 | 0.6379 | 4.6066** |
| Complications | 0.0735 | 0.0293 | 2.5075* | hp9 | 3.7234 | 0.6154 | 6.0505** |
| Acute Hospitalization Dummy | 0.4766 | 0.3848 | 1.2385 | hp10 | 2.2927 | 0.6767 | 3.3881** |
| Introduction Dummy | 0.1350 | 0.0841 | 1.6047 | hp11 | 3.2905 | 0.6327 | 5.2007** |
| Outpatient Dummy | -0.2224 | 0.2743 | -0.8106 | hp12 | 1.7504 | 0.8003 | 2.1873* |
| Discharge Dummy | -0.1413 | 0.1019 | -1.3992 | hp13 | 3.8800 | 0.5778 | 6.7149** |
| Principle Disease Dummies | | | | hp14 | 3.4865 | 0.6193 | 5.6300** |
| E112 | 0.2235 | 0.1498 | 1.4927 | hp15 | 2.0827 | 1.0278 | 2.0263* |
| E113 | 0.4239 | 0.2247 | 1.8865 | hp16 | 3.1170 | 0.6432 | 4.8463** |
| E114 | 0.1946 | 0.1368 | 1.4227 | hp17 | 3.8950 | 0.5899 | 6.6033** |
| E115 | 1.1726 | 0.6321 | 1.8551 | hp18 | 3.7658 | 0.6084 | 6.1894** |
| E116 | 0.2254 | 0.1265 | 1.7819 | hp19 | 4.7780 | 0.5566 | 8.5847** |
| E117 | 0.3315 | 0.1040 | 3.1879** | hp20 | 2.9777 | 0.6409 | 4.6464** |
| Hospital Dummies | | | | hp21 | 3.5196 | 0.5937 | 5.9280** |
| hp1 | 3.5884 | 0.7164 | 5.0088** | hp22 | 3.2285 | 0.6462 | 4.9959** |
| hp2 | 4.3726 | 0.6274 | 6.9688** | hp23 | 3.2080 | 0.6550 | 4.8975** |
| hp3 | 3.6472 | 0.6439 | 5.6645** | hp24 | 3.3222 | 0.6314 | 5.2614** |
| hp4 | 3.3481 | 0.7571 | 4.4222** | hp25 | 2.9464 | 0.6458 | 4.5624** |
| hp5 | 4.8031 | 0.5052 | 9.5076** | hp26 | 3.4311 | 0.7558 | 4.5398** |
| hp6 | 4.0281 | 0.6517 | 5.0846** | hp27 | 3.3474 | 0.9312 | 3.5948** |
| $\widehat{\lambda}_{BC}$ | 0.3935 | 0.0248 | 15.8535** | | | | |
| R2 | 0.3514 | | | | | | |
| LogL | -2908.5 | | | | | | |

*: Significant at the 1% level, **: Significant at the 1% level.

Table II. Results of estimation (Nawata's Estimator)

| Variable | Estimate | Standard Error | t-value | Variable | Estimate | Standard Error | t-value |
|---|---|---|---|---|---|---|---|
| Female Dummy | 0.0075 | 0.0599 | 0.1243 | Hospital Dummies | | | |
| Age | 0.0044 | 0.0025 | 1.7617 | hp7 | 3.1477 | 0.3337 | 9.4331** |
| Secondary Diseases | 0.1750 | 0.0318 | 5.4951** | hp8 | 2.8124 | 0.3708 | 7.5846** |
| Complications | 0.0655 | 0.0256 | 2.5629* | hp9 | 3.5134 | 0.3350 | 10.4892** |
| Acute Hospitalization Dummy | 0.4205 | 0.2051 | 2.0509* | hp10 | 2.2200 | 0.3513 | 6.3186** |
| Introduction Dummy | 0.1193 | 0.0736 | 1.6196 | hp11 | 3.1302 | 0.3463 | 9.0380** |
| Outpatient Dummy | -0.1992 | 0.1685 | -1.1823 | hp12 | 1.7137 | 0.5206 | 3.2915** |
| Discharge Dummy | -0.1259 | 0.0902 | -1.3960 | hp13 | 3.6334 | 0.4851 | 7.4907** |
| Principle Disease Dummies | | | | hp14 | 3.2913 | 0.3620 | 9.0917** |
| E112 | 0.2050 | 0.1329 | 1.5429 | hp15 | 2.0547 | 0.5027 | 4.0870** |
| E113 | 0.3764 | 0.1894 | 1.9878 | hp16 | 2.9764 | 0.3343 | 8.9035** |
| E114 | 0.1748 | 0.1198 | 1.4598 | hp17 | 3.6568 | 0.3644 | 10.0342** |
| E115 | 1.0396 | 0.5499 | 1.8906 | hp18 | 3.5473 | 0.3376 | 10.5090** |
| E116 | 0.2057 | 0.1087 | 1.8933 | hp19 | 4.4245 | 0.3612 | 12.2495** |
| E117 | 0.2956 | 0.0898 | 3.2910** | hp20 | 2.8470 | 0.3505 | 8.1236** |
| Hospital Dummies | | | | hp21 | 3.3269 | 0.3292 | 10.1047** |
| hp1 | 3.3861 | 0.3584 | 9.4469** | hp22 | 3.0775 | 0.3270 | 9.4121** |
| hp2 | 4.0666 | 0.4780 | 8.5072** | hp23 | 3.0583 | 0.3374 | 9.0631** |
| hp3 | 3.4435 | 0.3947 | 8.7249** | hp24 | 3.1591 | 0.3373 | 9.3662** |
| hp4 | 3.1750 | 0.4895 | 6.4859** | hp25 | 2.8202 | 0.3283 | 8.5895** |
| hp5 | 4.4494 | 0.3426 | 12.9857** | hp26 | 3.2456 | 0.5467 | 5.9363** |
| hp6 | 3.7839 | 0.3642 | 10.3907** | hp27 | 3.1603 | 0.7209 | 4.3840** |
| $\widehat{\lambda}_N$ | 0.3471 | 0.0006 | 585.33** | | | | |
| R2 | 0.3513 | | | | | | |

*: Significant at the 1% level, **: Significant at the 1% level.