東京大学 工学系研究科 総合研究機構
イノベーション政策研究センター

IPRC Discussion Paper Series No.13

縄田 和満
東京大学大学院工学系研究科 教授

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August 2014

Innovation Policy Research Center,
Institute of Engineering Innovation, School of Engineering, The University of Tokyo
http://ipr-ctr.t.u-tokyo.ac.jp/

A semiparametric estimator that requires neither specific distributions nor an i.i.d condition of the error terms and tests for the Box-Cox transformation model

Kazumitsu Nawata, Ph.D.

Professor, Graduate School of Engineering, University of Tokyo

7-3-1 Hongo, Bunkyo-kun Tokyo 113-8656, Japan

E-mail: nawata@tmi.t.u-tokyo.ac.jp

Abstract:

The Box-Cox (1964) transformation model (BC model) is widely used in various fields of econometrics and statistics. Generally, the maximum likelihood estimator under the normality assumption (BC MLE) is used. However, the BC MLE is inconsistent unless special conditions are satisfied. In this paper, I first propose a new estimator for the BC model that require neither specific distributions nor i.i.d assumptions of the error terms. Based on the new estimator, I propose a new test of whether or not the BC MLE can be used. We then analyze length of hospital stay for type 2 diabetes patients hospitalized for educational programs about managing diabetes at home by the proposed methods as an empirical example. A dataset of 970 patients collected from 27 general hospitals in Japan is used in the analysis.

Keywords: Box-Cox transformation model, power transformation model, diabetes, length of stay (LOS)

JEL classification: C2; C5; I18

Acknowledgments

This study was supported by a Grant-in-Aid for Scientific Research, "Analyses of the Large Scale Medical Survey Data and the Policy Evaluations in Japan (Grant Number: 24330067)," from the Japan Society of Science.

1. Introduction

The Box-Cox (1964) transformation model (BC model) is used in the analysis such as the length of stay (LOS) at the hospital. For the details of the model, see Sakia (1992) and Hossain (2011). For the estimation of the model, the maximum likelihood estimator (BC MLE) is usually used. However, the BC MLE is generally inconsistent and two conditions must be satisfied that it becomes a consistent estimator. They are: i) the "small σ" condition described in Bickel and Doksum (1981) and Nawata and Kawabuchi (2014), and ii) the error terms are independent and identically distributed (i.i.d.) random variables.

In this paper, I first introduce a new semiparametric estimator, which requires neither the "small σ" nor i.i.d. assumptions. Based on the proposed estimator, we propose tests of whether or not the BC MLE can be used based on the estimator proposed. Therefore, it is necessary for us to test these two assumptions to use the BC MLE. The tests consist of two different parts. We first test the "small σ" assumption based on the methods considered by Nawata (2013) and Nawata and Kawabuchi (2014). We then test the i.i.d. assumption using the newly proposed semiparametric estimator.

I then analyze the LOS for type 2 diabetes patients hospitalized for educational programs about managing diabetes at home by the proposed methods as an empirical example using the dataset developed by Nawata and Kawabuci (2014). A new inclusive payment system based on the Diagnosis Procedure Combination (DPC) was introduced in 82 special functioning hospitals in April 2003. The DPC Evaluation Division of the Central Social Insurance Medical Council (2010) now calls the new inclusive payment system based on the DPC the DPC/PDPS (per diem payment system), and I use this term and refer to hospitals participating in the DPC/PDPS as DPC hospitals throughout this paper[1)]. According to the DPC Evaluation Division (2013), as of April, 2013, a total of 1,496 hospitals, comprising about 20% of the 7,528 general hospitals in Japan, had joined the DPC/PDPS. These hospitals have 474,981 beds, which represents more than half of the total number of beds (899,385 beds) in all general hospitals. (The data for general hospitals were obtained from the 2011 survey of hospitals.) The DPC hospitals are required to computerize their medical information, and it has become possible for us to use large scale data sets consisted of many diseases, hospitals and patients. The effective usage of such large scale data sets is now an important issue in Japan (Shimizu et al. (2007)).

Diabetes has become a very serious medical concern in Japan. In 2007, the cost of medical care for diabetes reached 11,471 billion yen (Ministry of Health, Labour and Welfare, 2009). It is easier for hospitals to standardize educational programs than regular medical treatments, and improvement of the educational programs may also help hospitals reduce the LOS through the introduction of clinical paths and through the proper management of hospitalization schedules for regular medical treatments. A large portion of the medical costs of diabetic patients is determined by the LOS. Although Mutou et al. (1999) analyzed the data of diabetic patients under 18 years old, an econometric model was not used. Soumiya et al. (2004) analyzed the LOS by regression analysis using the data of 313 patients. However, only few studies have been done in this field in Japan. Therefore, it is absolutely necssary to analyze the LOS of diabetic patients using econometric models for the effective use of medical resources. A dataset of 970 patients collected from 27 general hospitals in Japan is used in the empirical analysis.

2. Estimators for the BC Model

2.1 The BC model and BC MLE

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 β are the k-th dimensional vectors of the explanatory variables and the coefficients, respectively, and λ is the transformation parameter. The BC likelihood function is given by

$$\log L(\theta) = \sum_t \log f_t(\theta), \text{ and}$$

$$\log f_t(\theta) = \log\phi\{(z_t - x_t'\beta)/\sigma\} - \log\sigma + (\lambda - 1)\log y_t \tag{2}$$

where ϕ is the probability density function of the standard normal assumption and σ^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 θ. Since $E[\frac{\partial \log L}{\partial \lambda}|_{\theta_0}] \neq 0$, the BC MLE is generally inconsistent. However, if the error terms are i.i.d. random variables and $\lambda_0\sigma_0/(1 + \lambda_0 x_t'\beta_0) \to 0$ (in practice, $P[y_t < 0]$ is small enough), the BC MLE is not an only consistent but also efficient estimator and "small σ asymptotics" (Showalter, 1994) of the BC MLE $\hat{\theta}_{BC}' = (\hat{\lambda}_{BC}, \hat{\beta}_{BC}', \hat{\sigma}_{BC}^2)$ are obtained by

$$\sqrt{T}(\hat{\theta}_{BC} - \theta_0) \to N[0, A^{-1}B(A')^{-1}], \tag{4}$$

where $A = -\frac{1}{T}E[\frac{\partial^2 \log L}{\partial\theta\partial\theta'}|_{\theta_0}]$, and $B = E[\frac{\partial \log f_t}{\partial\theta}|_{\theta_0}\ \frac{\partial \log f_t}{\partial\theta'}|_{\theta_0}]$.

2.2 Nawata's rstimator

Nawata (2013) considered the roots of the equations,

$$G_T(\theta) = \sum_t \Big[-\frac{1}{\sigma^2\lambda}\Big[\Big\{\frac{\log(\lambda x_t'\beta + 1)}{\lambda} + \frac{z_t - x_t'\beta}{\lambda x_t'\beta + 1}\Big\}y_t^{\lambda} - z_t\Big]\Big](z_t - x_t'\beta) \tag{5}$$

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

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

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

$$\sqrt{T}(\hat{\theta}_N-\theta_0)\rightarrow N[0,C^{-1}D(C')^{-1}], \tag{6}$$

where $C=-E[\frac{\partial \ell_t(\theta)}{\partial\theta'}|_{\theta_0}]$,

$D=E[\ell_t(\theta_0)\ell_t(\theta_o)']$, $\ell_t(\theta)'=[g_t(\theta),\xi_t(\theta)',\varsigma_t(\theta)]$,

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

2.3 A new semiparametric estimator

The N-estimator is not consistent if the error terms are not i.i.d. random variables (hereafter non-i.i.d. case). In this section, I propose a new robust estimator which is consistent for the non-i.i.d. case. The following assumptions are made:

Assumption 1. $\{(x_t,u_t)\}$ are independent but not necessarily identically distributed. The distribution of u_t may depend on x_t.

Assumption 2. u_t follows distributions in which the supports are bounded from below; that is, $f_t(u)=0$ if $u\le -a$ for some $a>0$ where $f_t(u)$ is the probability (density) function. For any t, the following moment conditions are satisfied: (i) $E(u_t\mid x_t)=0$, (ii) $E(u_t^3\mid x_t)=0$, and (iii) $\delta_1<E(u_t^6\mid x_t)<\delta_2$ for some $0<\delta_1<\delta_2<\infty$.

Assumption 3. $\{x_t\}$ are independent, and its fourth moments are finite. The distributions of $\{x_t\}$ and the parameter space of β are restricted so that $\inf_x(\lambda_0 x'\beta_0+1)>a\cdot\lambda_0$ and $\inf_{x,\lambda,\beta}(\lambda\, x'\beta+1)>c$ for some $c>0$ in the neighborhood of (λ_0,β_0) where (λ_0,β_0) are the true parameter values of (λ,β)..

Here, we use the first- and third-moment restrictions and consider the roots of the equations

$$M_T(\theta) = \sum_t m_t(\theta) = 0, \quad m_t(\theta) \equiv m(\theta, x_t, y_t) = (z_t - x_t'\beta)^3, \text{ and} \tag{7}$$
$$\sum_t x_t(z_t - x_t'\beta) = 0,$$

where $\vartheta' = (\lambda, \beta')$. Note that the second equation in (7) gives the least-squares estimator when the value of λ is given. Let $\vartheta_0' = (\lambda_0, \beta_0')$. Since $E[M(\vartheta_0)] = 0$, we obtain the following proposition:

Proposition 1

Among the roots of (2), there exists a consistent root.

The proof is given in Appendix A. Let $\hat{\vartheta}_R' = (\hat{\lambda}_R, \hat{\beta}_R')$ be the consistent root (hereafter robust estimator). The asymptotic distribution of $\hat{\vartheta}_R$ is obtained by the following proposition.

Proposition 2

Let $\psi_t(\theta) = x_t(z_t - x_t'\beta)$ and $\omega_t(\theta)' = [m_t(\theta), \psi_t(\theta)']$. Suppose that $\frac{1}{T}\sum_t \frac{\partial \omega_t(\theta)}{\partial \theta'}|_{\theta_0}$ converges to a nonsingular matrix F in probability and $\frac{1}{T}\sum_t E[\omega_t(\theta_0)\omega_t(\theta_o)']$. that converges to a nonsingular matrix H. Then the asymptotic distribution of $\hat{\vartheta}$ is given by

$$\sqrt{T}(\hat{\vartheta}_R - \vartheta_0) \to N[0, F^{-1}H(F')^{-1}]. \tag{8}$$

[Proof]

Let

$$\omega(\theta) = \sum_t \omega_t(\theta) = \begin{bmatrix} M_T(\theta) \\ \sum_t \psi_t(\theta) \end{bmatrix}. \tag{9}$$

Then

$$\sqrt{T}(\hat{\vartheta}_R - \hat{\vartheta}_0) = -[\frac{1}{T}\frac{\partial \omega}{\partial \vartheta'}|_{\vartheta^*}]^{-1}\frac{1}{\sqrt{T}}(\vartheta_0), \tag{10}$$

where ϑ^* is some value between $\hat{\vartheta}$ and ϑ_0. Here,

$$\omega_t(\theta_0) = \begin{bmatrix} u_t^3 \\ x_t u_t \end{bmatrix}. \tag{11}$$

Therefore, $E[\omega_t(\theta_0)] = 0$. Since the variables $\{\omega_t(\theta_0)\}$are independent and the Lindberg condition is satisfied under Assumptions 2 and 3, we obtain

$$\frac{1}{\sqrt{T}}\omega(\vartheta_0) \to N(0, H), \tag{12}$$

from Theorem 3.1.6 in Amemiya (1985, p. 92).

$$\text{Since } \partial\omega/\partial\vartheta' = \begin{bmatrix} \frac{3}{\lambda}\sum_t (z_t - x_t'\beta)^2\{z_t\log(y_t) - z_t\} & -3\sum_t (z_t - x_t'\beta)^2 x_t' \\ \frac{1}{\lambda}\sum_t x_t\{z_t\log(y_t) - z_t\} & -\sum_t x_t x_t' \end{bmatrix},$$

$$\frac{1}{T}\frac{\partial\omega(\vartheta)}{\partial\vartheta'}|_{\vartheta^*} \xrightarrow{P} F, \tag{13}$$

from Theorem 4.1.4 in Amemiya (1985, pp. 112-113). From Theorem 4.1.3 in Amemiya (1985, p. 111), the asymptotic distribution of $\hat{\vartheta}_R$ is given by Equation (8). Since $\lim_{\lambda_0\to 0}(y_t^{\lambda_0} - 1)/\lambda_0 = \log y_t$, we can get the asymptotic distribution given by the same formula even when $\lambda_0 = 0$.

3. Tests of the BC MLE

3.1 A test of "small σ assumption

Since $G_T(\theta_0) = \frac{\partial \log L}{\partial\lambda}|_{\theta_0}$ under the "small σ" and i.i.d. assumptions are satisfied, $B = D$ and we get

$$\sqrt{T}(\hat{\lambda}_N - \hat{\lambda}_{BC}) \to N(0,\delta), \tag{14}$$

where $\delta =$ the first element of $(A^{-1} - C^{-1})B(A^{-1} - C^{-1})'$.

Hence we can perform a more precise test than a test where the asymptotic variance is calculated by a difference of two variances in the Hausman (1978) type test. Using $t = \sqrt{T}(\hat{\lambda}_N - \hat{\lambda}_{BC})/\sqrt{\hat{\delta}}$ as the test statistic, where $\hat{\delta}$ is the estimator of δ, we can test the "small σ" 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 $\lim_{\lambda_0\to 0} F$ for A, B and F, and the test can be done using the same formula. Since the rank of the asymptotic variance-covariance matrix of $[\sqrt{T}(\hat{\lambda}_{BC} - \hat{\lambda}_N), \sqrt{T}(\hat{\beta}_{BC} - \hat{\beta}_N)']$ asymptotically becomes one, we cannot use any element of β in the Hausman type test (Nawata and McAleer (2014)).

2.2 A test for the i.i.d. assumption

In the previous section, we consider the BC MLE and the N-estimators, however, they are also not consistent for a non i.i.d. case even if the "small "small σ" is satisfied. Therefore, it is also necessary to test the i.i.d. assumption using the robust estimator defined in Section 3. If both of the "small σ" and i.i.d. assumptions are satisfied,

$$\sqrt{T}(\hat{\lambda}_{BC} - \lambda_0) = \frac{1}{\sqrt{T}}a'\sum_t \ell(\theta_0) + o_p(1),\ \sqrt{T}(\hat{\lambda}_N - \lambda_0) = \frac{1}{\sqrt{T}}c'\sum_t \ell(\theta_0) + o_p(1), \text{ and} \tag{15}$$

$$\sqrt{T}(\hat{\lambda}_R - \lambda_0) = \frac{1}{\sqrt{T}} d' \sum_t \omega(\theta_0) + o_p(1),$$

where a', c' and d' are the first rows of the A^{-1}, C^{-1} and D^{-1}. Therefore, the second test can be done as follows:

i) If the "small σ" is accepted, we compare the BC MLE and the robust estimator. The asymptotic variance of $\sqrt{T}(\hat{\lambda}_{BC} - \hat{\lambda}_N)$ is given by $a'Ba + d'Fd - 2a'E[\ell(\theta_0)\omega(\theta_0)']d$ and $E[\ell(\theta_0)\omega(\theta_0)']$ is estimated by $\frac{1}{T}\sum_t [\ell(\hat{\theta}_{BC})\omega(\hat{\theta}_{BC})']$. We use the BC MLE if the i.i.d. assumption is accepted, and the robust estimator otherwise.

ii) If the "small σ" is rejected, we compare the N-estimator and the robust estimator. The asymptotic variance of $\sqrt{T}(\hat{\lambda}_N - \hat{\lambda}_R)$ is given by $c'Bc + d'Hd - 2c'E[\ell(\theta_0)\omega(\theta_0)']d$. We use the N-estimator the i.i.d. assumption is accepted and use the robust estimator otherwise. Note that the N-estimator is not an efficient estimator, we cannot use a difference of two variances in this case.

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 as an empirical example. The dataset was developed by Nawata and Kawabuchi (2014). The survey period was July-December 2008, There were a total of 3,229 patients in 67 hospitals, and 1,036 (31.4%) joined the educational program. I excluded the data of patients treated in clinical departments that do not mainly treat diabetes, such as pediatric, orthopedic, psychiatric, ophthalmology, and otolaryngology. As shown in Figure 1, medical expenditures of some patients were unreasonably high compared to their LOS. Most of these patients belonged to other clinical departments. For example, unacceptably large hospital profits were reported for two patients who were children hospitalized in the pediatric department. I considered that these data might not be reliable, and hence they were excluded from the analysis.

Figure 2 shows the relationship between LOS and medical expenditure for patients in clinical departments that mainly treat diabetes. For the patients hospitalized to take part in educational programs, there was a very strong linear relationship between LOS and medical expenditure, with LOS virtually determining medical expenditure except in the case of one patient. For this patient, there was a large expense for medicine (about 1,500,000 yen, mainly for injections[3)]) after the Specific Hospitalization Period was reported. However, this patient did not affect the distribution of LOS. Therefore, we included the patient in the dataset of 970 patients in 27 hospitals (Hp1-27).

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 is working properly, the differences in 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 LOS were large, it could point to the need 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 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

Revising the model of Nawata and Kawabuchi (2014), I chose the following explanatory variables. The Female Dummy (0: male, 1: female) was used for gender. The proportion of male and female patients was 58.7% and 41.3%, respectively. Since LOS tends to increase with patient age, we used Age as an explanatory variable. The average patient age was 60.9 years, with a standard deviation of 13.1. Other explanatory variables representing characteristics of the patients included: Secondary Diseases (number of secondary diseases), Complications (number of complications), Acute Hospitalization Dummy (acute hospitalization: 1, otherwise: 0), Introduction Dummy (introduced from 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 the average was 2.05 complications per patient. The number of acute hospitalizations, outpatients before hospitalization, and patients discharged to another hospital or facility were 81, 933 and 384, respectively. Figure 3 shows the distribution of the LOS. It showed peaks on days eight (one week after hospitalization) and 15 (two weeks after hospitalization). Therefore, we added Day 8 and Day 15 Dummies (LOS is 8 or 15 days: 1, otherwise: 0).

For principal disease classifications, dummy variables based on the ICD-10 code E119 (type 2 diabetes mellitus without complications) were used. In terms of classification, 324 patients had diseases classified under E119; 49 had diseases classified under E112 (type 2 diabetes mellitus with kidney complications); 36 had diseases classified under E113 (type 2 diabetes mellitus with ophthalmic complications); 77 had diseases classified under E114 (type 2 diabetes mellitus with neurological complications); 2 had diseases classified under E115 (type 2 diabetes mellitus with circulatory complications); 199 had diseases classified under E116 (type 2 diabetes mellitus with other specified complications); and 296 had diseases classified under E117 (type 2 diabetes mellitus with multiple complications).

I used 27 hospital dummies, hp1, hp2,…,hp27 (if hospital *i*: 1, otherwise: 0) to represent the influence of hospitals, and did not include a constant term.

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

$$x_{ij}'\beta = \beta_1 \text{Female Dummy} + \beta_2 \text{Age} + \beta_3 \text{ Secondary Diseases} + \beta_4 \text{Complications} \quad (16)$$

$$+ \beta_5 \text{ Acute Hospitalization Dummy} + \beta_6 \text{ Introduction Dummy} + \beta_7 \text{ Outpatient Dummy}$$

$$+ \beta_8 \text{ Discharge Dummy} + \beta_9 \text{ Day 8 Dummy} + \beta_{10} \text{ Day 15 Dummy} +$$

$\sum_{\ell} \beta_{\ell}$ ℓ-th Principle Disease Dummy + $\sum_{i} \beta_{i}$ hp$i$ Dummy.

Tables 2, 3 and 4 present the results of the estimation by the BC MLE, N-estimator and robust estimators. The estimates of the transformation parameters were $\hat{\lambda}_{BC} = 0.4050$, $\hat{\lambda}_{N} = 0.4040$, and $\hat{\lambda}_{R} = 0.3799$, which were significantly smaller than 1.0; this result implied that some patients remained in the hospital for a long period of time.

I first tested the "small σ" assumption. I obtained $\hat{d}/\sqrt{n} = 0.0264$. Hence, the value of $t = \sqrt{T}(\hat{\lambda}_{N} - \hat{\lambda}_{BC})/\hat{d}$ was 0.0379. Therefore, the "small σ" assumption was accepted at the 5% significance level in either case. I then tested the i.i.d. assumption. The value of $\sqrt{V(\hat{\lambda}_{N} - \hat{\lambda}_{BC})}$ was 0.0234 and $t = (\hat{\lambda}_{R} - \hat{\lambda}_{BC})/\sqrt{V(\hat{\lambda}_{N} - \hat{\lambda}_{BC})}$ = 1.074, so the i.i.d. assumption was also accepted at the 5% significance level, indicating that the BC MLE could be used in this study. The remainder of this paper is thus an analysis of the results of the BC MLE.

The estimate of the Female Dummy was positive but not significant at the 5% level, so we did not admit the effects of gender in this study. The estimate of Age was positive and significant at the 5% level, with LOS becoming longer as patient age increased. The estimates of Secondary Diseases and Complications were positive and significant at the 1% and 5% levels, respectively, indicating that the presences of secondary diseases and complications made for longer LOS, as expected. The estimate of Acute Hospitalization was also positive and significant at the 5% level, with acute hospitalization making LOS longer. The estimates of 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. The estimate of the Day 8 Dummy was negative and significant the 1% level, but the estimate of the Day 15 Dummy was not significant at the 5% level. This indicated that many patients left the hospital after a one-week hospitalization, but not after a two-week hospitalization. These facts suggest that it may be possible for some hospitals to reduce LOS through proper management of hospitalization schedules. 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 were 4.933(hp19) and 1.730 (hp12), respectively. The difference between these two is much larger than the estimates of the other variables. Figure 4 shows the relationship between the ALOSs and the estimates of hospitals dummies. The correlation coefficient is 0.954 and there is an almost linear relationship between these two variables. Thus, despite the exclusion of the effects of patient characteristics, surprisingly large differences remain among hospitals. Although we tried to find out factors of hospitals such as sizes, occupational rates of beds and regions of hospitals, and populations and numbers of beds per 100,000 people of the prefectures where hospitals are located. However, we cloud no fine out any significant factor. Therefore, 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 program (Ghodeswar and Vaidyanathan, 2006) to reduce the LOS by themselves.

4. Conclusion

Although the BC MLE is widely used, it inconsistent unless special conditions are satisfied. In this paper, I first proposed a new estimator for the BC model that require neither specific distributions nor i.i.d assumptions of the error terms. The estimator uses only the first and third moment restrictions of the error terms. Based on the new estimator, I proposed a new test of whether or not the BC MLE can be used.

I then analyze length of hospital stay for type 2 diabetes patients hospitalized for educational programs about managing diabetes at home by the proposed methods as an empirical example. A dataset of 970 patients collected from 27 general hospitals, developed by Nawata and Kawabuchi (2014), was used in the analysis. I tested the "small σ" and i.i.d. assumptions, and both of them were accepted, indicating that the BC MLE could be used in this analysis. The variables found to affect the LOS were the age, numbers of secondary diseases and complications, acute hospitalization, Day 8 Dummy and the principal disease classification E117. We found large differences in the LOS among hospitals, even after eliminating the influence of patient characteristics and principal disease classifications. However, we could not find out factors of hospitals which affect the LOS. Therefore, 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 and adopting proper educational programs to reduce the LOS by themselves.

Appendix A: Proof of Proposition 1

The proof of the consistency of the estimator is given using a modification of Nawata (2013). When λ is given, β is uniquely estimated by the least-squares method. Let $\hat{\beta}(\lambda)$ be the estimator. Let

$$h_T(\lambda) = \frac{1}{T} M_T\{\lambda, \hat{\beta}(\lambda)\} = \frac{1}{T}\sum_t \{z_t - x_t'(\sum_s x_s x_s')^{-1}(\sum_s x_s z_s)\}^3. \tag{17}$$

We first assume that i) $\frac{1}{T}\sum_t x_t x_t'$ converges to a nonsingular matrix in probability, and ii) $\frac{1}{T}\sum_t x_t z_t$ converge to a vector of continuous functions of λ and their first derivatives are continuous in probability in the neighborhood of λ_0. Theorem 3.2.7 of Amemiya (1986. P.89),

$$\hat{\beta}(\lambda) \xrightarrow{P} \beta(\lambda) \equiv \operatorname*{plim}_{T\to\infty}(\sum_t x_t x_t')^{-1}(\sum_t x_t z_t). \tag{18}$$

We also assume that $\frac{1}{T}\sum_t x_t$ converges to a non-stochastic vector, and $\frac{1}{T}\sum_t x_t z_t^2$, $\frac{1}{T}\sum_t z_t x_t x_t'$ and $\frac{1}{T}\sum_t z_t^3$ converge to (vectors of) continuous function of λ in probability in the neighborhood of λ_0, then

$$h(\lambda) \equiv \operatorname*{plim}_{T\to\infty}\frac{1}{T} M_T\{\lambda, \beta(\lambda)\} = \operatorname*{plim}_{T\to\infty}\frac{1}{T}\sum_t \{z_t - x_t'\beta(\lambda)\}^3 \tag{19}$$

exists and a continuous function of λ in the neighborhood of λ_0. From Theorema 3.2.5 of Amemiya (1085, p. 88)

$$\underset{T\to\infty}{p\lim} h_T(\lambda) = h(\lambda). \tag{20}$$

Let $h_T'(\lambda) = dh_T / d\lambda$. Then

$$h_T'(\lambda) = \frac{1}{T}\left[\frac{\partial M_T\{\lambda, \hat{\beta}(\lambda)\}}{\partial \lambda} + \frac{\partial M_T\{\lambda, \hat{\beta}(\lambda)\}}{\partial \hat{\beta}(\lambda)} \frac{\partial \hat{\beta}(\lambda)}{\partial \lambda}\right] \tag{21}$$

$$= \frac{3}{T}\sum_t \{z_t - x_t'\hat{\beta}(\lambda)\}^2 \left[\frac{1}{\lambda}\{y_t^\lambda \log(y_t) - z_t\} - x_t'(\sum_s x_s x_s')^{-1}\sum_s \frac{1}{\lambda}\{\log(y_s) y_s^\lambda - z_s\} x_s\right] \text{ if } \lambda \neq 0, \text{ and}$$

$$h_T'(\lambda) = \lim_{\lambda\to 0} h_T'(\lambda) = \frac{3}{2\cdot T}\sum_t \{z_t - x_t'\hat{\beta}(\lambda)\}^2 \left[\{\log(y_t)\}^2 - x_t'(\sum_s x_s x_s')^{-1}\sum_s \{\log(y_s)\}^2 x_s\right] \text{ if } \lambda = 0.$$

Therefore, if the first derivatives of $\frac{1}{T}\sum_t x_t z_t$ $\frac{1}{T}\sum_t x_t z_t^2$, $\frac{1}{T}\sum_t z_t x_t x_t'$ and $\frac{1}{T}\sum_t z_t^3$ converges to (vectors of) continuous functions function of λ, $dh_T(\lambda)/d\lambda$ converges to $h'(\lambda) = dh/d\lambda$, which is a continuous function λ, in the neighborhood of λ_0.

When $\lambda = \lambda_0$, the model becomes an ordinary regression model and $\hat{\beta}(\lambda_0)$ is consistent. Therefore,

$$h(\lambda_0) = \underset{T\to\infty}{p\lim}\frac{1}{T} G_T(\theta_0) = \lim_{T\to\infty}\frac{1}{T}\sum_t u_t^3. \tag{22}$$

Since $E(u_t^3) = 0$, we get

$$h(\lambda_0) = 0, \tag{23}$$

by Theorem 3.3.1 of Amemiya (1985, p. 90).

Since $h_T(\lambda)$ and $h_T'(\lambda)$ are continuous functions of λ at $\lambda = 0$, we can treat the $\lambda = 0$ case the same as the $\lambda \neq 0$ case. $h'(\lambda)$ is continuous in the neighborhood of λ_0 and $h'(\lambda_0)$ does not become zero except in very special cases. Therefore, we can assume that $h'(\lambda_0) \neq 0$, and that there exists $\delta > 0$ such that $sign\{h'(\lambda)\} = sign\{h'(\lambda_0)\}$ and $|h'(\lambda)| \geq \gamma \equiv \frac{1}{2}|h'(\lambda_0)| > 0$ if $\lambda \in [\lambda_0 - \delta, \lambda_0 + \delta]$. By the mean value theorem, for any $\varepsilon \in (0, \delta)$,

$$h(\lambda_0 + \varepsilon) = h(\lambda_0 + \varepsilon) - h(\lambda_0) = h'(\lambda^*)\varepsilon \text{ and } h(\lambda_0 - \varepsilon) = h(\lambda_0 - \varepsilon) - h(\lambda_0) = -h'(\lambda^{**})\varepsilon \tag{24}$$

where λ^* and λ^{**} are values in $[\lambda_0 - \varepsilon, \lambda_0 + \varepsilon]$. Therefore,

$$sign\{h(\lambda_0 - \varepsilon)\} \neq sign\{h(\lambda_0 + \varepsilon)\},\ |h(\lambda_0 - \varepsilon)| > \gamma\varepsilon, \text{ and } |h(\lambda_0 + \varepsilon)| > \gamma\varepsilon. \tag{25}$$

Since $h_T(\lambda_0 - \varepsilon) \xrightarrow{P} h(\lambda_0 - \varepsilon)$ and $h_T(\lambda_0 + \varepsilon) \xrightarrow{P} h(\lambda_0 + \varepsilon)$,

$$P\left[\ sign\{h_T(\lambda_0 - \varepsilon)\} \neq sign\{h_T(\lambda_0 + \varepsilon)\}, |h_T(\lambda_0 - \varepsilon)| > 0, \text{ and } |h_T(\lambda_0 + \varepsilon)| > 0\ \right] \to 1. \tag{26}$$

From the intermediate value theorem, $h_T(\lambda) = 0$ for some $\lambda \in [\lambda_0 - \varepsilon, \lambda_0 + \varepsilon]$ if $sign\{h_T(\lambda_0 - \varepsilon)\} \neq sign\{h_T(\lambda_0 + \varepsilon)\}$, $|h_T(\lambda_0 - \varepsilon)| > 0$, and $|h_T(\lambda_0 + \varepsilon)| > 0$. Therefore,

$$P[\text{ There exists } \hat{\lambda} \text{ such that } h_T(\hat{\lambda}) = 0 \text{ and } \hat{\lambda} \in [\lambda_0 - \varepsilon, \lambda_0 + \varepsilon]\ ] \to 1. \tag{27}$$

Since (27) holds for any $\varepsilon \in (0,\delta)$, $h_T(\lambda) = 0$ has a consistent root of λ_0. Since $\hat{\beta}(\hat{\lambda})$ is obtained by the least-squares method, it is a consistent estimator when $\hat{\lambda} \xrightarrow{P} \lambda_0$. Hence, there exists a consistent root among the roots of (7).

Notes:

1. The DPC is an original system developed in Japan. The DPC classifies diseases, operations, treatments, and patient conditions using a 14-digit code. The first 6 digits classify principal diseases on the basis of the International Classification of Diseases-10 (ICD-10), which classifies principal diseases, using 1 alphabetical character with up to 3-digit code. The DPC code (and therefore, medical payment) is determined by the principal disease where the medical resource is spend most during the hospitalization, not by the disease that is a cause hospitalization. The remaining 8 digits pertain to information on operations, treatments, and patient conditions such as the presence of a secondary disease. Unlike the diagnosis-related group/prospective payment system (DRG/PPS) used in the U.S and other countries, the Japanese DPC system is a per diem prospective payment system. The per diem payment becomes less as the LOS becomes longer. Three periods, Period I, Period II, and Specific Hospitalization Period, are determined for each DPC code. Period I is set as the 25th percentile of the LOS of the surveyed hospitals. Period II is set as the average length of hospital stay, that is, the 50th percentile (although this value is actually the median, it is called the "average length of hospital stay" in the DPC/PDPS). Finally, the Specific Hospitalization Period is given by the following equation: (average length of hospital stay) + 2 × (standard deviation). The basic per diem payment is determined according to the length of hospital stay. For stays below Period I, the per diem payment to hospitals is 15% more than the average per diem payment of the patients whose stays were within the average LOS. For hospital stays between Periods I and II, the per diem payment is determined such that (per diem payment in Period I – average per diem payments)× (number of days in Period I) equals (the average per diem payments – per diem payment between Periods I and II) × (number of days between Periods I and II). For stays between Period II and the Specific Hospitalization Period, the per diem payment is reduced by an additional 15%. For stays over the Specific Hospitalization Period, the per diem payment is determined through the conventional fee-for-service system. For the details of the system, see Nawata et al. (2009). For type 2 diabetes patients, the DPC code is 100070xxxxxx0x (without secondary disease) and 100070xxxxxx1x (with secondary disease), and Periods I, II and Specification Hospitalization Period were 7, 15 and 29 days, respectively, in 2008 independent of the DPC codes and the purposes of hospitalization.

2. The type 2 diabetes occupies more than 90 % of diabetes patients in Japan. The shortage of insulin caused by declines in an insulin secretion is its diagnostic sign. The cause of the disease has not been unknown, yet.

3. This figure seems to be reported by a mistake. The medical expenditure is measured in points and 10 yen is paid per point in Japan. Therefore, if a hospital report in terms of yen, the medical expenditure becomes 10 times as large as the true value.

4. Powell (1996) proposed a consistent estimator for a non-i.i.d. case based on the moment restriction $E(w_t \cdot u_t) = 0$ where w_t is a vector of instrumental variables which satisfy and are

not included in x_t. Since Powell suggested a function of x_t as w_t, we choose $w_t = (x_t'\hat{\beta})^2$. Powell's estimator performs poorly, and the estimate of λ is 0.0469; that is, an unacceptably small value. Although other types of functions of x_t have been used for w_t, the conclusion of this study does not change.

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Table 1. Summary of LOSs by hospitals

Hosoital	Average	Standard deviation	Skewness	Kurtosis
hp1	15.39	6.07	1.14	6.34
hp2	20.90	8.87	0.07	2.22
hp3	15.57	5.00	0.29	2.42
hp4	15.82	5.89	1.21	3.73
hp5	23.28	7.60	1.01	5.90
hp6	16.38	3.67	1.63	5.69
hp7	14.55	2.80	1.06	8.15
hp8	9.92	3.36	-0.41	1.40
hp9	16.06	2.68	0.83	2.70
hp10	9.88	7.73	2.69	10.67
hp11	12.37	3.96	0.52	2.97
hp12	6.91	5.35	0.74	1.70
hp13	18.07	10.39	0.75	2.47
hp14	15.93	8.29	1.51	6.26
hp15	10.49	3.14	1.52	8.64
hp16	13.24	2.67	2.30	17.39
hp17	15.84	7.01	0.06	1.96
hp18	16.50	5.31	0.56	3.00
hp19	23.16	5.40	1.46	4.41
hp20	12.28	6.89	0.25	3.58
hp21	15.30	3.53	-1.79	5.91
hp22	12.86	5.97	2.79	16.09
hp23	14.00	3.85	3.73	16.44
hp24	13.80	1.30	0.00	9.50
hp25	12.50	1.42	-0.48	5.18
hp26	14.60	4.63	1.38	8.39
hp27	14.33	6.92	0.69	2.27
All	14.67	6.53	1.33	6.47

Table 2. Results of estimation (BC MLE)

Variable	Estimate	Standard Error	t-value	Variable	Estimate	Standard Error	t-value
lambda	0.4050	0.0017	235.32 **	Hospital Dummies			
Female Dummy	0.0012	0.0668	0.0173	hp6	4.0512	0.4170	9.7144 **
Age	0.0055	0.0027	2.0253 *	hp7	3.3462	0.3828	8.7423 **
Secondary Diseases	0.1851	0.0365	5.0789 **	hp8	2.9447	0.4184	7.0375 **
Complications	0.0729	0.0300	2.4327 *	hp9	3.7570	0.3803	9.8798 **
Acute Hospitalization Dummy	0.4684	0.2323	2.0165 *	hp10	2.6235	0.4187	6.2655 **
Introduction Dummy	0.1351	0.0846	1.5968	hp11	3.3010	0.3917	8.4268 **
Outpatient Dummy	−0.1740	0.1966	−0.8851	hp12	1.7301	0.5859	2.9529 **
Discharge Dummy	−0.1320	0.1018	−1.2964	hp13	4.3368	0.5030	8.6217 **
Day 8 Dummy	−1.3617	0.1413	−9.6393 **	hp14	3.6039	0.4154	8.6754 **
Day 15 Dummy	0.0959	0.0840	1.1415	hp15	2.1210	0.5667	3.7426 **
E112	0.2183	0.1483	1.4719	hp16	3.1832	0.3769	8.4459 **
E113	0.3896	0.2177	1.7892	hp17	4.2246	0.4050	10.4305 **
E114	0.2291	0.1281	1.7879	hp18	3.8306	0.3822	10.0215 **
E115	1.1446	0.6484	1.7654	hp19	4.9330	0.4052	12.1754 **
E116	0.1984	0.1217	1.6306	hp20	3.0567	0.3928	7.7815 **
E117	0.3138	0.0995	3.1540 **	hp21	3.6630	0.3720	9.8478 **
Hospital Dummies				hp22	3.2625	0.3686	8.8518 **
hp1	3.7160	0.4106	9.0511 **	hp23	3.2401	0.3807	8.5111 **
hp2	4.4678	0.5601	7.9772 **	hp24	3.3579	0.3817	8.7974 **
hp3	3.7058	0.4509	8.2179 **	hp25	2.9867	0.3700	8.0718 **
hp4	3.4145	0.5569	6.1312 **	hp26	3.4850	0.6295	5.5361 **
hp5	4.9094	0.3921	12.5213 **	hp27	3.4078	0.8196	4.1582 **
R2	0.3931			LogL	−2956.61		

*: Significant at the 5% level, **: Significant at the 1% level.

Table 3. Results of estimation (N-estimator)

Variable	Estimate	Standard Error	t-value	Variable	Estimate	Standard Error	t-value
lambda	0.4040	0.0252	16.0502	Hospital Dummies			
Female Dummy	0.0012	0.0666	0.0176	hp6	4.0457	0.6492	6.2314
Age	0.0055	0.0036	1.5139	hp7	3.3422	0.6637	5.0361
Secondary Diseases	0.1847	0.0388	4.7583	hp8	2.9420	0.6585	4.4681
Complications	0.0727	0.0301	2.4193	hp9	3.7523	0.6316	5.9411
Acute Hospitalization Dummy	0.4671	0.3940	1.1853	hp10	2.6210	0.6756	3.8793
Introduction Dummy	0.1347	0.0858	1.5707	hp11	3.2975	0.6517	5.0596
Outpatient Dummy	−0.1736	0.2857	−0.6076	hp12	1.7294	0.8238	2.0994
Discharge Dummy	−0.1317	0.1016	−1.2964	hp13	4.3300	0.5293	8.1800
Day 8 Dummy	−1.3580	0.1859	−7.3057	hp14	3.5993	0.6313	5.7017
Day 15 Dummy	0.0959	0.0813	1.1794	hp15	2.1204	1.0562	2.0075
E112	0.2179	0.1476	1.4760	hp16	3.1800	0.6603	4.8162
E113	0.3886	0.2272	1.7108	hp17	4.2184	0.5869	7.1871
E114	0.2285	0.1299	1.7597	hp18	3.8255	0.6226	6.1448
E115	1.1417	0.6471	1.7643	hp19	4.9246	0.5623	8.7581
E116	0.1980	0.1243	1.5927	hp20	3.0536	0.6530	4.6760
E117	0.3130	0.1019	3.0714	hp21	3.6582	0.6011	6.0860
Hospital Dummies				hp22	3.2591	0.6664	4.8907
hp1	3.7111	0.7360	5.0421	hp23	3.2368	0.6746	4.7981
hp2	4.4607	0.6452	6.9134	hp24	3.3543	0.6492	5.1666
hp3	3.7011	0.6620	5.5909	hp25	2.9839	0.6646	4.4900
hp4	3.4105	0.7723	4.4163	hp26	3.4808	0.7756	4.4880
hp5	4.9011	0.5141	9.5331	hp27	3.4036	0.9602	3.5446
R2	0.3931						

Table 4. Results of estimation (Robust estimator)

Variable	Estimate	Standard Error	t-value	Variable	Estimate	Standard Error	t-value
lambda	0.3799	0.0234	16.2156	Hospital Dummies			
Female Dummy	0.0015	0.0624	0.0235	hp6	3.9148	0.5291	7.3992
Age	0.0051	0.0027	1.8558	hp7	3.2493	0.5637	5.7639
Secondary Diseases	0.1747	0.0407	4.2954	hp8	2.8769	0.5150	5.5864
Complications	0.0685	0.0290	2.3627	hp9	3.6394	0.5095	7.1436
Acute Hospitalization Dummy	0.4373	0.3211	1.3618	hp10	2.5631	0.5986	4.2817
Introduction Dummy	0.1261	0.0776	1.6248	hp11	3.2131	0.5129	6.2647
Outpatient Dummy	−0.1641	0.2387	−0.6873	hp12	1.7121	0.6780	2.5251
Discharge Dummy	−0.1240	0.0956	−1.2976	hp13	4.1708	0.4977	8.3796
Day 8 Dummy	−1.2712	0.1310	−9.7058	hp14	3.4898	0.6343	5.5020
Day 15 Dummy	0.0965	0.0809	1.1938	hp15	2.1055	0.8515	2.4726
E112	0.2078	0.1453	1.4304	hp16	3.1036	0.5257	5.9033
E113	0.3657	0.2114	1.7298	hp17	4.0725	0.5055	8.0560
E114	0.2157	0.1239	1.7402	hp18	3.7063	0.5104	7.2614
E115	1.0727	0.6170	1.7387	hp19	4.7282	0.4853	9.7424
E116	0.1896	0.1269	1.4944	hp20	2.9801	0.5390	5.5286
E117	0.2948	0.0981	3.0066	hp21	3.5466	0.5086	6.9739
Hospital Dummies				hp22	3.1792	0.5172	6.1470
hp1	3.5967	0.6097	5.8991	hp23	3.1578	0.5425	5.8205
hp2	4.2938	0.5871	7.3141	hp24	3.2671	0.5261	6.2102
hp3	3.5918	0.5360	6.7015	hp25	2.9165	0.5316	5.4868
hp4	3.3156	0.6716	4.9370	hp26	3.3809	0.6849	4.9363
hp5	4.7075	0.4428	10.6316	hp27	3.3025	0.8623	3.8298
R2	0.3929						

Fig. 1 Medical expenditures and LOS (all patients hospitalized for educational purposes)

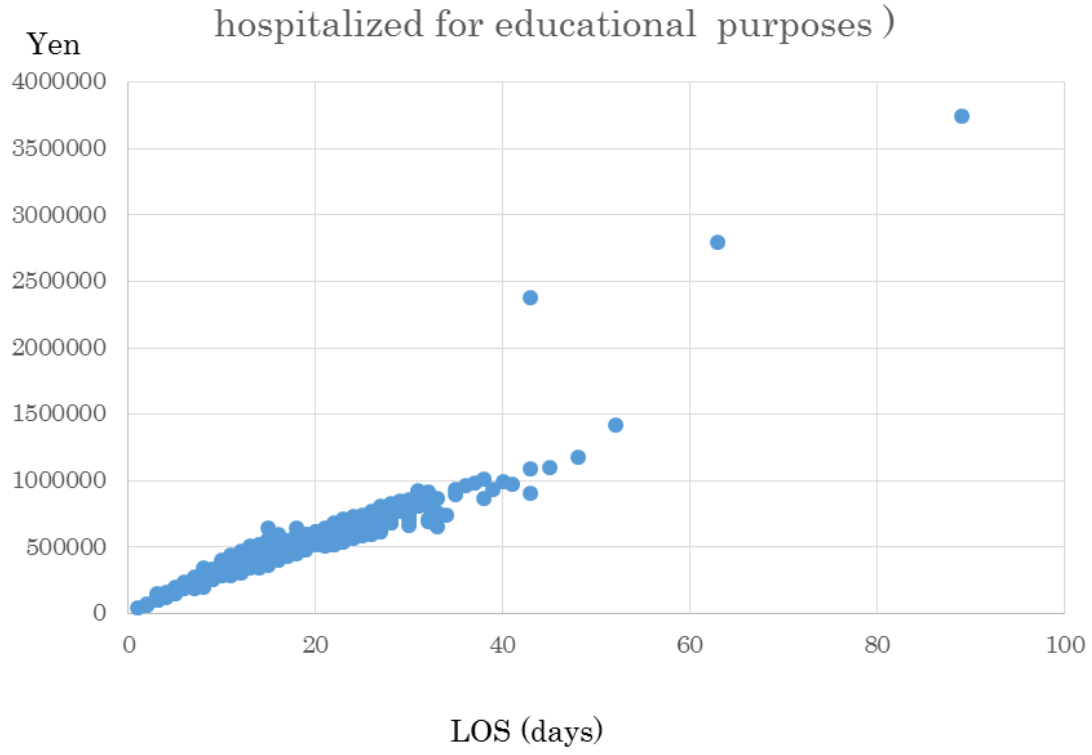

Fig.2 Medical expenditures and the LOS (excluding paitents belonging to departments that do not mainly treat diabetes)

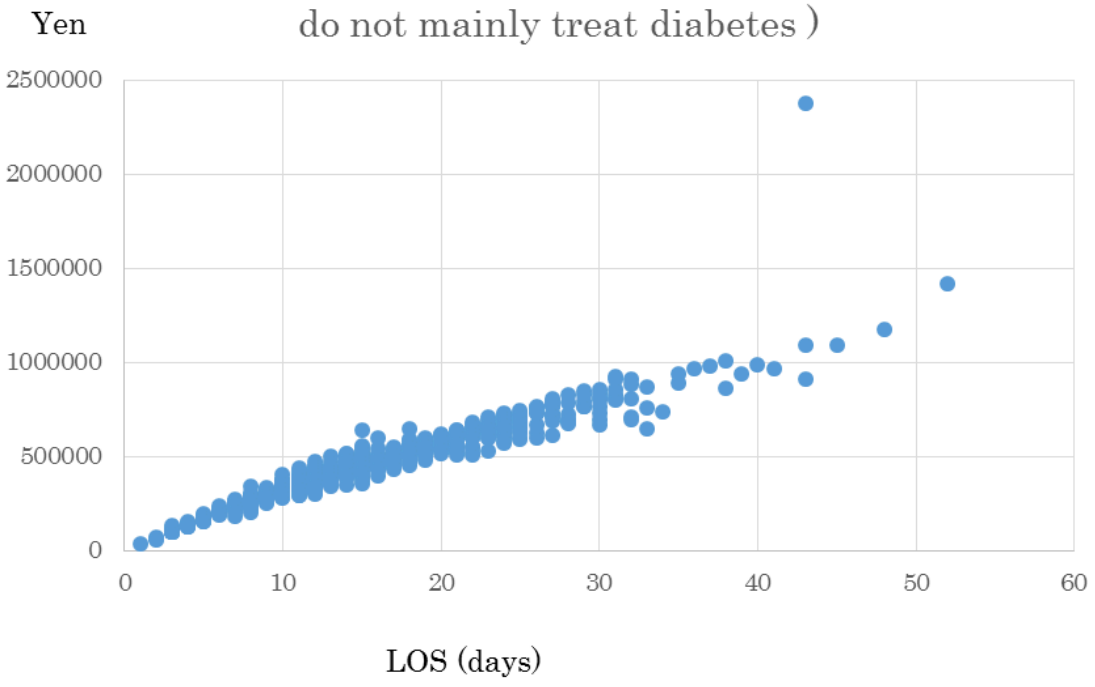

Fig. 3 Numer of patients by LOS

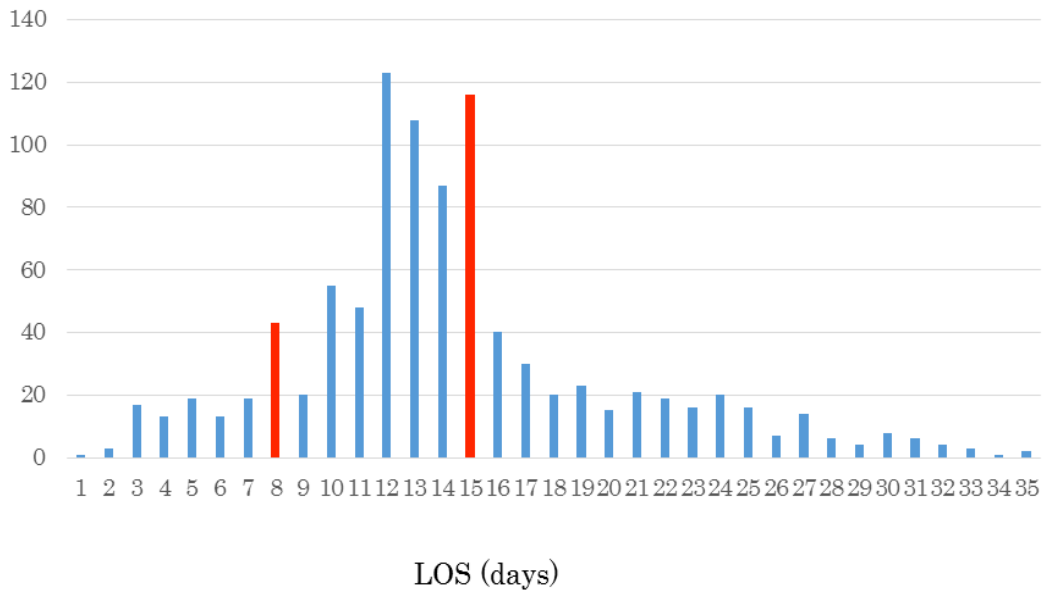

Fig.4 ALOSs and estimates of hospital dummies