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ESRI Research Note No.34

Quality and Cost of Health Care in Japan

- Quality-Cost Trade-off and Cost-Benefit Analysis -

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- Quality-Cost Trade-off and Cost-Benefit Analysis[†] -

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Abstract

Quality relative to cost is important in any field of economics. Health care is not an exception. If quality is superb relative to cost, it is worth incurring the cost. If quality is poor, cheap care is of little use. Cost-benefit analysis has been performed on a lot of individual treatments. It is unclear, however, whether health care expenditures of a country as a whole is worth spending specifically in Japan. Virtually no attempts are made to measure the benefits of health care for the country. We quantify the trade-off between quality and cost of health care in Japan and perform cost-benefit analysis for the country as a whole. Due to data availability, our analysis is restricted to AMI patients in a small number of hospitals. The results are suggestive, however. We find strong evidence that there is a positive trade-off: higher quality requires a higher cost, or, a lower cost induces lower quality. Whether the cost is worth it depends the value of life, of course. With the value of life of reasonable range, lower mortality more than compensates higher costs.

1. Introduction

Quality relative to cost is important in any field of economics. Health care is not an exception. If quality is superb relative to cost, it is worth incurring the cost. If quality is poor, cheap care is of little use.

Cost-benefit analysis has been performed with respect to a lot of individual treatments. It is unclear, however, whether health care expenditures of a country as a whole is worth spending specifically in Japan. Virtually no attempts are made to measure the benefits of health care for the total health system.

We quantify the trade-off between quality and cost of health care in Japan and perform a cost-benefit analysis for the care of AMI patients. Although the methods are applicable to the health care system as a whole, due to data limitation, we restrict our analysis to a small sample of Japanese hospitals.

In examining the quality-cost trade-off, it is important to recognize the endogeneity or simultaneous determination of quality and cost. A simple regression of quality on cost will generate a biased estimate of the effect of cost on quality. Basically following Timbie and Normand (2008), we will examine three models to accommodate the endogeneity: the cost-in-regression model with instrumental variables, the simultaneous equations model and the two-part model.

The structure of the paper is as follows. Section 2 gives an overview of the method and presents three types of models incorporating the endogeneity of quality and cost. Section 3 describes the data used and descriptive statistics. Sections 4, 5 and 6 estimate the cost-in-regression model, the hierarchical model and the two-part model, respectively. Section 7 concludes.

2. Methods

In examining the relationship between quality and cost, simple comparison of outcome and cost is not appropriate. Quality and cost are endogenous variables so that we should control for the endogeneity.

For example, low quality of care may manifest itself in increased complications which result in higher costs. Alternatively, low quality of care may induce early death thereby shorten length of stay which implies lower costs.

We examine three ways to model the relationship between quality and cost: cost-in-regression model with instrumental variables, the simultaneous equations model and the two-part model.

Timbie and Normand (2008) proposed three methods for combining quality and efficiency measures including univariate models, regression and cost-effectiveness analysis which uses two-part model. Our analysis follow their approach with a slight modification that we replace their univariate models with simultaneous equations model by allowing random errors of mortality and cost equations to be correlated.

Cost-effectiveness analysis:

We perform standard cost-effectiveness analysis just as Timbie and Normand (2008). Incremental net benefit is defined as change in benefits multiplied by the value of unit benefit minus change in cost.

$$\text{Incremental Net Benefit} = \lambda \cdot \Delta E - \Delta C,$$

where λ is the value of life (quality of life), ΔE is the change in benefits and ΔC is the change in costs. Since how much life is worth is controversial, we calculate various levels of incremental net benefits by changing the value of life.

The remainder of this section will outline the three approaches to modeling joint determination of quality and cost.

(a) Regression of quality on cost

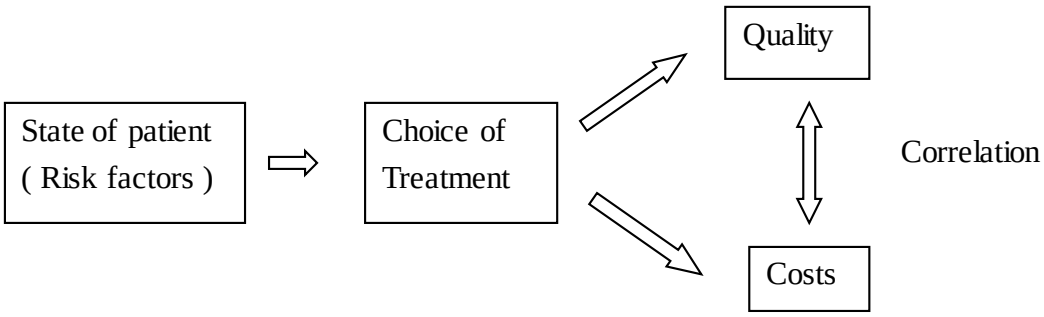
A simple way to examine the relationship between quality and cost is to regress quality on cost. We try simultaneous estimation of mortality and cost equations instead of single mortality equation with cost as an explanatory variable. In other words, we explicitly model determination of cost in conjunction with determination of mortality. We allow correlation between error terms in mortality and cost equations.

To identify the effect of cost on mortality, we need an exogenous variable which is included in the cost equation but excluded from the mortality equation. As instrumental variables we use variables which indicate whether a hospital is participating in the DPC arrangement. As is explained below, the DPC system is analogous to the DRG system and provides a strong incentive to reduce costs.

(b) Simultaneous equations: Correlation between random effects

In this approach, we directly model joint determination of quality and cost. Cost is excluded from the mortality equation.

Figure 1 Joint Determination of Quality and Cost



There are two hospital-specific random effects, one which adversely affects outcomes and the other which increases costs. If higher costs reduce mortality, these random effects will be negatively correlated. Hence, by examining the correlation between two random effects, we can infer the quality-cost trade-off.

Simultaneous estimation of mortality and cost equations require instrumental variables to distinguish two equations. Here, again, we use variables which represent DPC statuses as instruments.

(c) Two-part model

The third way to model correlation between mortality and cost is the two-part model. The two-part model decomposes the joint distribution of mortality and cost into two parts. One is the distribution of mortality and the other the distribution of cost conditional on mortality.

$$p(y_{it}, l\cos t_{it}) = p(y_{it}) \cdot p(l\cos t_{it} \mid y_{it})$$

We first estimate the mortality equation and second estimate cost equation according as the patient dies or not. For each part, we estimate excess mortality and excess costs.

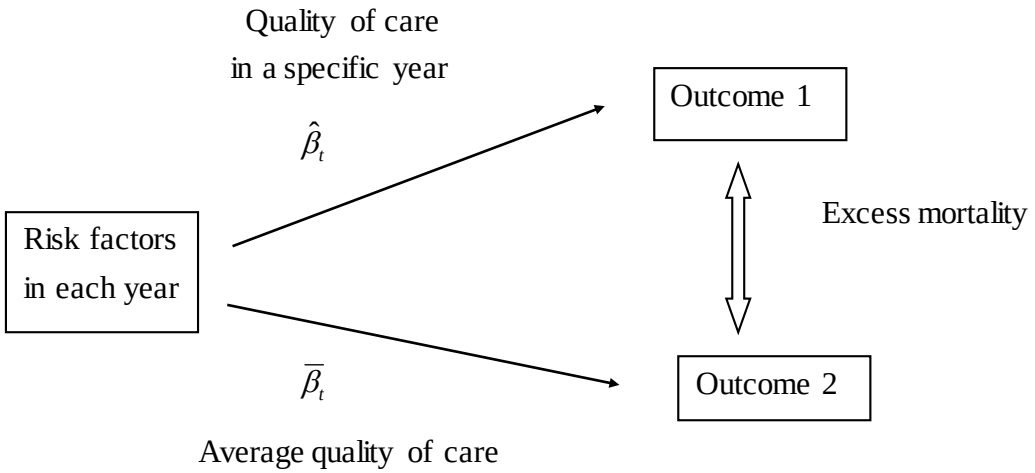
Since risk factors change from year to year, proper risk adjustment is needed. Risk adjustment is done by estimating a logistic regression model to measure the influence of

risk factors on mortality. We re-transform the linear predictor in the logistic regression back to the probability scale for individuals. Then, we average across all patients within each year to obtain the predicted outcome.

To adjust for case mix differences across years, we follow Timbie, et al. (2009:Cost-Effectiveness paper) who adopted indirect standardization. We estimate counterfactual outcomes for each year assuming underlying quality levels of the entire population while conditioning on each year's case mix. We take the difference between this expected outcome and the predicted outcome to yield an excess mortality for each year.

More concretely, in the indirect standardization, patient mix (distribution of risk factors) is fixed at actual mix in each year for both predicted and expected outcomes. We compare mortality rates of the following two cases for each year. Outcome 1 uses realized quality of care with the relationship between risk factors and outcome being actual one for each year. Outcome 2 uses average quality of care with the hypothetical relationship between risk factors and outcome being estimated by supposing that each year's quality of care is the same as the total year. Then, excess mortality is calculated as the difference between two outcomes.

Figure 2 Indirect Standardization



3. Data and basic statistics

Data were collected on AMI patients in 9 hospitals with a record of hospitalization at some period of time from 2004.4.1 to 2007.3.31. These hospitals had agreed to cooperate in the research for the consecutive years upon approval of in-hospital ethical committee.

We created structured questionnaires for data collection. Questionnaire I asked for detailed clinical information on the patient as well as information on the treatment the patient received. Claim data and physicians profile were collected by Questionnaire II. Questionnaire III collected overall information on AMI treatment at the hospital, such as the annual total number of CABG conducted. A part-time lecturer with physician's license in Thoracic-Cardiovascular Surgery Section of Tokyo Medical and Dental University stayed throughout the research to fill Questionnaire I from patient medical records including nursing records and discharge summary at each hospital. Questionnaire II and III were filled by hospital staffs who were approved of the access to claim data at each hospital.

Sample is restricted to ST-Elevation AMI in the following analyses. This choice is intended to secure homogeneity in the sample as is epitomized by the separate compilation of ACC/AHA guidelines for the management of patients with ST-Elevation myocardial infarction from those for the management of patients with Non-ST-Elevation myocardial infarction.

Nine hospitals were included in the data set. Only the hospitals with more than ten STEMI patients in every year are retained in the analysis. Observations are 2631 in total, of which 598 are in 2004, 612 in 2005, 672 in 2006 and 749 in 2007.

Table 1 shows basic statistics of patients for all hospitals. The Average age is 68.9 years old and a little less than a third patients is female. About a half of patients are in the Killip class 1, a quarter in the class 2 and a little less than 15% in classes 3 and further 14% in the class 4. Occlusion of the left main trunk, left bundle branch block and ventricular fibrillation account for around 4 to 6% of patients, respectively. More than a half of patients are with hypertension and a little less than 40% and a little more than a third are with hyperlipidemia and diabetes mellitus. 8% of patients suffer from heart failure and 10% from renal failure. The share of patients with cancer is 8%.

Table 2 exhibits characteristics of sample hospitals. Three out of nine hospitals are designated as tertiary critical care hospitals and all except one hospitals are designated as teaching hospitals. The average number of beds is 434. Hospitals in the sample are large in general, but the size varies. One hospital holds nearly 1000 beds while two

hospitals have less than 200 beds. The average number of AMI patients is 86, but the variation is large. Two hospitals admitted more than 150 AMI patients while two hospitals admitted only around 20. The average number of PCI performed is 297, which is a large number in the Japanese standard. Again, there is a great variation among hospitals. A hospital performed more than 700 PCI while two hospitals performed only a little more than 100 PCI.

Cost is charge billed either to the Social Insurance Funds if the medical activity is covered by the social insurance or to individuals if not. Of course, this is not a true cost, but a cost to the patients or taxpayers. The use of this concept of cost could be justified because this is the cost the society has to pay in order to obtain better quality of health care.

Figure 3 depicts crude mortality and cost over time. In 2004, crude mortality rate is a little above 9 % while mean cost is a little less than 2.6 million yen. In 2005, mean cost declined by around 0.1 million yen with a rise in mortality rate. The year 2006 saw a dramatic fall of cost to nearly 2.1 million yen together with a commensurate rise in mortality rate to more than 12 %. Then, in 2007, mortality rate declined with virtually no change in cost.

The decline in cost parallels with a decline in average length of stay (Figure 4). During this period, heavy pressures to reduce medical expenditures are felt by hospitals. The introduction of the DPC system may have been especially powerful to induce hospitals to reduce length of stay.

The Diagnosis Procedure Combination (DPC) system was introduced in 2003 as a prospective payment system for acute care of patients treated by the Specific Function Hospitals. Thereafter, the DPC system has been expanded to include other eligible hospitals. As of July 2010, the DPC system covers 1,391 hospitals and around 460,000 beds, which account for 50.4% of total beds.

The classification of patients starts with the diagnosis which absorbed resources the most among their diagnoses. Patients are further classified by whether specified operations are performed or not. Then, the final classification is reached according as whether the patient has comorbidities or not.

The DPC system is intended for use in a Prospective Payment System. But it retains characteristics of fee-for-service. For example, payments are per diem, not for

the whole hospitalization episode, and the system does not apply to operations and some other costly procedures. Therefore, it provides incentives to reduce LOS as well as incentives to increase operations. Overall, the former effect is larger than the latter effect as is verified in the estimation result of, for example, the cost-in-regression model shown in Appendix Table A1.

In 2004, of nine hospitals in the sample, one was applied the DPC system, six were in preparation for it and two were neither applied nor in preparation. In 2006, seven were applied, one was in preparation and one was neither applied nor in preparation.

Figure 5 shows crude mortality and cost by hospital. Mortality represented by bar chart differs substantially among hospitals. Hospital 3 has the highest mortality rate of more than 18 % while hospital 5 has the lowest mortality rate of only a little more than 6 %.

Average cost represented by line graph also varies substantially. Hospital 9 has the highest cost of nearly 300 million yen while hospital 3 has the lowest cost of much less than 200 million yen. Overall, it seems that hospitals with higher mortality tend to have lower costs. The relationship between mortality and cost will be examined in detail below.

Risk factors used in the regressions are shown in Table 1. Risk factors include age, female, Killip classes 2, 3 and 4, occlusion of the left main trunk, Left Bundle Branch Block, ventricular fibrillation(VF), history of myocardial infarction, history of PCI, history of CABG, hypertension, diabetes mellitus, hyperlipidemia, chronic obstructive pulmonary disease (COPD), bleeding tendencies, renal failure, cerebrovascular diseases and cancer.

4. Cost-in-regression model

We start with the estimation of cost-in-regression model. Since cost is endogenous variable, we explicitly model the determination of cost and to better identify the effect of cost on mortality, we include instrumental variables in the cost equation as is explained below.

We estimate simultaneous equations for the sample of all years assuming that the impact, γ, of cost on mortality is the same for all years. Since costs are very much skewed, we take log-transformation to make them more “normal”.

$$y_{ij} = 1[\alpha + \sum_{k=1}^{K} \beta_k \cdot x_{ij} + \gamma \cdot l\cos t_{ij} + c_i^y + u_{ij} > 0]$$

$$l\cos t_{ij} = \kappa + \sum_{k=1}^{K} \varphi_k \cdot x_{ij} + \delta \cdot z_{ij} + c_i^{lc} + v_{ij},$$

where y_{ij} denotes the outcome of the *j*-th patient in the *i*-th hospital. The outcome variable, y_{ij} takes the value 1 if a patient dies during the hospitalization and 0 if she survives. 1[.] represents an indicator function which takes the value 1 if the condition within the square bracket is true and 0 otherwise.

$l\cos t_{ij}$ denotes logarithms of costs of the *j*-th patient in the *i*-th hospital.

x_{ij}'s are risk factors of a patient listed above.

z_{ij} denotes instrumental variables which sill be detailed below.

c_i^y is an unobserved random effect specific to *i*-th hospital which affects y_{ij}.

c_i^{lc} is an analogous random effect which affects $l\cos t_{ij}$

As was pointed out above, cost is an endogenous variable so that in the mortality equation $l\cos t_{ij}$ is correlated with the error term u_{ij}.

We chose to model the simultaneous determination of mortality and cost. We estimate the mortality equation and cost equation simultaneously allowing error terms u_{ij} and v_{ij} to be correlated.

To identify the impact of cost on mortality, we searched for instrumental variables which are correlated with cost but uncorrelated with the error term, u_{ij}. Variables which indicate whether a hospital is participating in the DPC program should be good candidates for IVs because it can be assumed that DPC participants have strong incentives to reduce costs by way of reducing the length of stay while affecting mortality only through cost. In reality, the DPC system may induce hospitals to perform

operations more aggressively. However, the net effects can be assumed to be reduced medical expenditures. This assumption is validated by the estimation results shown below.

We have two variables which show participation in the DPC program according to differing status. “DPC preparation” indicates that the hospital is in preparation of participating in the DPC program. “DPC participation” indicates that the hospital is reimbursed by the DPC program.

Prior specifications are as follows. Correlated random intercepts are assumed to be bivariate normal with mean zero and precision matrix Σ^{-1}: $c_i \sim N(0,\Sigma^{-1})$ with $c_i \equiv \begin{pmatrix} c_i^{y} \\ c_i^{lc} \end{pmatrix}$. The random effect, c_i, for each hospital comes from the same normal distribution so that shrinkage toward the overall mean is expected.

The precision matrix is assumed to follow Wishart distribution with scale matrix Ω and 2 degrees of freedom: $\Sigma^{-1} \sim Wishart(\Omega,2)$. The choice of the 2 degrees of freedom is intended to represent vague prior. Ω is, in turn, specified as I_2.

The coefficient, γ, on *lcost* is assumed to follow a normal distribution with mean zero and variance σ^2: $\gamma \sim N(0,\sigma^2)$. A uniform prior on the standard deviation, σ, is adopted: $\sigma \sim Uniform(0,100)$. The choice of the variance of 100 is intended to represent a diffuse prior. Gelman and Hill (2007) give a thoughtful discussion on the appropriateness of this value in the context of the logistic models or log-transformed regressors. They argue that in logistic and logarithmic regressions, typical changes in outcomes are on the scale of 0.1 or 1, but not 10 or 100, so that one would not expect to see coefficients much higher than 10 in absolute values as long as the regressors are also on a reasonable scale. Although their choice of the value of variance is 100^2, we believe that their argument applies to our choice, 100. In fact, mean estimates of γ obtained below is -0.82.

The model was estimated with Markov chain Monte Carlo methods using WinBUGS software. To check the convergence, three parallel chains were run to calculate the Gelman-Rubin statistic. A burn-in of 10,000 iterations for each chain was allowed for the model to converge. Additional 20,000 samples for each chain were drawn from the joint posterior distribution for the estimation of all model parameters.

Table 2 shows estimate of the coefficient on cost. Full results are in Appendix Table A1. The mean is -0.820 and the standard error is 0.092. The 95 % credible interval

is from -1.006 to -0.643. The probability of the coefficient being positive is zero. Hence, it is very likely that higher cost reduces mortality.

From 2004 to 2007, the average cost decreased by 16.9 % which corresponds to a decline of around 432 thousand yen. Plugging this change into the mortality equation reveals that this decline in costs raised mortality rate (i.e. reduced survival rate) by 0.57 % points from 9.20 % to 9.76 %. (The actual mortality rate increased to 10.8 %, which is influenced by random fluctuations and factors other than decreased costs.)

We can perform incremental cost-benefit analysis from this relationship. Recall the following formula:

$$\text{Incremental Net Benefit} = \lambda \cdot \Delta E - \Delta C,$$

where λ is the value of life, ΔE is incremental benefit (change in survival rate) and ΔC is incremental cost.

First, we calculate the break-even value of life, which is the critical value of λ that equates the incremental gross benefit and incremental costs. We reversed the signs of the actual changes in survival rate and costs so that $\Delta E = +0.57\%$ increase in survival rate corresponding to $\Delta C = 432{,}042$ yen increase in costs. INB is calculated as

$$\lambda^* = \frac{\Delta C}{\Delta E} = \frac{432042}{0.005658} = 76{,}357 \text{ thousand yen.}$$

Hence, if we value life at around 76.4 million yen, a 432 thousand-yen increase in costs is compensated by a 0.57 % increase in survival rate (decrease in mortality rate). If we value life more than 76.4 million yen, the 0.57 % increase in mortality more than compensate the 432 thousand-yen increase in costs.

Second, we estimate incremental net benefits according as the value of life changes. How much life is worth is controversial, at best. It is nearly impossible to pin down exact value of life, although Viscusi and Aldy(2007) find that half of the studies of the U.S. labor market reveal a value of a statistical life ranges from $5 million to $12 million and the median is $7 million when converted into year 2000 dollars. (In terms of yen, the range is from 550 million yen to 1 billion and 320 million yen with a median of 770 million yen at the exchange rate of 110 yen per dollar.) Therefore, it is common to

calculate incremental net benefits by changing the value of life.

We can draw a diagram which shows the incremental net benefit as a function of the value of life. Figure 6 shows this relationship between the value of life and incremental net benefit. As the value of life increases, the net benefit from an increase in costs and corresponding decrease in mortality (increase in survival rate) becomes larger.

5. Simultaneous equations model

In this approach, we directly model joint determination of quality and cost. Compared with the cost-in-regression model, cost is excluded from the mortality equation. For *t*-th year, we checked correlation between c_t^y and c_t^{lc} in the mortality and cost equations.

The outcome variable, y_{it}, takes the value one if a patient *i* in time *t* dies and zero if she is discharged alive.

$$y_{it} = 1[\alpha + \sum_{k=1}^{K} \beta_k \cdot x_{it} + c_t^y + u_{it} > 0]$$

$$l\cos t_{it} = \kappa + \sum_{k=1}^{K} \varphi_k \cdot x_{it} + \delta \cdot z_{it} + c_t^{lc} + v_{it}$$

Since costs are very much skewed, we take log-transformation to make them more "normal". Notations for variables are the same as the cost-in-regression model. Instrumental variables are also the same.

The model was estimated with Markov chain Monte Carlo methods using WinBUGS software. The number of chains, check of convergence, burn-in and samples for estimation are the same as the cost-in-regression model.

Prior specifications are also similar. Namely, correlated random intercepts are assumed to be bivariate normal with mean zero and precision matrix Σ^{-1}: $c_t \sim N(0, \Sigma^{-1})$ with $c_t \equiv \begin{pmatrix} c_t^y \\ c_t^{lc} \end{pmatrix}$. The random effect, c_t, for each year comes from the same normal distribution so that shrinkage toward the overall mean is expected.

The precision matrix is assumed to follow Wishart distribution with scale matrix Ω and 2 degrees of freedom: $\Sigma^{-1} \sim Wishart(\Omega, 2)$. Ω is, in turn, specified as I_2.

Results of the estimation of simultaneous equations model are shown in Appendix Table A2. The upper part of Table 3 presents overall correlation between random effects for mortality and those for cost. The estimate is almost zero. This is because correlations within each year are very low, which are shown in the lower part of the table.

Correlation among years seems to be high as is depicted in Figure 7. One can see negative relationship between mortality random effects and cost random effects. Overall picture is the similar to Figure 3 of crude mortality and cost. A remarkable difference is that mortality random effect in 2005 is lower than that in 2004. Estimates of random effects are after adjustment for risk factors.

The case of hospital random effects

As an alternative viewpoint, we checked the correlation between hospital random effects of mortality and cost for hospital. Namely, for *i*-th hospital and *j*-th patient, we checked correlation between c_i^y and c_i^{lc} in the mortality and cost equations.

$$y_{ij} = 1[\alpha + \sum_{k=1}^{K} \beta_k \cdot x_{ij} + c_i^y + u_{ij} > 0]$$

$$l\cos t_{ij} = \kappa + \sum_{k=1}^{K} \varphi_k \cdot x_{ij} + \delta \cdot z_{ij} + c_i^{lc} + v_{ij}$$

When we replace year random effects with hospital random effects in the estimation of the simultaneous equations model, we obtain correlation between mortality and cost random effects of hospitals. Full results are shown in Appendix Table A2.

The upper part of Table 4 shows overall correlation. Again, the correlation is low and this is because of low correlation within hospital. Once again, correlation among hospitals seems to be high. A clear downward-sloping line is observable in Figure 8. This line would represent the trade-off between mortality and cost. Rather surprisingly, almost all hospitals lie on the line although hospitals 4 and 5 may have slightly better survival rate with lower costs.

How much confidence can we place on these estimates of random effects? Figure 9 shows mean level of random effects for mortality together with 95 % credible intervals. These random effects are not exponentiated. Overall, mortality random effects are significantly above or below zero. The probability that the random effect is above zero

is shown at the bottom of the figure. Except hospitals 3, 7 and 9, the probabilities are more than 0.9 or less than 0.1.

Figure 11 shows mean level of random effects for cost together with 95 % credible intervals. Cost random effects are above or below zero less significantly than mortality random effects. The probability that the random effect is above zero is again shown at the bottom of the figure. Four hospitals out of nine have probabilities more than 0.9 or less than 0.1 and the probabilities of other hospitals are not so different from these.

6. Two-part model

The two-part model decomposes the joint distribution of mortality and cost into two parts. One is the distribution of mortality and the other the distribution of cost conditional on mortality.

$$p(y_{it}, l\cos t_{it}) = p(y_{it}) \cdot p(l\cos t_{it} \mid y_{it})$$

The outcome variable, y_{it}, takes the value one if a patient *i* in time *t* dies and zero if she survives. We proceed in following steps.

First, as for the $p(y_{it})$ part, we estimate the mortality equation:

$$logit[\,p(y_{it} = 1 \mid x_{it})] = \alpha_t + \beta_t \cdot x_{it},$$

where x_{it} is severity index. We follow Timbie, et al. (2008:Cost-Effectiveness paper) in creating a measure of disease severity, severity index, for each patient. A logistic regression was used to model the effect of demographic and clinical risk factors on in-hospital mortality. Risk factors are selected by checking statistical significance and signs of estimated coefficients. Risk factors are the same as those used in the cost-in-regression model or the simultaneous equations model. Estimation result is shown in Appendix Table A3. The severity index is estimated as a linear predictor using the coefficients from the estimated logistic regression: $severity_{it} = \sum_{p=1}^{P} \hat{\beta}_p \cdot x_{itp}$, where x_{itp} denotes *p*-th covariate of *i*-th patient at time *t*.

Then, we obtain predicted mortality.

$$p(y_{it}=1|x_{it})=\frac{\exp(\alpha_t+\beta_t\cdot x_{it})}{1+\exp(\alpha_t+\beta_t\cdot x_{it})}\equiv\Lambda(\alpha_t+\beta_t\cdot x_{it}),$$

Second, as for the $p(l\cos t_{it}\,|\,y_{it})$ part, we estimate cost equations separately according as $y_{it}=1$ or 0.

$$l\cos t_{it}=\kappa+\varphi\cdot x_{it}+\delta\cdot z_{it}+v_{it}$$

Since costs are very much skewed, we take log-transformation to make them more "normal". We should be careful when retransforming log-cost into the original scale because expected log-cost is not equal to log of expected cost. We utilize smearing estimator proposed by Duan (1983) just as Timbie and Normand (2008).

The model was estimated with Markov chain Monte Carlo methods using WinBUGS software. The number of chains, check of convergence, burn-in and samples for estimation are the same as the cost-in-regression model.

Prior specifications are as follows. Two random effects are assumed to follow bivariate normal with mean μ and precision matrix Σ^{-1}: $c_t\sim N(\mu,\Sigma^{-1})$ with $c_t\equiv\begin{pmatrix}\alpha_t\\ \beta_t\end{pmatrix}$. The random effect, c_t, for each year comes from the same normal distribution so that shrinkage toward the overall mean is expected.

Overall mean, μ, is assumed to follow a normal distribution with mean 0 and variance 100: $\mu\sim N(0,100)$. The precision matrix is assumed to follow Wishart distribution with scale matrix Ω and 2 degrees of freedom: $\Sigma^{-1}\sim Wishart(\Omega,2)$. The choice of the 2 degrees of freedom is intended to represent vague prior. Ω is, in turn, specified as I_2.

Now, we give a detailed account of indirect standardization. As is explained above, we compare mortality rates of the following two cases for each year: Outcome 1 which uses realized quality of care and Outcome 2 which uses average quality of care.

(i) Estimation of the mortality equation: Indirect standardization

First, we estimate the mortality equation adjusting for risk factors by indirect standardization. To standardize case mixes, we compared two outcomes, actual and hypothetical.

Outcome 1 utilizes actual relationship between risk factors and outcome for each year so that parameters are estimated using the sample of each year separately. Parameters, α_t and β_t, depend on time *t*.

We estimate a logit regression model for each year,

$$logit[\,p(y_{it}=1\,|\,x_{it})] = \alpha_t + \beta_t \cdot x_{it}$$

to obtain estimates, $\hat{\alpha}_t$ and $\hat{\beta}_t$. We re-transform back into the original probability scale: $p(y_{it}=1\,|\,x_{it}) = \dfrac{\exp(\alpha_t + \beta_t \cdot x_{it})}{1+\exp(\alpha_t + \beta_t \cdot x_{it})} \equiv \Lambda(\alpha_t + \beta_t \cdot x_{it})$.

Then, we average individual probabilities of death for each year: *t* = 2004, 2005, 2006 and 2007.

$$\hat{D}_t = \frac{1}{n_t}\sum_{i=1}^{n_t} \Lambda(\hat{\alpha}_t + \hat{\beta}_t \cdot x_{it})$$

Then survival rate is $\hat{E}_t = 1 - \hat{D}_t$.

Outcome 2 sets up a hypothetical relationship between risk factors and outcome for each year by supposing that each year's quality of care is the same as the total year. Parameters are estimated using the sample from all years so that parameters, α and β, do not depend on *t*: common parameters for all years.

We estimate a logit regression model for all years,

$$logit[\,p(y_{it}=1\,|\,x_{it})] = \alpha + \beta \cdot x_{it}$$

to obtain estimates, $\overline{\alpha}$ and $\overline{\beta}$. We re-transform back into the original probability scale: $\overline{p}(y_{it}=1\,|\,x_{it}) = \Lambda(\overline{\alpha} + \overline{\beta} \cdot x_{it})$.

Again, we average individual probabilities for each year: t = 2004, 2005, 2006 and 2007.

$$\overline{D_t} = \frac{1}{n_t}\sum_{i=1}^{n_t} \Lambda(\overline{\alpha} + \overline{\beta} \cdot x_{it})$$

Then survival rate is $\overline{E_t} = 1 - \overline{D_t}$.

Excess mortality is the difference between Outcome 1 and Outcome 2, $\hat{E}_t - \overline{E_t}$.

The first column of Table 5 shows the incremental benefit derived from the estimated excess mortality for each year and from 2004 to 2007.

Incremental benefit is a small positive in 2005, a large negative in 2006 and a moderate positive in 2007.

From 2004 to 2007, the incremental benefit is slight negative.

(ii) Estimation of cost equations separately according as $y_{it} = 0$ or 1.

Second, we estimate cost equations conditional on whether the patient died or not.

$$l\cos t_{it} = \kappa_t + \varphi_t \cdot x_{it} + v_{it}$$

(a) Corresponding to $y_{it} = 1$: Expirer

Case1: Use realized quality of care

Parameters, $\hat{\kappa}_{1t}$ and $\hat{\varphi}_{1t}$, are estimated using the sample of each year separately. By re-transforming the estimated log-cost, $\hat{l\cos t}_{1it} = \hat{\kappa}_{1t} + \hat{\varphi}_{1t} \cdot x_{1it}$, into the original scale and averaging, we obtain for each year, t = 2004, 2005, 2006, 2007,

$$\hat{C}_{1t} = \frac{1}{n_{1t}}\sum_{i=1}^{n_{1t}} (\hat{\kappa}_{1t} + \hat{\varphi}_{1t} \cdot x_{1it})$$

Cost has been transformed into logarithms. When re-transforming *lcost* back into the

natural scale, smearing estimator is applied to avoid biases due to non-linearity of log-transformation.

Suppose that cost is log-transformed, $l\cos t_i = \log(\cos t_i)$, and the model is $l\cos t_i = \kappa + \varphi \cdot x_i + u_i$. The expected cost of individual 0 is, even with $E(u \mid x) = 0$,

$$E(\cos t_0 \mid x_0) = E[\exp(\kappa + \varphi \cdot x_0 + u)] \neq \exp(\kappa + \varphi \cdot x_0)$$

Smearing estimator proposed by Duan (1983) is:

$$E(\cos t_0 \mid x_0) = E[\exp(\hat{\kappa} + \hat{\varphi} \cdot x_0 + \hat{u}_i)] = \frac{1}{n}\sum_{i=1}^{n} \exp(\hat{\kappa} + \hat{\varphi} \cdot x_0 + \hat{u}_i),$$

where $\hat{u}_i \equiv l\cos t_i - (\hat{\kappa} + \hat{\varphi} \cdot x_i)$

Case2: Use average quality of care: Common parameters

Parameters are estimated using the sample of all years to obtain $\overline{\kappa}_1$ and $\overline{\varphi}_1$. Then, $\overline{l\cos t}_{1it} = \overline{\kappa}_1 + \overline{\varphi}_1 \cdot x_{1it}$. We re-transform back to the original scale using smearing estimator. Finally, we average for each year: t = 2004, 2005, 2006 and 2007.

$$\overline{C}_{1t} = \frac{1}{n_{1t}}\sum_{i=1}^{n_{1t}} (\overline{\kappa}_1 + \overline{\varphi}_1 \cdot x_{1it} + \overline{u}_{1t})$$

(b) Corresponding to $y_{it} = 0$: Survivor

Case1: Use realized quality of care

Parameters, $\hat{\kappa}_{0t}$ and $\hat{\varphi}_{0t}$, are estimated using the sample of each year separately. By re-transforming the estimated log-cost, $l\hat{\cos} t_{0it} = \hat{\kappa}_{0t} + \hat{\varphi}_{0t} \cdot x_{0it}$, into the original scale and averaging, we obtain for each year, t = 2004, 2005, 2006, 2007,

$$\hat{C}_{0t} = \frac{1}{n_{0t}}\sum_{i=1}^{n_{0t}} (\hat{\kappa}_{0t} + \hat{\varphi}_{0t} \cdot x_{0it})$$

Case2: Use average quality of care

Parameters are estimated using the sample of all years to obtain $\overline{\kappa}_0$ and $\overline{\varphi}_0$. Then, $\overline{l\cos t}_{0it} = \overline{\kappa}_0 + \overline{\varphi}_0 \cdot x_{0it}$. We re-transform back to the original scale using smearing

estimator. Finally, we average the re-transformed costs for each year: t = 2004, 2005, 2006 and 2007.

$$\overline{C}_{0t} = \frac{1}{n_{0t}} \sum_{i=1}^{n_{0t}} (\overline{\kappa}_0 + \overline{\varphi}_0 \cdot x_{0it})$$

Excess cost is weighted average of costs for expirers or survivors with mortality rates as weights.

$$\Delta C_t = \hat{C}_{1t} \times \hat{E}_t + \hat{C}_{0t} \times (1 - \hat{E}_t) - \{\overline{C}_{1t} \times \overline{E}_t + \overline{C}_{0t} \times (1 - \overline{E}_t)\}$$

Excess mortality and excess cost calculated from the two-part model are shown in Figure 11. Overall picture is similar to Figure 7 which shows year random effects in the simultaneous equation model with a main difference being that excess mortality in 2007 is below zero.

We can perform incremental cost-benefit analysis using estimates from this relationship. Recall that the following formula.

Incremental Net Benefit = $\lambda \cdot \Delta E - \Delta C$,

where λ is the value of life, ΔE is incremental benefit (change in survival) and ΔC is incremental cost. The excess survival rate decreased from 0.21% in 2004 to 0.05% in 2007. The excess cost decreased from 253562 yen in 2004 to -184646 yen in 2007. The change in the excess survival is 0.16 % while the change in the excess cost is 438,208 yen resulting in the break-even value of life of 2billion and 7810 million yen (27.8 million dollar).

7. Conclusion

This paper quantitatively examined the trade-off between quality and cost of health care in Japan and performed cost-benefit analysis for the country as a whole. Due to data

availability, our analysis was restricted to AMI patients in a small number of hospitals.

The results are suggestive, however. We find strong evidence that there is a positive trade-off: higher quality requires a higher cost, or, a lower cost induces lower quality. Whether the cost is worth it depends the value of life, of course. With the value of life of reasonable range, lower mortality more than compensates higher costs.

In the sequel of this paper, we are planning to investigate into the determinants of quality of care. From our data, quality measures can be calculated for each hospital such as Door-to-Balloon time and drug therapies at arrival or discharge. By contrasting quality measures and quality of each hospital, we can examine the question: what determines the quality? For example, Figure 12 shows the relationship between Door-to-Balloon time and hospital-specific random effects for mortality. Whether quality measures are related to outcomes are hotly debated. A small sample of the literature includes Granger, et al. (2005), Bradley, et al. (2006) and Peterson, et al. (2006). Only after we identify the determinants of quality of care can we take steps to improve the quality of health care.

Quality-cost trade-off and cost-benefit analysis are similar but not identical to the concept of productivity. We are planning to measure productivity of health care more in line with economics tradition as proposed by Castelli, et al. (forthcoming).

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Table 1 Basis Statistics of Risk Factors

	Average	2004	2005	2006	2007
Age	68.9	68.9	68.8	69.0	69.0
Female	0.296	0.298	0.289	0.275	0.320
Killip1	0.482	0.527	0.430	0.510	0.462
Killip2	0.237	0.199	0.288	0.211	0.248
Killip3	0.147	0.124	0.119	0.153	0.183
Killip4	0.135	0.151	0.163	0.125	0.107
Left main trunk occluded	0.051	0.042	0.052	0.058	0.052
LBBB	0.067	0.057	0.072	0.061	0.075
Ventricular fibrillation	0.044	0.030	0.031	0.064	0.048
Hypertension	0.539	0.587	0.565	0.487	0.525
Hyperlipidemia	0.375	0.375	0.355	0.360	0.405
Diabetes mellitus	0.348	0.370	0.364	0.351	0.314
Heart failure	0.078	0.100	0.078	0.063	0.075
History of myocardial infarction	0.108	0.100	0.127	0.112	0.093
History of PCI	0.095	0.107	0.101	0.095	0.081
History of CABG	0.015	0.007	0.018	0.022	0.013
Cancer	0.076	0.060	0.056	0.098	0.087
Bleeding	0.019	0.020	0.029	0.015	0.015
Renal failure	0.102	0.119	0.090	0.116	0.085
Cerebrovascular diseases	0.123	0.097	0.124	0.125	0.140
Aneurysm	0.025	0.027	0.023	0.030	0.023
COPD	0.021	0.023	0.028	0.018	0.015
Severity index	−3.663	−3.786	−3.575	−3.647	−3.653

Table 2

hpid		Critical Care	Teaching	Number of beds	Number of inpatients	Number of AMI patients	Number of PCI	DPC	Owenership
1	1	◎	○	956	304,183	164	483		
2	2	○	○	524	89,224	69	103		
8	3	○	○	322	7,839	19	109		
9	4	○	○	530	1,601	81	299		
10	5	○	○	202	72,410	186	712		
15	6	◎	○	592	187,739	89	253		
16	7	◎	○	469	159,961	93	185		
17	8	○	–	151	27,275	22	163		
26	9	○	○	165	3,198	50	367		
			Average	434	94,826	86	297		

(note) In the column 'Critical Care' ○ indicates second and ◎ tertial critical care designation.

Table 3 Simultaneous Equations Model

Year Random Effetcs

Overall correlation

node	mean	sd
rho.beta[1,	−0.01838	0.4333

Correlation within year

2004	−0.025
2005	−0.025
2006	−0.024
2007	−0.025

Table 4 Simultaneous Equations Model

Hospital Random Effetcs

Overall correlation

node	mean	sd
rho.beta[1,	−0.3728	0.2891

Correlation within hospital

Hospital 1	−0.197
Hospital 2	−0.193
Hospital 3	−0.156
Hospital 4	−0.178
Hospital 5	−0.190
Hospital 6	−0.172
Hospital 7	−0.191
Hospital 8	−0.152
Hospital 9	−0.175

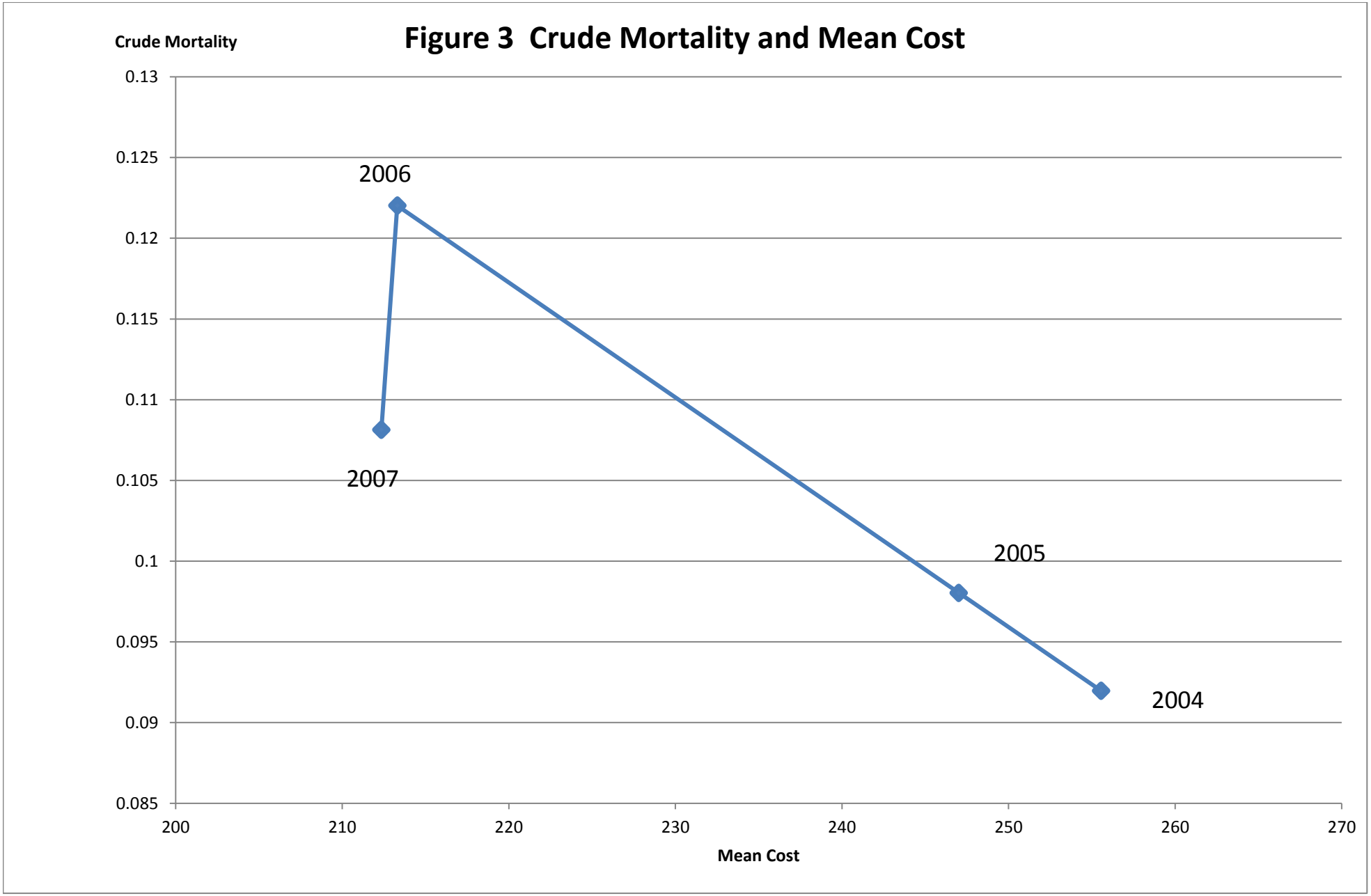


Figure 3 Crude Mortality and Mean Cost
Crude Mortality
0.13
0.125
0.12
0.115
0.11
0.105
0.1
0.095
0.09
0.085
2006
2007
2005
2004
200
210
220
230
240
250
260
270
Mean Cost

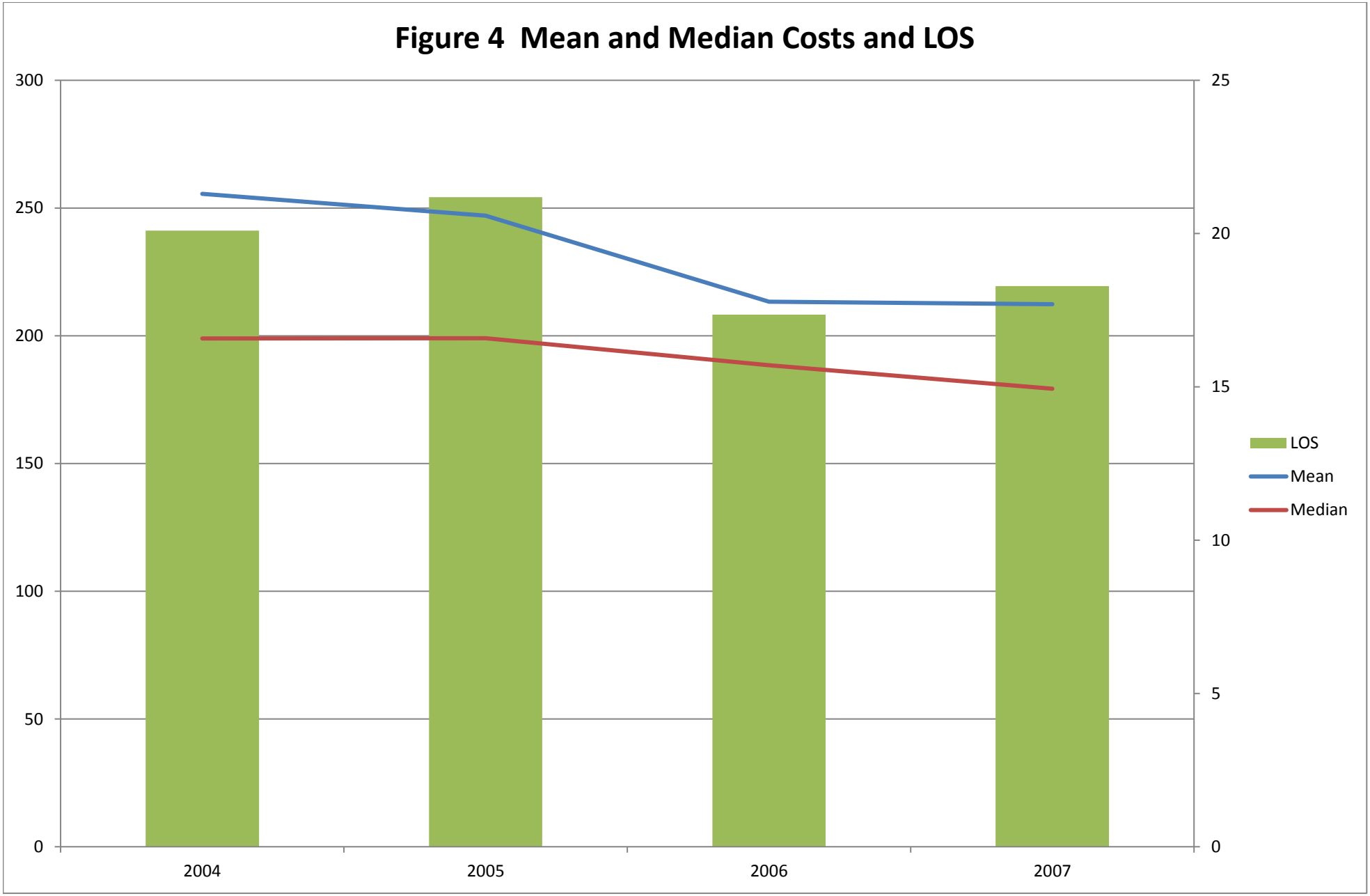
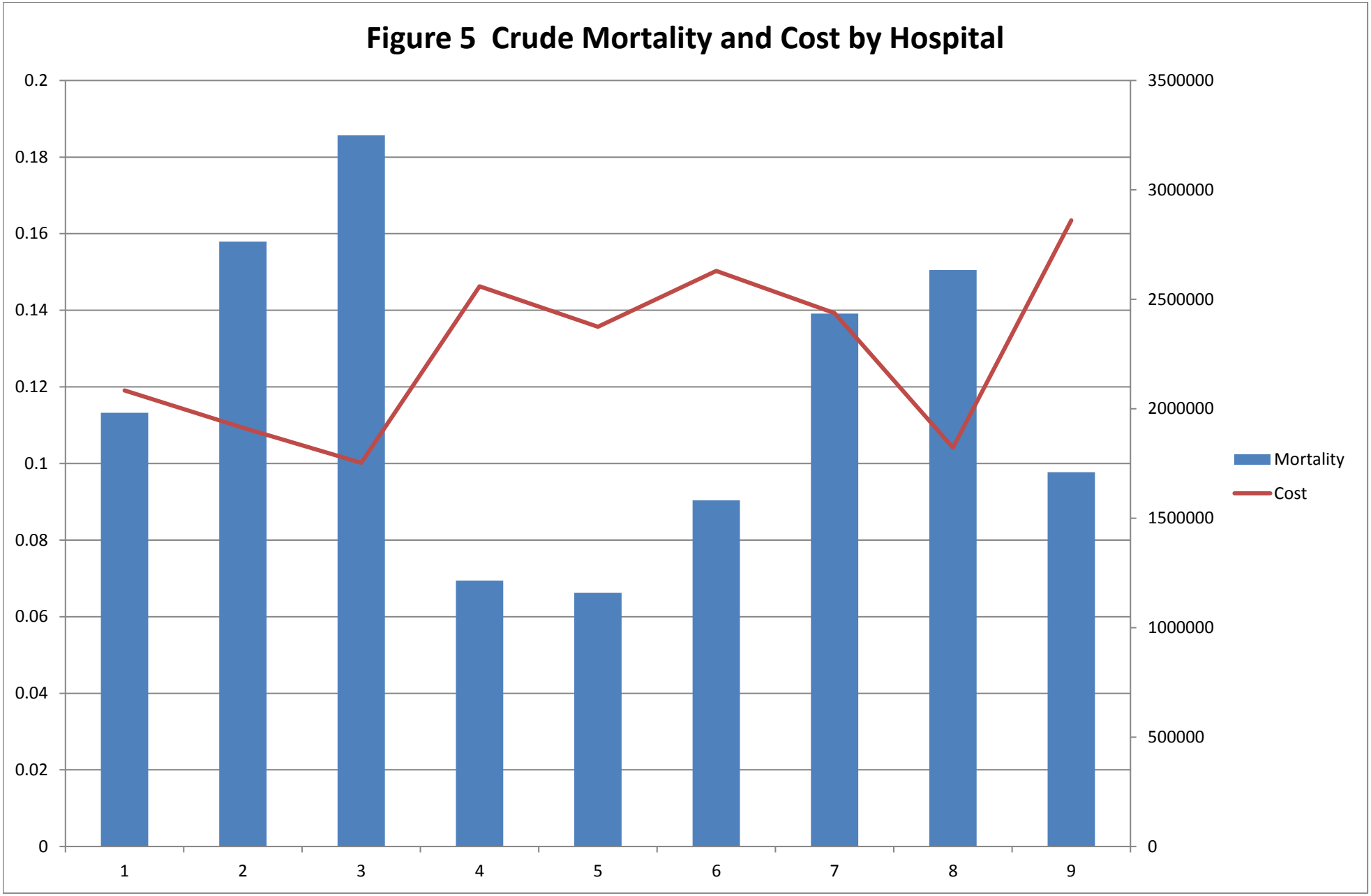
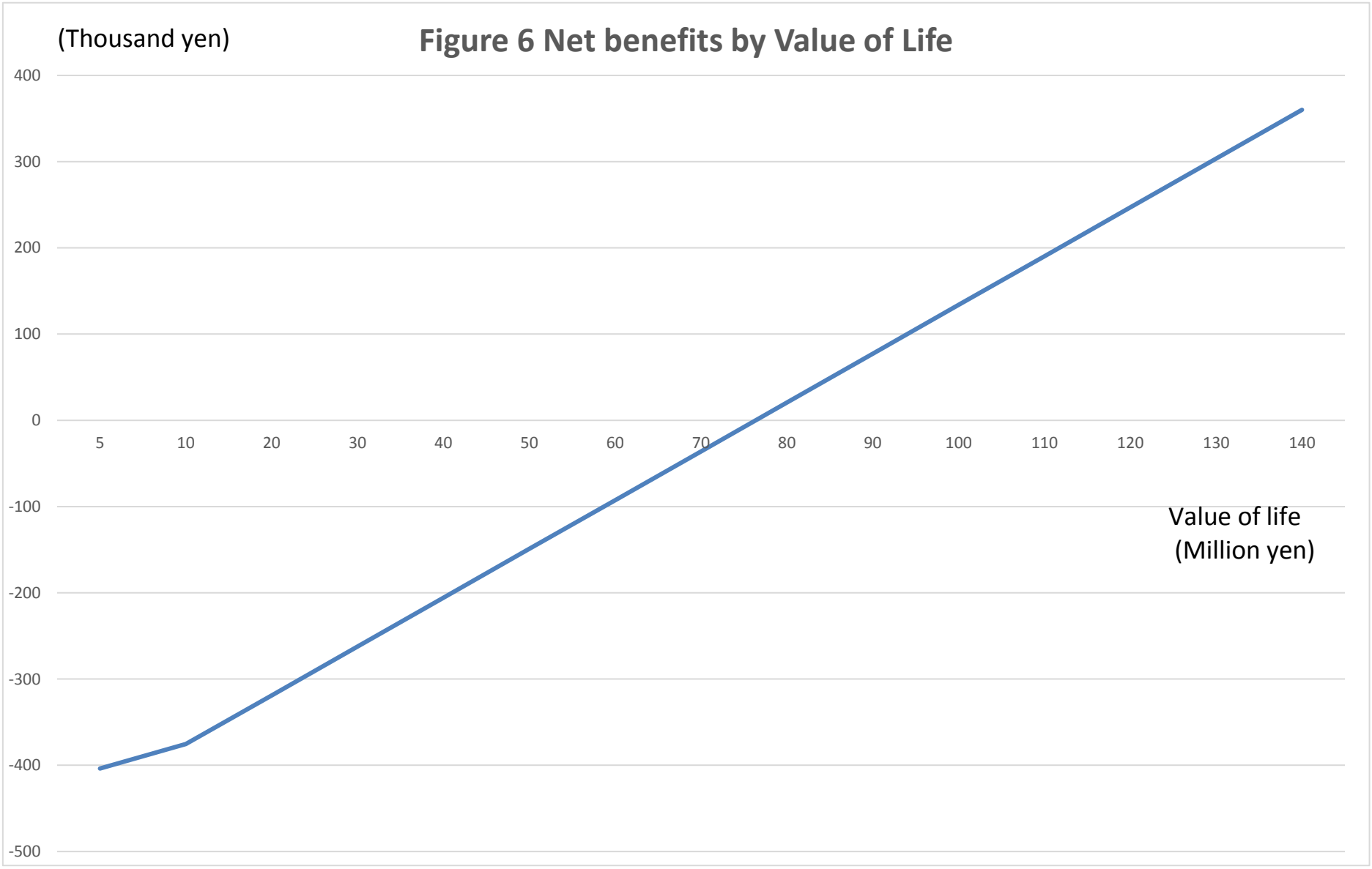


Figure 4 Mean and Median Costs and LOS
300
250
200
150
100
50
0
25
20
15
10
5
0
2004
2005
2006
2007
LOS
Mean
Median

Figure 5 Crude Mortality and Cost by Hospital




(Thousand yen)
Figure 6 Net benefits by Value of Life
400
300
200
100
0
-100
-200
-300
-400
-500
5
10
20
30
40
50
60
70
80
90
100
110
120
130
140
Value of life
(Million yen)

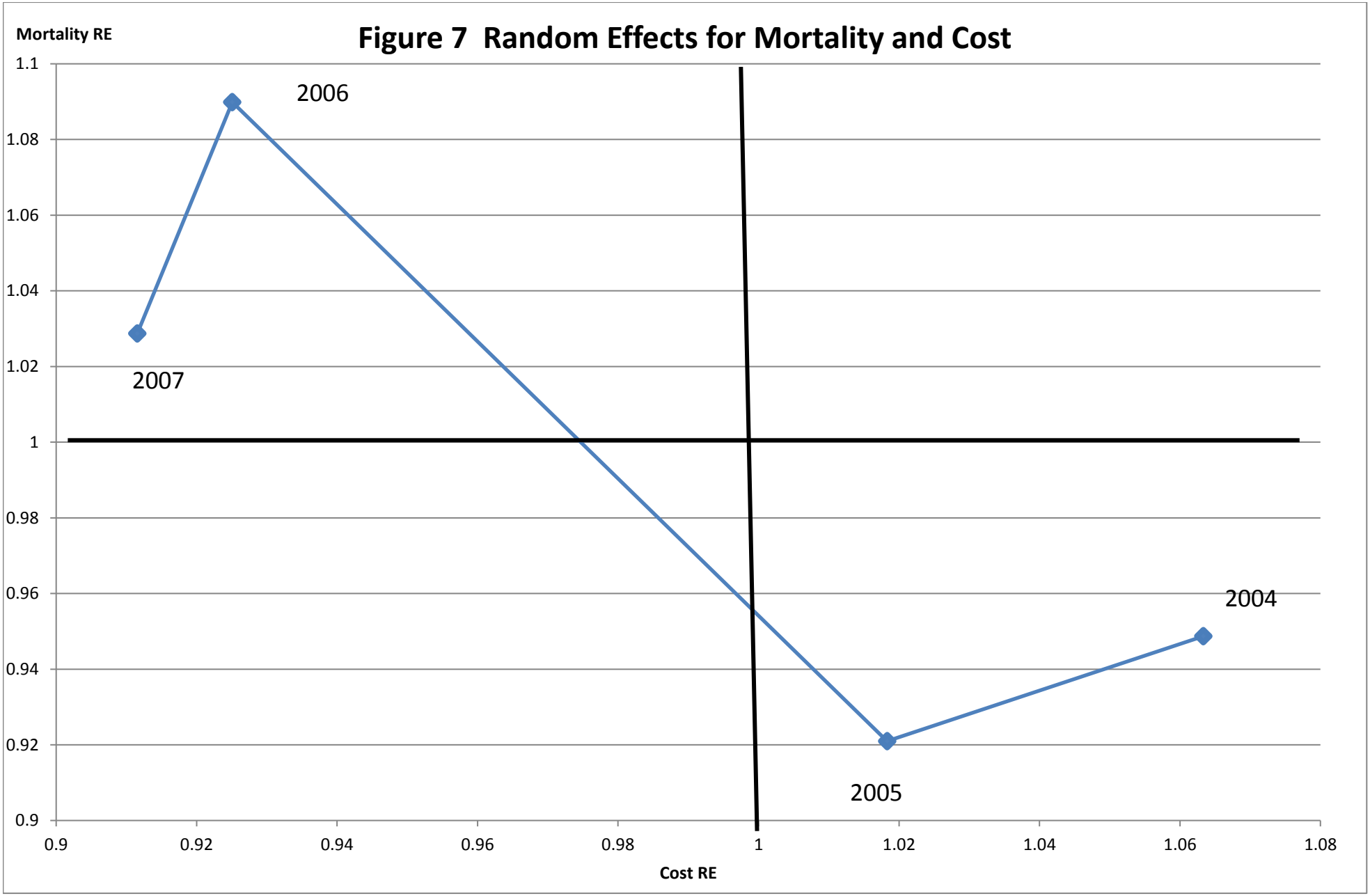


Figure 7 Random Effects for Mortality and Cost
Mortality RE
1.1
1.08
1.06
1.04
1.02
1
0.98
0.96
0.94
0.92
0.9
2006
2007
2004
2005
0.9
0.92
0.94
0.96
0.98
1
1.02
1.04
1.06
1.08
Cost RE

Figure 8 Random Effects in the Simulataneous Eqautions Model

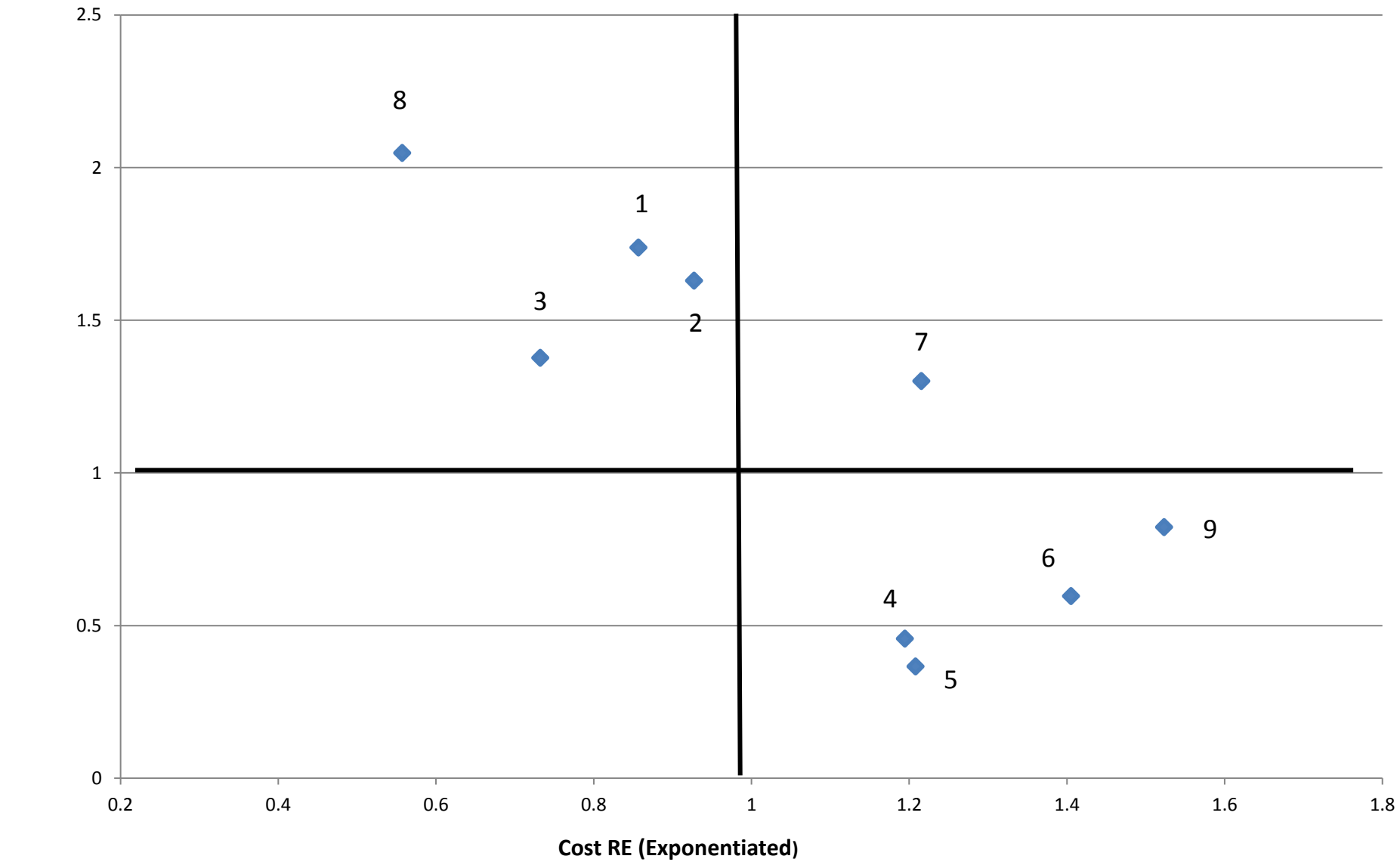
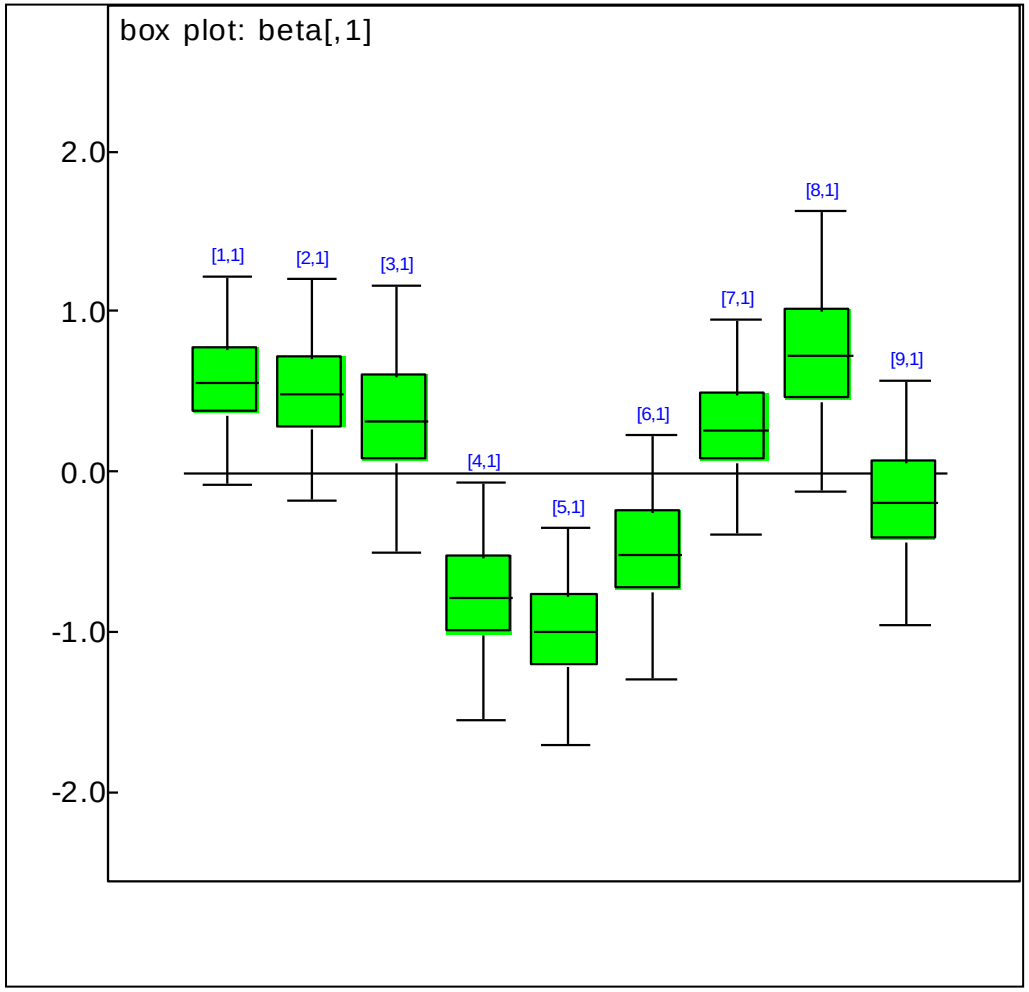
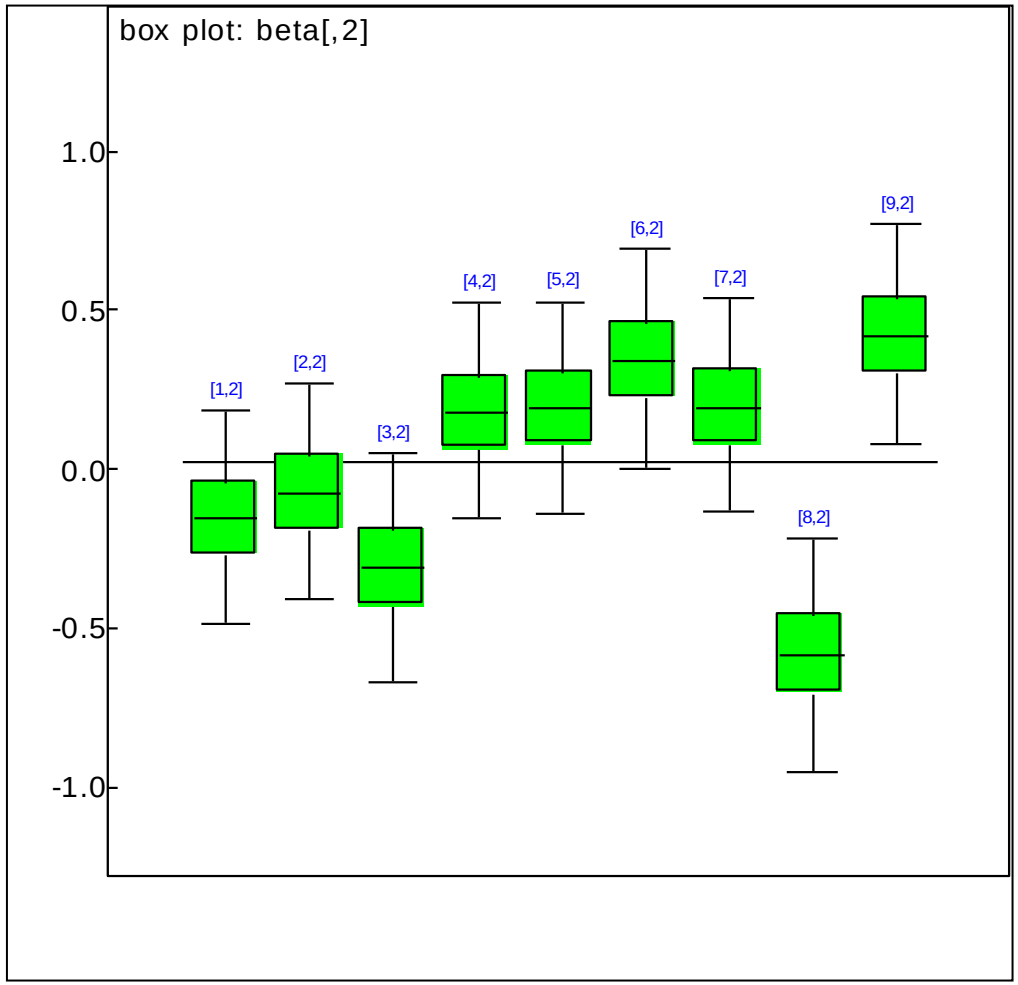


Figure 9 Random Effect for Mortality Simultaneous Eqautions



Hospital	1	2	3	4	5	6	7	8	9
Probability	0.958	0.924	0.782	0.016	0.002	0.086	0.789	0.952	0.300

Figure 10 Random Effect for Cost Simultaneous Eqautions



Hospital	1	2	3	4	5	6	7	8	9
Probability	0.187	0.330	0.046	0.844	0.863	0.975	0.869	0.000	0.992

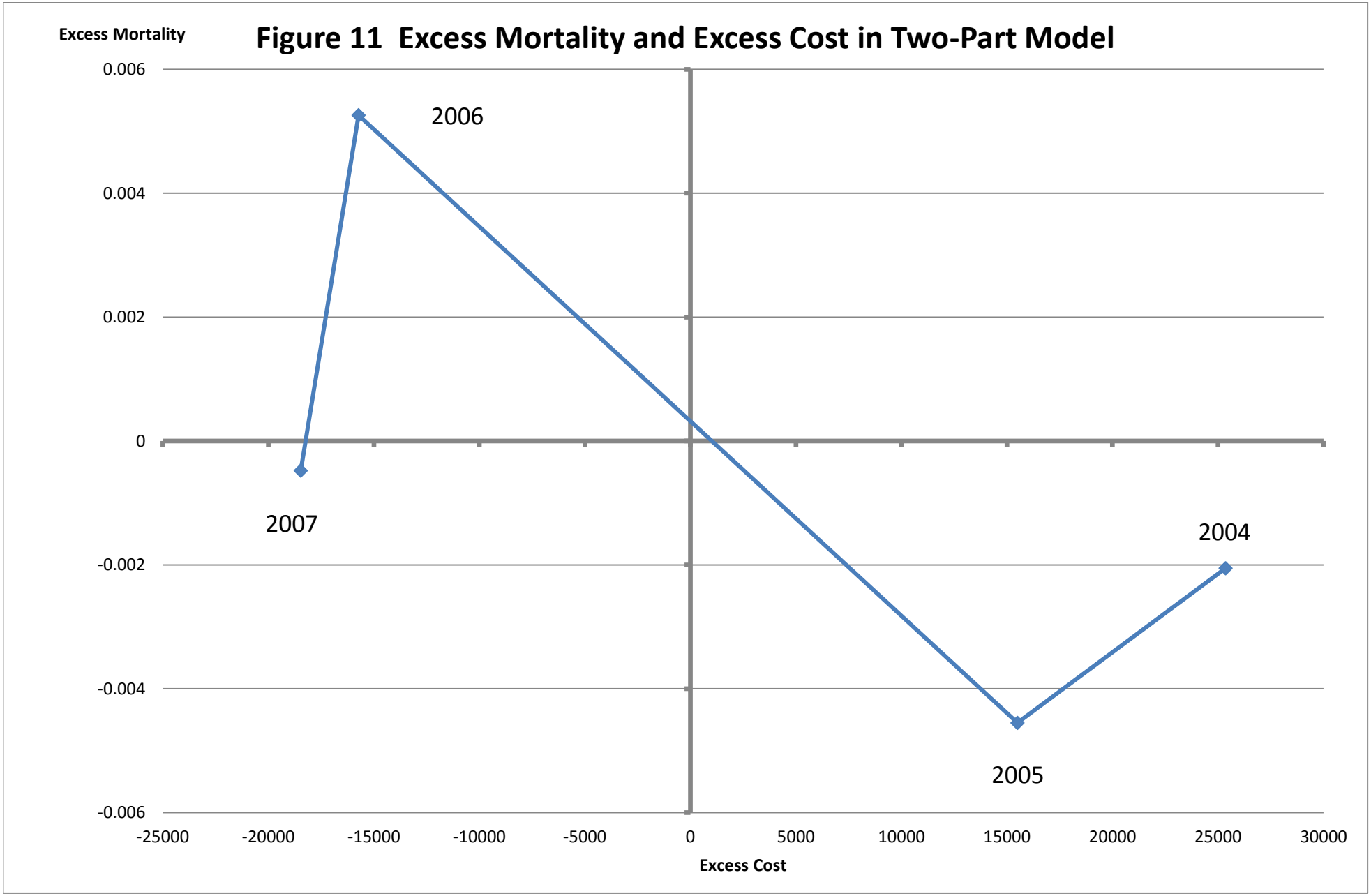


Figure 11 Excess Mortality and Excess Cost in Two-Part Model
Excess Mortality
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
2006
2007
2004
2005
-25000
-20000
-15000
-10000
-5000
0
5000
10000
15000
20000
25000
30000
Excess Cost

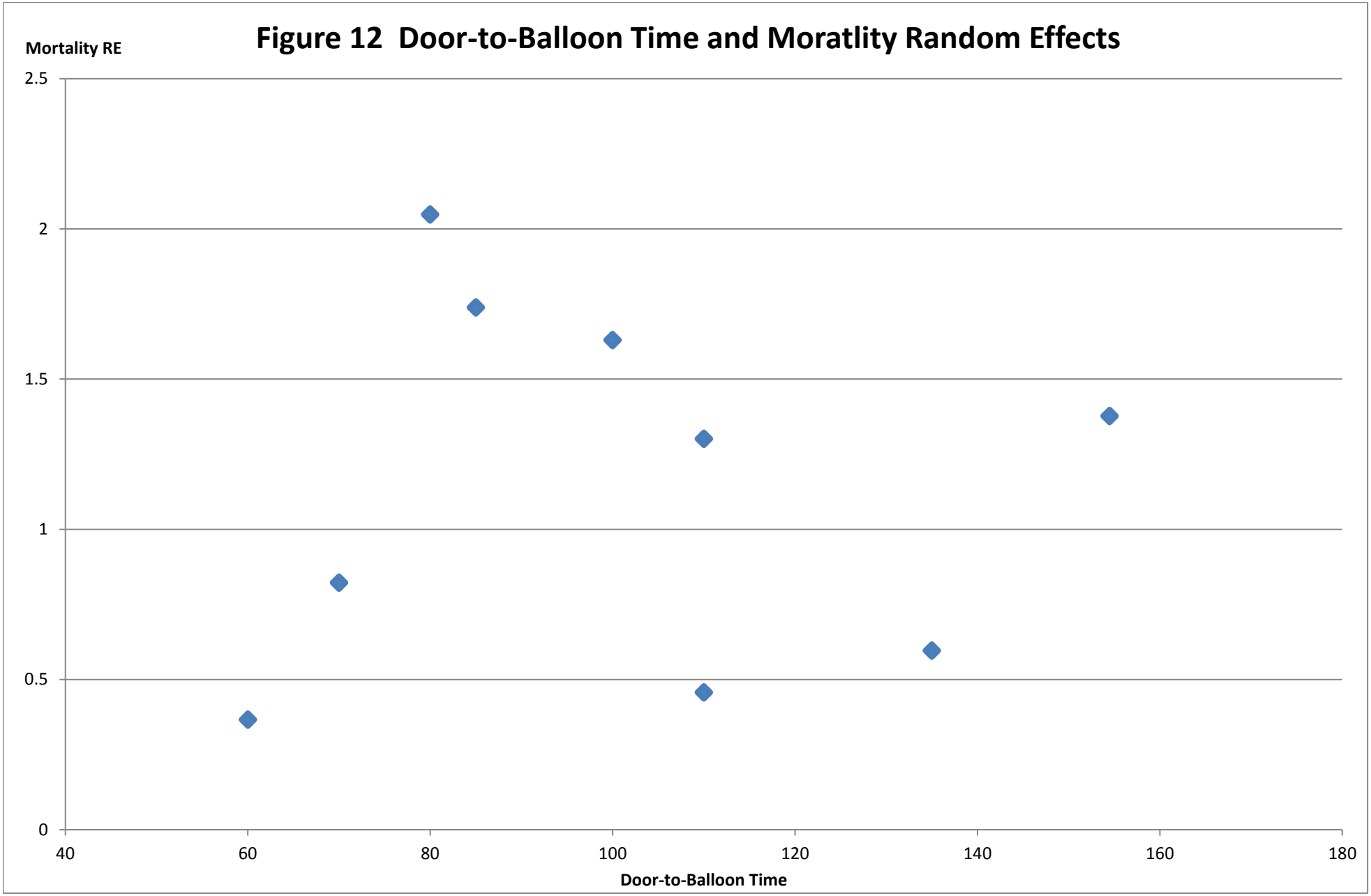


Figure 12 Door-to-Balloon Time and Moratlity Random Effects
Mortality RE
2.5
2
1.5
1
0.5
0
40
60
80
100
120
140
160
180
Door-to-Balloon Time

Table A1 Cost in Regression

	mean	sd	2.50%	97.50%
Mortality equation				
Constant	4.493	1.115	2.309	6.729
Age	0.041	0.009	0.025	0.058
Bleeding	0.644	0.479	−0.307	1.569
History of CABG	0.714	0.558	−0.406	1.776
Cancer	0.818	0.256	0.313	1.318
COPD	0.753	0.445	−0.128	1.619
Cost	−0.820	0.092	−1.006	−0.643
Diabetes mellitus	0.179	0.186	−0.188	0.543
Heart failure	0.230	0.257	−0.279	0.723
Hypertension	−0.287	0.180	−0.639	0.067
Killip2	1.835	0.382	1.100	2.597
Killip3	3.315	0.359	2.632	4.037
Killip4	4.299	0.374	3.585	5.048
Hyperlipidemia	−0.982	0.258	−1.497	−0.488
LBBB	0.392	0.253	−0.106	0.886
History of myocardial Infarction	0.083	0.288	−0.481	0.644
Cerebrovascular diseases	−0.047	0.213	−0.471	0.367
Left main trunk occluded	0.833	0.306	0.227	1.425
History of PCI	−0.187	0.364	−0.920	0.510
Renal failure	0.665	0.210	0.253	1.075
Aneurysm	0.795	0.408	−0.025	1.580
Female	0.489	0.179	0.135	0.838
Ventricular fibrillation	0.879	0.280	0.332	1.430
Cost equation				
Constant	12.320	0.186	11.930	12.670
Age	−0.007	0.001	−0.009	−0.004
Female	−0.069	0.105	−0.277	0.136
History of CABG	−0.131	0.120	−0.364	0.105
Cancer	−0.165	0.056	−0.275	−0.056
COPD	−0.044	0.103	−0.247	0.158
Diabetes mellitus	0.110	0.031	0.051	0.170
DPC preparation	−0.396	0.059	−0.512	−0.280
DPC applied	−0.499	0.070	−0.636	−0.361
Heart failure	−0.008	0.056	−0.119	0.102
Hypertension	0.054	0.031	−0.006	0.114

Killip2		0.075	0.038	0.000	0.151
Killip3		0.104	0.046	0.012	0.195
Killip4		0.183	0.052	0.081	0.285
Hyperlipidemia		0.054	0.032	−0.009	0.117
LBBB		0.048	0.061	−0.072	0.166
History of myocardial Infarction		−0.092	0.056	−0.202	0.017
Cerebrovascular diseases		−0.077	0.045	−0.166	0.012
Left main trunk occluded		0.471	0.065	0.341	0.599
History of PCI		−0.006	0.059	−0.120	0.110
Renal failure		0.083	0.049	−0.014	0.179
Aneurysm		0.015	0.091	−0.164	0.194
Female		−0.074	0.034	−0.140	−0.008
Ventricular fibrillation		−0.174	0.077	−0.326	−0.022
Random effects					
Hospital 1	Mortality	0.508	0.305	−0.091	1.113
	Cost	−0.164	0.180	−0.510	0.216
Hospital 2	Mortality	0.394	0.334	−0.263	1.055
	Cost	−0.085	0.182	−0.430	0.300
Hospital 3	Mortality	0.150	0.406	−0.659	0.947
	Cost	−0.320	0.192	−0.686	0.079
Hospital 4	Mortality	−0.758	0.361	−1.501	−0.084
	Cost	0.166	0.182	−0.180	0.553
Hospital 5	Mortality	−0.923	0.325	−1.597	−0.315
	Cost	0.178	0.180	−0.165	0.557
Hospital 6	Mortality	−0.341	0.376	−1.103	0.379
	Cost	0.329	0.184	−0.016	0.722
Hospital 7	Mortality	0.291	0.322	−0.344	0.925
	Cost	0.185	0.180	−0.157	0.569
Hospital 8	Mortality	0.528	0.429	−0.304	1.392
	Cost	−0.593	0.195	−0.969	−0.192
Hospital 9	Mortality	0.112	0.369	−0.620	0.840
	Cost	0.410	0.184	0.058	0.800
Correlation coefficient of constant and coefficient		−0.272	0.310	−0.782	0.395
Variance of constant		0.564	0.382	0.176	1.542
Correlation of constant and coefficient		−0.113	0.182	−0.535	0.158
Variance of coefficient		0.271	0.176	0.096	0.719
Number of observations		2631			

Table A2 Simultaneous Equations

	mean	sd	2.50%	97.50%
Mortality equation				
Constant	−5.163	0.453	−6.084	−4.305
Age	0.055	0.008	0.039	0.072
Bleeding	0.750	0.438	−0.120	1.601
History of CABG	0.877	0.528	−0.188	1.884
Cancer	0.898	0.245	0.414	1.376
COPD	0.697	0.427	−0.151	1.522
Diabetes mellitus	0.130	0.178	−0.220	0.479
Heart failure	0.211	0.243	−0.274	0.682
Hypertension	−0.384	0.171	−0.719	−0.047
Killip2	1.835	0.384	1.108	2.611
Killip3	3.164	0.358	2.495	3.902
Killip4	4.023	0.367	3.329	4.766
Hyperlipidemia	−1.016	0.247	−1.511	−0.544
LBBB	0.318	0.242	−0.160	0.789
History of myocardial infarction	0.078	0.278	−0.469	0.618
Cerebrovascular diseases	0.068	0.203	−0.334	0.463
Left main trunk occluded	0.395	0.295	−0.195	0.965
History of PCI	−0.184	0.358	−0.900	0.498
Renal failure	0.547	0.202	0.148	0.937
Aneurysm	0.760	0.388	−0.011	1.506
Female	0.530	0.173	0.192	0.871
Ventricular fibrillation	0.995	0.269	0.467	1.524
Cost equation				
Constant	12.310	0.179	11.950	12.650
Age	−0.007	0.001	−0.009	−0.004
Female	−0.069	0.106	−0.276	0.139
History of CABG	−0.131	0.119	−0.366	0.102
Cancer	−0.165	0.056	−0.274	−0.055
COPD	−0.044	0.103	−0.245	0.158
Diabetes mellitus	0.110	0.031	0.050	0.170
DPC Preparation	−0.397	0.060	−0.514	−0.280
DPC Applied	−0.501	0.070	−0.639	−0.364
Heart failure	−0.009	0.056	−0.119	0.102
Hypertension	0.054	0.030	−0.006	0.114
Killip2	0.075	0.038	0.000	0.151

Killip3		0.104	0.046	0.013	0.195
Killip4		0.183	0.052	0.080	0.285
Hyperlipidemia		0.053	0.032	−0.010	0.117
LBBB		0.047	0.061	−0.072	0.166
History of myocardial infarction		−0.092	0.056	−0.202	0.018
Cerebrovascular diseases		−0.077	0.045	−0.165	0.012
Left main trunk occluded		0.470	0.066	0.340	0.598
History of PCI		−0.006	0.058	−0.120	0.109
Renal failure		0.083	0.049	−0.014	0.179
Aneurysm		0.016	0.092	−0.165	0.195
Female		−0.074	0.034	−0.140	−0.008
Ventricular fibrillation		−0.174	0.077	−0.325	−0.023
Random effects					
Hospital 1	Mortality	0.553	0.327	−0.084	1.212
	Cost	−0.155	0.173	−0.488	0.183
Hospital 2	Mortality	0.489	0.351	−0.185	1.201
	Cost	−0.076	0.174	−0.409	0.268
Hospital 3	Mortality	0.320	0.422	−0.509	1.161
	Cost	−0.312	0.185	−0.673	0.050
Hospital 4	Mortality	−0.783	0.378	−1.557	−0.070
	Cost	0.178	0.174	−0.156	0.521
Hospital 5	Mortality	−1.005	0.342	−1.704	−0.352
	Cost	0.189	0.171	−0.138	0.525
Hospital 6	Mortality	−0.517	0.388	−1.303	0.226
	Cost	0.340	0.177	0.001	0.690
Hospital 7	Mortality	0.263	0.339	−0.400	0.943
	Cost	0.195	0.173	−0.134	0.537
Hospital 8	Mortality	0.717	0.442	−0.127	1.623
	Cost	−0.585	0.188	−0.954	−0.218
Hospital 9	Mortality	−0.195	0.385	−0.963	0.561
	Cost	0.421	0.177	0.082	0.772
Correlation coeffcient of constant and coefficient		−0.373	0.289	−0.820	0.285
Variance of constant		0.679	0.469	0.215	1.870
Correlation of constant and coefficient		−0.167	0.200	−0.642	0.112
Variance of coefficient		0.268	0.163	0.098	0.690
Number of observations		2631			

Table A3 Creating Severity Index

Logistic regression Number of obs = 2631
Log likelihood = −551.31298 Pseudo R2 = 0.3789

death	Coefficient	Standard Error	t statistics	p−value
Age	0.051	0.008	6.500	0.000
Female	0.475	0.166	2.860	0.004
Killip2	1.663	0.369	4.500	0.000
Killip3	2.993	0.351	8.530	0.000
Killip4	3.668	0.355	10.330	0.000
Left main trunk occluded	0.230	0.278	0.830	0.408
LBBB	0.300	0.225	1.340	0.182
Ventricular fibrillation	0.965	0.251	3.850	0.000
Hypertension	−0.409	0.162	−2.530	0.011
Hyperlipidemia	−1.012	0.232	−4.360	0.000
Diabetes mellitus	0.149	0.168	0.890	0.374
Heart failure	0.040	0.230	0.170	0.861
History of myocardial infarction	0.232	0.262	0.880	0.377
History of PCI	−0.349	0.338	−1.030	0.302
History of CABG	0.901	0.494	1.820	0.068
Cancer	0.728	0.226	3.230	0.001
Bleeding	0.564	0.405	1.390	0.164
Renal failure	0.478	0.195	2.450	0.014
Cerebrovascular diseases	0.014	0.192	0.070	0.941
Aneurysm	0.574	0.372	1.540	0.123
COPD	0.435	0.407	1.070	0.285
Constant	−4.809	0.349	−13.800	0.000
Number of observations	2631			

Table A4 Two-Part Model

		mean	sd	2.50%	97.50%
Mortality equation					
2004	Constant	−4.079	0.353	−4.825	−3.444
	Severity	1.150	0.125	0.919	1.411
2005	Constant	−4.063	0.333	−4.767	−3.453
	Severity	1.128	0.117	0.910	1.372
2006	Constant	−3.677	0.287	−4.262	−3.140
	Severity	1.034	0.097	0.849	1.229
2007	Constant	−3.284	0.236	−3.763	−2.836
	Severity	0.839	0.085	0.677	1.012
Cost equation for expirer					
2004	Constant	12.370	0.241	11.900	12.850
	Severity	−0.169	0.071	−0.310	−0.030
2005	Constant	11.810	0.251	11.320	12.300
	Severity	0.032	0.075	−0.114	0.179
2006	Constant	10.790	0.201	10.390	11.180
	Severity	0.151	0.057	0.039	0.263
2007	Constant	11.960	0.166	11.630	12.290
	Severity	−0.194	0.054	−0.300	−0.090
Cost equation for survivors					
2004	Constant	12.260	0.033	12.200	12.320
	Severity	0.064	0.017	0.031	0.097
2005	Constant	12.200	0.032	12.140	12.260
	Severity	0.039	0.017	0.006	0.072
2006	Constant	12.170	0.031	12.110	12.230
	Severity	0.045	0.015	0.015	0.075
2007	Constant	12.120	0.029	12.060	12.170
	Severity	0.037	0.014	0.009	0.065
Overall mean of random effects					
Mortality equation					
	Constant	−3.767	0.493	−4.735	−2.824
	Severity	1.036	0.372	0.303	1.775
Cost equation for expirer					
	Constant	11.690	0.581	10.540	12.760
	Severity	−0.039	0.365	−0.749	0.690
Cost equation for survivors					
	Constant	12.170	0.359	11.440	12.870
	Severity	0.044	0.353	−0.657	0.746
Correlation coefficient of constant and coefficient					

Mortality equation	−0.146	0.443	−0.869	0.743
Cost equation for perishers	−0.176	0.439	−0.875	0.728
Cost equation for survivors	0.001	0.449	−0.811	0.818
Mortality equation				
Variance of constant	0.846	1.697	0.132	3.653
Correlation of constant and coefficient	−0.114	0.785	−1.288	0.712
Variance of coefficient	0.537	0.928	0.098	2.223
Cost equation for expirer				
Variance of constant	1.286	4.249	0.204	5.262
Correlation of constant and coefficient	−0.151	1.042	−1.577	0.825
Variance of coefficient	0.542	1.409	0.098	2.228
Cost equation for survivors				
Variance of constant	0.511	1.011	0.091	2.145
Correlation of constant and coefficient	0.000	0.555	−0.716	0.741
Variance of coefficient	0.494	0.830	0.089	2.072

Number of observations

2004	598
2005	612
2006	672
2007	749
Total	2631