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Measuring Health Care Output

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Measuring Health Care Output[1]

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Abstract

This paper explores the possibilities of measuring health care output adjusting for quality of care. We explore methods to incorporate quality of health care. First of these adjusts for quality using crude mortality and complication rates. Adjustment of crude rates can be misleading, however, because risk factors change from year to year and chance variation may dominate yearly fluctuations in mortality and complication rates. Hence, second set of indexes incorporates risk-adjusted mortality and complication rates. In controlling for chance variations, we compared three estimation methods which may differ in their ability to control variability of estimates: maximum likelihood, the hierarchical model and autoregressive (AR) restrictions on random effects. Further, to examine how much information is required for reasonable risk adjustment, we compared three risk adjustment models with differing degrees of detailed risk factors. Overall conclusion of the paper is that we do need adjustment of quality of care in the construction of output index of health care. Risk adjustment is also of crucial importance although the choice of method of estimation to control for chance variation may be less crucial. As for the risk factors, the more detailed, the better.

1. Introduction

Measurement of output and deflators in non-market service sectors such as health care is problematic because in these sectors prices are not determined by competitive markets. Often, governments try to correct market mechanisms in these areas through regulation, public insurance, and other measures. Even when governments do not intervene, prices determined in the market do not reflect true consumer preferences thanks to asymmetric information and externalities. Without market prices, proper deflators to use in the calculation of output are hard to obtain.

Recently direct measures of output of non-market service sectors are actively studied and advocated. The Atkinson Review (2005) recommends to measure output directly by counting the number of units for whom services are provided instead of measuring output by aggregating costs of producing the services. In addition, the Atkinson Review (2005) encourages that output is adjusted for the change in quality of services. Eurostat (2001) also recommends direct measurement and quality adjustment. In the United Kingdom, the Office for National Statistics calculates and publishes direct and quality-adjusted output indexes for public sector activities. (Office for National Statistics, 2007, 2008, 2015.) These are based on work done by U.K. researchers (Dawson, et al., 2005). German researchers are investigating how to utilize the DRG system in the direct measurement of health care output (Pierdzioch, 2008). In the United States, pioneering research has been conducted during the 1990s, particularly at the National Bureau of Economic Research, measuring the quality of health care and adjusting for quality change in the calculation of deflators (Cutler and Berndt,eds. 2001). The Bureau of Economic Analysis is now developing a Health Care Satellite Account based on treatments of diseases (Dun, et al., 2015).

A major trend in the practice of National Accounts especially in EU countries is, as is mentioned above, activity-based output index. Activity-based output index measures health care activities such as the number of patients treated or operations performed, and so on. Simple activity-based measure is not appropriate because it is assumed that the more activities are appended, the better. Furthermore, activity-based measure is not unlike input.

A refinement may be to use the DRG system to account for quality of care. This is valid as long as the classification of the DRG system corresponds to quality of care delivered by hospitals. Quality adjustment by the DRG system is not adequate, however. Because the classification typically depends on operations and major procedures, thanks to the choice of treatment on the part of hospitals, not all the patients in the same DRG have the same severity and, conversely, patients with the same severity do not necessarily belong to the same DRG. Further, output index based on the numbers of patients of DRG classifications could have adverse effects. For example, simply increasing the number of patients by way of “three-minute consultation” will raise the measured output although the quality of care could decline.

Hence, search for more direct methods to adjust for the quality of care are warranted.

In sum, there are two ways to adjust for quality of care. One is activity-based output index, which tries to control quality of care through disaggregation, where disaggregation of health care activities into homogenous activities is assumed to guarantee uniform quality of care within each activity. The other is quality-adjusted output index, which tries to control quality by utilizing explicit measures of quality of care. The goal of these two indexes is the same: adjustment for the quality of care. There is a trade-off between the robustness and refinement of adjustment. Quality adjustment through disaggregation is robust because it does not depend on specific models, while its resultant adjustment is not so complete because the criteria of classification is relatively crude. Quality-adjusted indexe can utilize a rich set of risk factors which affect patients’ outcomes so that its quality adjustment can be refined, while it is not so robust because of its dependency on models used to adjust for risk factors.

This paper first gives examples of construction of activity-based output index covering all diseases. Next, we try to construct output indexes which reflect quality of care. Due to data limitations, we restrict our construction to health care of hospitalized AMI patients. Qualities we consider are mortality and complications. In adjusting for mortality and complications, we first use crude rates, then, we adjust for risk factors of patients.

As for adjustment using crude mortality and complication rates, we compile two indexes. The first one adjusts only for mortality by simply putting utility at zero if a patient dies during hospitalization. In this case, all the patients who are discharged alive are assumed to have the same health utility as the healthy people.

Next, we will try to attach utilities to the case where a patient is discharged alive. We do not have data on the quality of life when a patient survives. We have data on complications, however. We follow Timbie, et al. (2009:Composite Measures paper) in assigning health utilities to individual complications and, then, infer utilities according as they have the specified complications.

Since risk factors change from year to year, proper risk adjustment is essential. Without controlling for such changes in underlying risk factors, output indexes adjusted for quality of care can be misleading with too much or too little adjustment.

There is no lack of controversies concerning risk adjustment methods. This paper specifically deals with two questions. One is whether it is possible to properly adjust for risk factors despite wild random variation of outcomes in the context of small sample size. The other is how detailed the risk adjustment model should be in view of costly information gathering.

As to the first question, we investigate how statistical methods can cope with chance variation of outcomes by comparing methods differing in their ability to control chance variation.

We consider three estimation methods of a risk adjustment model: the MLE (maximum likelihood estimates), the hierarchical model and AR regression. The second method, the hierarchical model, is especially suitable for controlling chance variation by shrinking individual estimates toward overall mean. The third method imposes restrictions on the rate that quality of care can vary.

As to the second question posed above, we estimated several risk models with various degrees of detailed information. If they imply different mortalities and complications after adjustment, modeling risk factors is of crucial importance.

In sum, we measure health output by adjusting, first, for quality of care and, second, for risk factors. The process and ingredients are summarized as follows.

Quantity	+	Quality adjustment	+	Risk adjustment
		Mortality		MLE
		QOL (Complications)		Hierarchical model
				AR regression

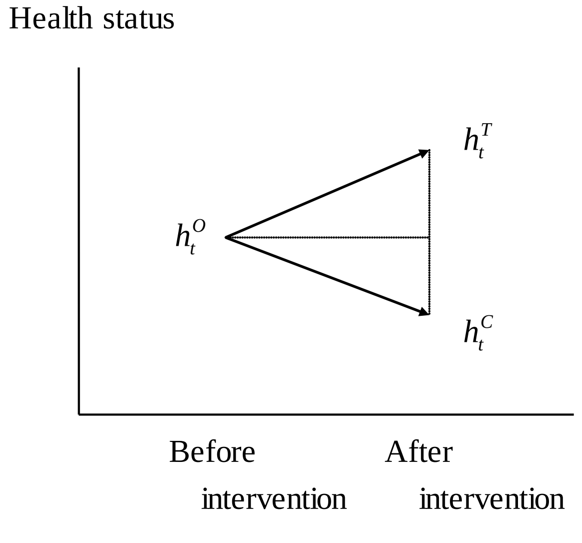
The paper is structured as follows. The second section explains the general framework for output indexes which adjust for quality of care. The third and fourth sections incorporate quality of care into the output indexes, of which the former calculates output indexes adjusted for crude mortality and complications while the latter adjusts risk factors in measuring the quality of care. The fifth section concludes.

2. A Digression on the Concept of the Quality of Health Care

Output of health care is the improvement of health caused by medical interventions. Therefore, output index should include not only the number of patients but also the improvement of health status attributable to health care. This is what quality-adjusted output index is intended to do.

The concept of the quality of health care can be explained as follows. This exposition is inspired by the discussion in Jacobs, et al. (2006) although much modified. Let the original health status of a patient at time *t* be h_t^O=0.5. Suppose that when she undergoes a treatment, her health status will be h_t^T=0.7 and that when she does not undergo a treatment, her health status will be h_t^C=0.4. The true quality of care is $h_t^T - h_t^C$=0.3 while we can observe only $h_t^T - h_t^O$=0.2 because we usually do not know the natural history of disease h_t^C.

The Concept of Quality of Health Care Services



Now suppose that in the next year we have h_{t+1}^{O}=0.5, h_{t+1}^{T}=0.8 and h_{t+1}^{C}=0.4. Namely, the original health status and the natural history are the same as time *t*. Then, the quality of health care at time *t*+1 is $h_{t+1}^{T}-h_{t+1}^{C}$=0.4 while we observe only $h_{t+1}^{T}-h_{t+1}^{O}$=0.3. However, since $h_{t+1}^{O}=h_{t}^{O}$ and $h_{t+1}^{C}=h_{t}^{C}$, we can calculate the change in the true quality of health care as $(h_{t+1}^{T}-h_{t+1}^{O})-(h_{t}^{T}-h_{t}^{O})=h_{t+1}^{T}-h_{t}^{T}$.

It is not necessarily the case that the original statuses, h_{t}^{O} and h_{t+1}^{O}, are equal. Hence, we have to adjust the original statuses in order to compare outcomes, h_{t}^{T} and h_{t+1}^{T}. Risk adjustment just does this. Somewhat formally, we can model the health status of the treated patient as a function of the original status: $h_{t}^{T}=f_{t}(h_{t}^{O})$ and $h_{t+1}^{T}=f_{t+1}(h_{t+1}^{O})$. Adjusted health statuses with a common original status, $\bar{h}^{O}$, are $\bar{h}_{t}^{T}=f_{t}(\bar{h}^{O})$ and $\bar{h}_{t+1}^{T}=f_{t+1}(\bar{h}^{O})$. Then, the difference between these two outcomes is the change in quality of health care.

3. Activity-Based Output Indexes

In this section we calculate activity-based indexes with two kinds of units of measure, the ICD and the DPC. These measures cover all diseases. Data used in the construction of activity-based output indexes are taken from public statistics, the Patient Survey and the Analysis and Evaluation of the Effects of the Introduction of the DPC System, which present aggregate data, while the construction in the fifth section of the quality adjusted output index utilizes data collected by authors which consist of data on individual patients. This is because we are not able to classify each patient contained in the latter data set into DPC categories, hence, calculation based on the DPC classification is impossible in the latter data set.

By disaggregating unit of measurement, a homogenous classification of activities may obtain and, hence, quality of output could be accounted for by such detailed classification. The assumption is that activities directed to a specific classification are of the same quality and that activities directed to different activities are of different quality. Its success depends on, of course, how the classification is done. We will return to this point later.

These indexes are cost-weighted. The quantity of output is weighted by cost assuming that cost is proportional to the marginal social value of output (Castelli, et al., 2007).

$$I_{t+1}^{x} = \frac{\sum_{i} x_{i,t+1} \cdot c_{it}}{\sum_{i} x_{it} \cdot c_{it}},$$

where x_{it} is the quantity of *i*-th output at time *t and* c_{it} is unit (average) cost of *i*-th output at time *t*.

(1) ICD-based unit of measure

Here, activity is defined relative to the ICD diseases. Health care activities devoted to a specific disease are compounded into an activity. It is assumed that quality of health care is the same within a specific disease and different among different diseases. Surely, this assumption is hard to justify. As a reference, however, we calculate output according to this definition. This index is for inpatient services.

Diseases disaggregated to the block level diseases (three digits classification with one alphabet and two numbers) in the ICD system. The data source is the Patient Survey conducted every three years. A finer classification of diseases is available, but we cannot find corresponding costs form the source sited below.

The index is cost-weighted. Cost is the average charge for each ICD disease which is taken from the Survey of Medical Care Activities in Public Health Insurance.

We were able to compile a consistent classification going back from 2008 to 1984. The classification before 1984 is so different that we cannot connect it to the current classification. Further, the 1984 Survey of Medical Care Activities did not include patients covered by the National Health Insurance System. Therefore, we constructed output index from 1987 onward.

The result is shown in Figure 1. Output of inpatient services increased sharply from 1987 to 1990. After that, inpatient output followed a declining trend with especially rapid decrease during the 2000s.

(2) DPC-based unit of measure

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.

To calculate output index based on the DPC classification the number of patients of each DPC is aggregated with the average length of stay of each DPC as weight. In theory, we should use billing rates as weights. But, since some DPC categories are reimbursed on the fee-for-service basis, billing rates are not available for these categories in the published data. Therefore, we used length of stay as a proxy for cost. It is well documented that the correlation between length of stay and cost is high.

The DPC classification is revised every two years. It is not possible to re-classify patients retrospectively without patient-level data. Every year's publication of statistics provides data for two years, the current and the previous years, from which we calculated output indexes for two years. Then, we linked these indexes at the overlapping year.

Since the number of hospitals covered by the DPC system is being expanded over time, we cannot simply aggregate the output of hospitals in each year. We restrict the calculation to hospitals which started their participation in 2003, 2004 and 2005. We can obtain data on these hospitals from 2005 through 2009. These hospitals are only a subset of all hospitals and, clearly, early participants in the DPC system have different characteristics from other hospitals. They are large and high-technology-oriented hospitals, in general.

Therefore, the DPC-based output index we constructed is not representative for the entire health care system. However, by comparing the DPC-based index to the raw number of patients, we can obtain some insight into the extent to which quality adjustment using DPCs as unit of measurement has impact on output index.

Figure 2 shows the growth rates of the output index based on the DPC classification together with the raw number of patients. Overall trend in the output index is similar to the number of patients, but there is a noticeable difference between the two. The difference translates into around 1 % difference in the growth rates in 2006 and 2007.

The DPC classification is meant to be used as a payment system. It is intended to group together diseases with homogenous costs, not disease with homogenous health care activities.

Hence, the classification is heavily dependent on operations performed. This is reasonable from the point of view of the original intention of grouping diseases with homogenous cost. Further, it could be that a specific treatment represents a specific quality of care as in the case of high-technology treatments.

Quality adjustment by the DPC system is not adequate, however.

First, outcomes such as mortality which are expected from specified operations or procedures differ among hospitals and doctors. The same operations and procedures do not always represent the same quality in different hospitals.

Second, the DPC classification is based on the medical procedures selected by health care providers. Inclusion of choice variables into classification criteria may result in problems as statistics. Increase in inappropriate but costly use of medical procedures, such as PCIs for stable coronary patients or low back pain surgeries, will increase the output of health care!

Third, the level of quality of each DPC category is fixed at the beginning. As medical technologies progress, better outcomes are expected to obtain. The measurement based on the DPC system cannot take into account such improvements of outcomes over time.

Fourth, while the DPC system is intended to create homogeneous categories with respect to cost, cost does not necessarily reflect relative levels of quality of DPCs. Costly operations and procedures do not always result in superior outcomes. It is only after we validate the outcomes of individual operations and procedures that we can properly calibrate relative value of each DPC.

Fifth, introduction of output index based on the DPC system could have adverse effects. For example, “three-minute consultation”, for which the Japanese health care system is notorious, will increase measured output by treating more patients within a given time. “The sooner, the sicker” phenomenon, observed in the United States when the DRG system was introduced, is also a cause for concern. The DPC system imposes a very strong incentive to shorten the length of stay. If shorter length of stay is dictated by economic incentives, there is no guarantee that we have higher quality of care, but again the measured output will rise. Last example to mention is selection bias caused by the gap between the classification and payment systems. Since operations are not included in the DPC payment system, hospitals may be eager to increase the number of operations. Since the DPC classification is dependent on operations, increased operation will result in increase in health care output.

4. General Framework of Quality Adjusted Output Index

We follow Dawson, et al. (2005) and Castelli, et al. (2007) in the construction of quality adjusted output index. Output consists of three components: unit of measurement, quality of care and valuation of the quality. Schematically, we can write:

$$\boxed{\text{Output}} = \boxed{\text{Unit of measurement}} \times \boxed{\text{Quality of care}} \times \boxed{\text{Valuation}}$$

In terms of equation, the above scheme is expressed as follows.

$$I_{t+1}^{x} = \frac{\sum_{i} x_{i,t+1} \sum_{j} q_{ij,t+1} \pi_{jt}}{\sum_{i} x_{it} \sum_{j} q_{ijt} \pi_{jt}},$$

where x_{it} is the quantity of i-th output at time t, q_{ijt} is the quantity of j-th attribute of i-th output at time t and π_{it} is the value of j-th attribute of i-th output at time t.

In this paper, we use data on hospitalized AMI patients, hence, i = AMI. In this case, the above formula simplifies to

$$I_{t+1}^{x} = \frac{x_{AMI,t+1} \sum_{j} q_{AMI,j,t+1} \pi_{jt}}{x_{AMI,t} \sum_{j} q_{AMI,j,t} \pi_{jt}}$$

Unit of measurement is episode of inpatient care. Although cooperation between hospital care and primary care is important factor determining total quality of care, no data are available to evaluate the care process as a whole.

The attributes we will consider include: death, survival with complications and survival without complications. Health utilities we assign are: π=0 for death, π=0.9 for survival without complications and π=0.7 for survival with complications. These numbers will be explained later.

Note that we assigned health utilities to attributes (death and complications). Health utilities are not, strictly speaking, the value of the quality of life in terms of money. In view of the difficulty in evaluating the value of life, however, we avoid assigning monetary valuation of quality of care.

In this section, we construct two indexes adjusting for mortality and complication rates. The first one adjusts only for mortality and the second incorporates quality of life of survivors by adjusting for complications.

First, we adjust only for mortality by simply putting utility at zero if a patient dies during hospitalization. In this case, all the patients who survived are assumed to have the same utility as the healthy people, namely π=1.

Next, we will try to attach utilities to the case where a patient is discharged alive. In the case of output as discharge alive, all the survivors are counted as 1. However, survived patients have different quality of life. Output measure should incorporate this difference, although difficult.

We do not have data on the quality of life when a patient survives. We have data on complications, however. One important factor that affects quality of life is complications during hospitalization. We follow Timbie, et al. (2009) in assigning utilities to individual complications and, then, infer utilities according as patients have the specified complications.

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 compare three methods of estimation of the logistic regression model. The first is maximum likelihood, which is a standard estimation method in statistics. It is pointed out, however, that when estimating random effects as we will do in this paper, their estimates tend to take on extreme values because of small sample variability. Therefore, some shrinkage is desired by "borrowing" information from other years and shrinking their estimates toward the overall mean. The second approach does just this.

The second estimation method adopts the hierarchical approach to achieve shrinkage. This approach assumes that random effects are exchangeable so that they come from a probability distribution with common mean and variance.

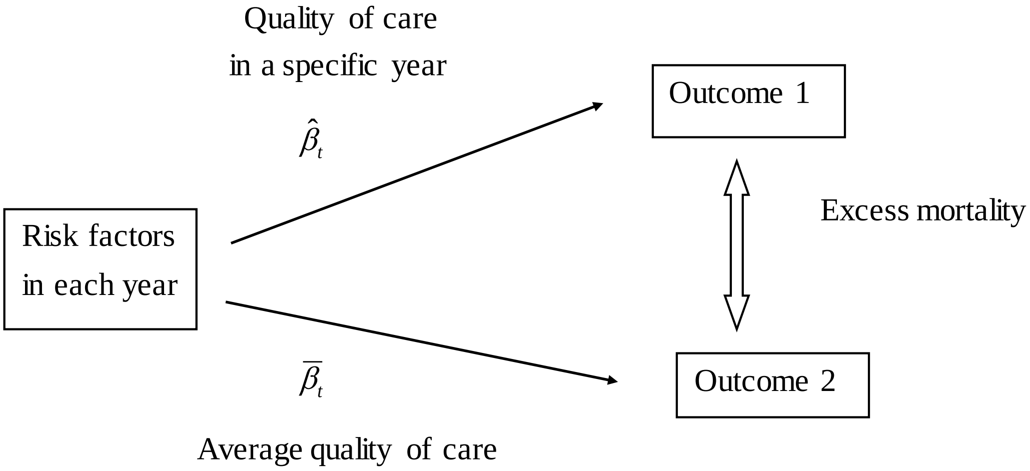
The difference between the first and the second methods is succinctly explained as follows (Spiegelhalter, et al., 2004). Suppose that random variables c_t's come from a normal distribution $c_t \sim N(0,\sigma^2)$. MLE corresponds to the case where $\sigma^2 = \infty$ while the hierarchical model corresponds to the case where $0 < \sigma^2 < \infty$.

The third method imposes autoregressive restrictions on random effects. In this method, a year effects is related to the previous year in the spirit of autoregressive models. Future variability is constrained by the realization of previous year's random effect and this year's random errors.

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.

Concrete steps of indirect adjustment are the following. 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



5. Adjusting for the Quality of Health Care I: Crude Mortality and Complication

(1) Data and Basic statistics

We take as unit of measurement episode of hospitalization of AMI patient. Figure 3 depicts long-term trend of hospitalization of AMI patients in the Patient Survey. The number of AMI patients continued to decline after it peaked in 1990 at a little above 9 thousands. In 2008, the number of hospitalization is a little below 5 thousands, nearly half the level in 1990.

Data were collected on AMI patients in 9 hospitals with a record of hospitalization at some period of time from April 1, 2004 to March 31, 2007 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.

A data set of patients hospitalized in nine hospitals was constructed. Only the patients hospitalized in 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 upper panel contains outcome variables: mortality and complications. The average mortality rate is 10.6% with an upward trend from 2004 to 2007. The average complications rate is 18.4% also with an upward trend. A vast majority of complications is repeat revascularization. Around 5% of survived patients experience complications such as cardiovascular disorder, renal failure and new infarction. The lower panel of Table 1 exhibits basic statistics of risk factors. 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.

Figure 4 shows mortality and complication rates during the sample period. In-hospital mortality increased from 9.2% in 2004 to 12.2% in 2006, then, slightly dropped to 10.8% in 2007. Complication rate is on the upward trend during this period. The complications we use in this paper will be listed below.

(2) Adjusting for crude mortality and complication rates

Two measures are calculated which accounts for quality change. One incorporates only changes in crude mortality. The other adjusts not only for mortality but also for complication rate.

In the case of the first output index which adjusts only for mortality, we put the value of utility π=0 if a patient dies during hospitalization and π=1 if a patient is discharged alive. In this case, no distinction is made between being discharged alive but with complication and being discharged alive without complication.

In the case of the second output index which adjusts not only for mortality but also for complications, the assumed values of utility are as follows (Table 3). We put π=0 if a patient dies during hospitalization. When she survives, we put π=0.9 without complication and π=0.7 with complication. The value of survival without complications is taken from Weintraub, et al. (2008). The value of survival with complications is calculated as follows.

In the adjustment of output for quality of care, complications we use include myocardial infarction, stroke, cardiovascular diseases, renal failure, repeat PCI/emergency CABG and cardiac arrest or shock within 48 hours. Timbie, et al. (2009:Composite Measures paper) provide utility estimates for stroke, renal failure and repeat PCI/emergency CABG. We were unable to find good estimates for the quality of life (QOL) for cardiovascular diseases and cardiac arrest or shock within 48 hours, however. We then proceed in two steps. First, we calculate weighted average of utilities of complications using only stroke, renal failure and repeat PCI/emergency CABG. Weights are the number of patients of each complication in the sample while utility estimates are those of Timbie, et al. (2009:Composite Measures paper). The result is π=0.77. Second, we adjust the estimate downward a bit to π=0.7 considering that the remaining complications, cardiovascular diseases and cardiac arrest or shock within 48 hours, appear to be serious ones. The downward adjustment is rather arbitrary, it should be admitted. Caution must be exerted in interpreting the results. In the future, we will improve on the utility estimates of complications to obtain more accurate quality adjustment.

Figure 5 shows growth rates of output indexes adjusted for crude mortality and complications. The impact of adjustment is substantial, especially in 2006. In 2006, output declined by nearly 4 % without adjustment for mortality while after adjusting for crude mortality, it declined more than 6 %. The difference between growth of output with and without complication adjustment is small. To conclude that adjustment of complications is not essential is premature, though. As is noted above, utility estimates of complications are far from perfect. We should investigate further to answer the question whether complication adjustment is required or not.

It could be very important to adjust for mortality, at least. But this conclusion can be premature again because change in mortality reflects not only underlying change in the quality of care, but also change in risk factors and chance variation of mortality. The next section will deal with this problem.

6. Adjusting for the Quality of Health Care II: Risk Adjustment

(1) Methods

We follow the method taken by Timbie, et al. (2008:Cost-Effectiveness paper). We created 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 of in-hospital mortality. Risk factors are selected by checking statistical significance and signs of estimated coefficients. Risk factors include age, female, Killip classes 2, 3 and 4, occlusion of the left main trunk, left bundle branch block (LBBB), ventricular fibrillation, hypertension, hyperlipidemia, diabetes mellitus, heart failure, history of myocardial Infarction, history of PCI, history of CABG, cancer, bleeding tendency, renal failure, cerebrovascular diseases, aneurysm and Chronic Obstructive Pulmonary Disease (COPD). The adopted risk factors are not far from those proposed in Krumholz, et al. (2006: Administrative Claims Model paper) on which Timbie, et al. (2008) base their construction of severity variable. Estimation result is shown in Appendix Table A1.

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. Age is centered at the sample mean.

(i) MLE

To adjust for risk factors, we estimated logistic regression models with outcomes as dependent variables. The outcome variable, y_{it}, takes the value one if a patient i in time t dies and zero if she survives. In this subsection, we estimated this model by the maximum likelihood method.

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

where x_{it} is severity index. Then we re-transform the linear predictor into the original probability scale:

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

The resulting estimates are used to calculate excess mortality by way of indirect standardization. As is explained above, indirect standardization compares 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.

Outcome 1 utilizes actual relationship between risk factors and mortality 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.

$$y_{it}=1[\alpha_t+\beta_t\cdot x_{it}+u_{it}>0]$$

Once we obtain estimates, $\hat{\alpha}_t$ and $\hat{\beta}_t$, we re-transform the linear predictor into the original probability scale:

$$\hat{p}(y_{it}=1|x_{it})=\Lambda(\hat{\alpha}_t+\hat{\beta}_t\cdot x_{it})$$

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 mortality for each year by supposing that each year's quality of care is the same as the average 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.

$$y_{it} = 1[\alpha + \beta \cdot x_{it} + u_{it} > 0]$$

With the estimates, $\overline{\alpha}$ and $\overline{\beta}$, we re-transform the linear predictor into the original probability scale:

$$\overline{p}(y_{it} = 1 \mid x_{it}) = \Lambda(\overline{\alpha} + \overline{\beta} \cdot x_{it})$$

Again, we average individual probabilities of death 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 survival rate is the difference between Outcome 1 and Outcome 2, $\hat{E}_t - \overline{E}_t$.

(ii) Hierarchical Model

Logistic regression model is estimated with random intercept, α_t, for each year and random coefficient, β_t, for each year.

$$y_{it} = 1[\alpha_t + \beta_t \cdot x_{it} + u_{it} > 0]$$

Prior specifications are as follows. Two random coefficients are assumed to follow bivariate normal with a mean vector, μ, and a 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, μ, is expected.

μ is assumed to follow a normal distribution with mean 0 and variance 100: $\mu \sim N(0,100)$. 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. Their choice of the value of variance is 100^2 (standard deviation of 100), which states, roughly, that we expect the coefficient to be in the range (-100, 100). Our choice 10^2 implies that the expected range is (-10, 10). We believe that this range is wide enough so that the prior distribution is providing little information in the inference. In fact, mean estimates of μ obtained below are (-3.77, 1.03), which are well in the range (-10, 10).

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 diffuse prior. Ω is, in turn, specified as I_2.

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.

(iii) AR Restrictions

Logistic regression model is estimated with random intercept, α_t, for each year and random coefficient, β_t, for each year. AR restrictions are imposed on the movement of random effects over time.

$$y_{it} = 1[\alpha_t + \beta_t \cdot x_{it} + u_{it} > 0]$$

$$\alpha_t = \gamma_{\alpha t} \cdot \alpha_{t-1} + v_t$$

$$\beta_t = \gamma_{\beta t} \cdot \beta_{t-1} + w_t$$

To calculate the effect on mortality of random effect for each year, we re-transform the linear predictor into the original probability scale in the same way as MLE.

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 hierarchical model.

Prior specifications are also similar. Random intercept for each year, α_t, is assumed to follow a normal distribution with mean $\mu_{\alpha t}$ and variance, $\sigma^2_{\alpha t} \equiv \frac{1}{\sigma^2_{\alpha t}}$:

$\alpha_t \sim N(\mu_{\alpha t}, \sigma^2_{\alpha t})$. $\mu_{\alpha t}$ is assumed to follow a normal distribution with mean 0 and variance 100: $\mu_{\alpha t} \sim N(0{,}100)$.

A uniform prior on the standard deviation, $\sigma_{\alpha t}$, is adopted: $\sigma_{\alpha t} \sim Uniform(0{,}100)$ The coefficient, $\gamma_{\alpha t}$, on AR relations between α_t's and other parameters are assumed to follow normal distributions with mean zero and variance 100: $\gamma_{\alpha t} \sim N(0{,}100)$, etc.

Similar priors are specified for β_t and $\gamma_{\beta t}$.

(2) Results

Estimation results for the cases of MLE, hierarchical priors and AR restrictions are shown in Appendix Tables A2, A3 and A4 for mortality and Table A6, A7 and A8 for complications. Pooled estimations are in Tables A5 for mortality and A9 for complication.

Figure 6 contrasts crude mortality rates together with risk-adjusted mortality rates.

Crude and adjusted rates differ more than one percentage point in 2004 and 2006. Hence, risk adjustment exerts significant influences on the mortality. The difference among different risk-adjustment methods is small. One possibility is that the sample includes several hundreds of patients for each year so that chance variations are well controlled by even the MLE.

Figure 7 contrasts crude complication rates with risk-adjusted complication rates. The complication rates estimated with MLEs are not greatly different from the crude rates. In the cases of hierarchical prior and AR restriction, crude and adjusted rates differ significantly. The differences between the case of MLE and the cases of hierarchical prior and AR restriction are relatively large. Recognizing that our adjustment for complications is rudimentary, we may suspect that the hierarchical model may be required in the case of noisy data.

Figures 8, 9 and 10 show growth rates of output indexes with risk adjustment by MLE, hierarchical priors and AR restrictions. Overall behavior is the same as the case of adjustment by crude rates shown in Figure 6. However, the magnitude of adjustment is much smaller than the latter case.

To see this more clearly, Figures 11 and 12 superimpose growth rates by various adjustment methods. In 2006, for example, the magnitude of adjustment with risk adjustment is around half the magnitude of the case by crude rates.

This indicates that quality adjustment by crude rates is too much. Change in the mortality and complication rates include not only true change in the quality of care but also change in risk factors. Therefore, not all the changes in the output index adjusting for quality by crude rates does not represent changes in quality-adjusted output.

(3) How much is enough? – Comparing Various Severity Indexes

A remaining question is: do we need detailed risk adjustment or is it sufficient to adjust for only basic demographic factors? To examine this question, we created two additional severity indexes which involve different degrees of risk adjustment. First one, denoted as severity 2, includes only age and female. The second one, denoted as severity 3 includes, in addition to age and female, Killip classes, ventricular fibrillation and renal failure.

Excess mortalities are calculated using these additional severity indexes. Here, excess mortality means deviation from the four-year average. The results are shown in Figure 13. The mortality adjusted with severity 2 is not very different from the crude mortality. The mortality adjusted with severity 3 is half way between the crude mortality and the mortality with baseline severity index.

Therefore, the extent of risk adjustment exerts significant impact on the estimates of adjusted mortality, and hence on the output index.

7. Conclusion

In this paper we investigated the question: how to measure output of health care. We explored methods to incorporate quality of health care.

First of these adjusts for crude mortality and complication rates. Adjustment of crude rates can be misleading, however, because risk factors change from year to year and chance variation may dominate yearly fluctuations in mortality and complication rates.

Hence, second set of indexes incorporates risk-adjusted mortality and complication rates. In controlling for chance variations, we compared three estimation methods: maximum likelihood, the hierarchical model and autoregressive (AR) restrictions on random effects.

Further, to examine how much information is required for reasonable risk adjustment, we compared three risk adjustment models with differing degrees of detailed risk factors.

Overall conclusion of the paper is that we do need adjustment of quality of care in the construction of output index of health care. Mortality adjustment has much larger impact than complication adjustment. However, our adjustment of complications is far from perfect. It is very important to improve on adjustment of complications in the future research.

Risk adjustment is also of crucial importance although the choice of method of estimation to control for chance variation may be less crucial. This is especially true in the case of mortality adjustment. One possibility is that the sample includes several hundreds of patients for each year so that chance variations are well controlled by even the MLE. In the case of complication adjustment, however, the differences between the results of MLE and the hierarchical model are relatively large. Recognizing that our adjustment for complications is rudimentary, we may suspect that the hierarchical model may be effective in the case of noisy data with measurement error.

As for the risk factors included in risk adjustment, the more detailed, the better.

In this paper, we restrict our attention to the quality of care of AMI patients. This is only because of data limitation. Methods in this paper (or improved ones) to incorporate quality of care in output index can be applied to health care in general.

The fundamental barrier to the measurement of health care output is data limitation. It is imperative to enrich our data environment by routinely collecting detailed data on risk factors and outcomes, especially quality of life.

It would be best to directly measure health utility by way of established instruments such as EQ-D5 or SF-36, but such direct measurement may be impractical. Stewart, et al. (2005) proposed to relate data on symptoms and impairments to health utility in order to monitor population health. If we collect data on symptoms and impairments of patients, we can infer health utility of individual patients by assigning health utilities to complications.

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Table 1 Basic Statistics

	Total	2004	2005	2006	2007
Mortality	0.106	0.092	0.098	0.122	0.108
Complication rate	0.184	0.177	0.168	0.190	0.198
Gappei	0.046	0.042	0.024	0.053	0.061
New infarction	0.006	0.007	0.005	0.007	0.004
Cardiovascular disorder	0.033	0.026	0.013	0.044	0.045
Renal failure	0.010	0.011	0.007	0.005	0.015
Stroke	0.001	0.004	0.000	0.000	0.001
Repeat revascularization	0.183	0.176	0.169	0.192	0.192
Repeat PCI	0.164	0.153	0.142	0.181	0.177
Emergency CABG	0.022	0.029	0.032	0.010	0.016
Change within 48 hours	0.002	0.002	0.005	0.000	0.000
Cardiac arrest	0.000	0.000	0.000	0.000	0.000
Shock	0.002	0.002	0.005	0.000	0.000

Note: Figures for complications are based on survivors only.

Risk fctors	Total	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 infarc	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

Table 2 Characteristics of Hospitals

		The level of designated Emergency Care 1)	The status of clinical resident training hospital	The number of hospital beds (Average/year) (2006−2009)	Total hospital patients (Average/year) (2006−2009)	AMI patients (Average/year) (2006−2009)	The number of PCI (Average/year) (2006−2009)
hospital ID	1	◎	○	956	304,183	164	483
	2	○	○	524	89,224	69	103
	3	○	○	322	7,839	19	109
	4	○	○	530	1,601	81	299
	5	○	○	202	72,410	186	712
	6	◎	○	592	187,739	89	253
	7	◎	○	469	159,961	93	185
	8	○	−	151	27,275	22	163
	9	○	○	165	3,198	50	367

Average of 9 hospitals	434	94,826	86	297

1) ◎: Tertiary Emergency Care, ○ : Secondary Emergency Care
″Tertiary Emergency Care″−provide patients with high−acuity conditions who require admission to the intensive care or emergency surgery.
″Secondary Emergency Care″−provide patients with moderate−acuity conditions who require admission to a general inpatient bed.

Table 3 Assumed Utilities of Complications	Utility	Reference
Baseline	0.9	Weintraub, et al.
Stroke	0.52	Timbie, et al.
Renal failure	0.63	Timbie, et al.
Repeat PCI/Emergency CABG	0.78	Timbie, et al.

Figure 1 Output Index of Inpatient Services: Patient Survey

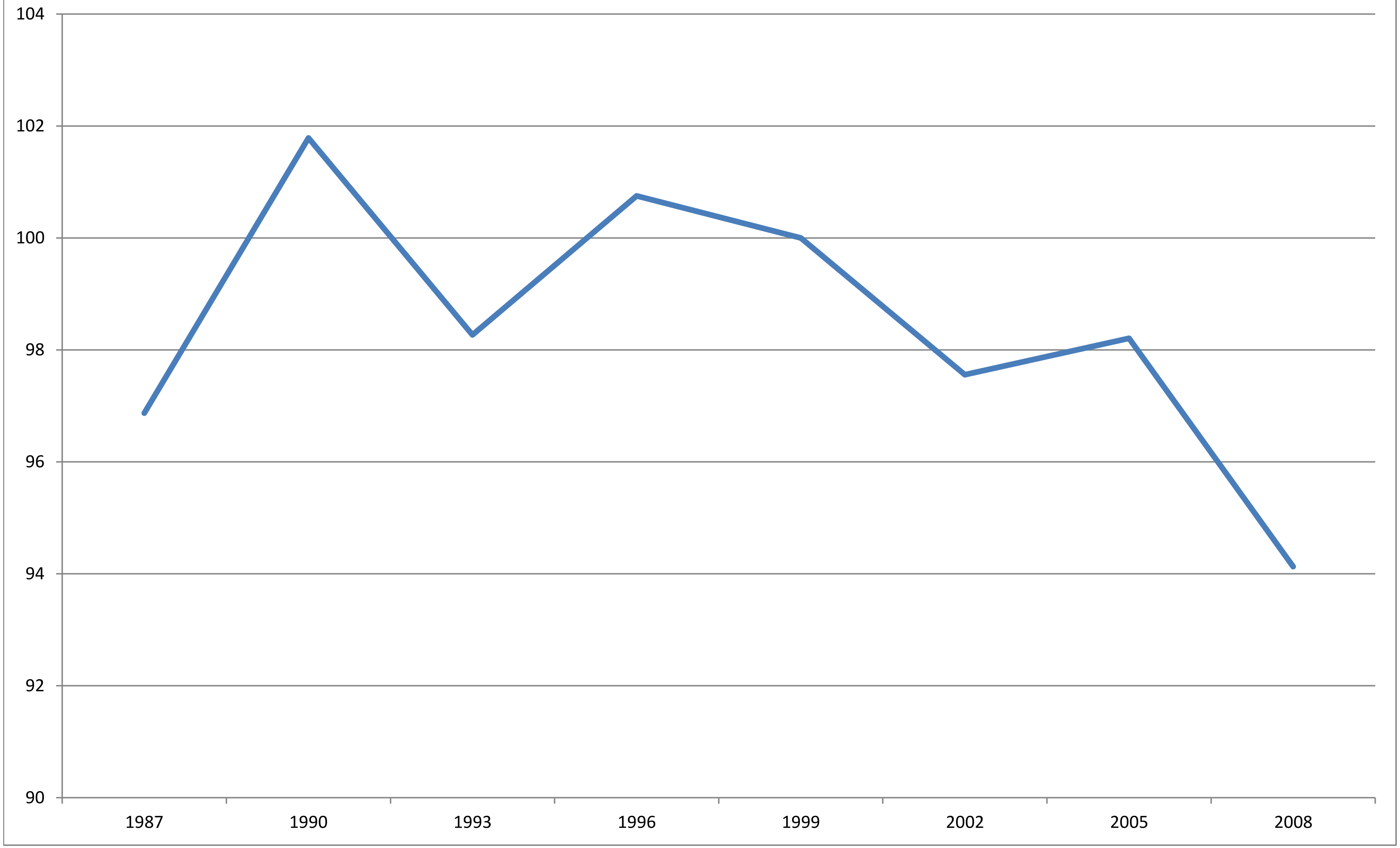


Figure 2 Growth of DPC-Based Output Index and the Number of Patients

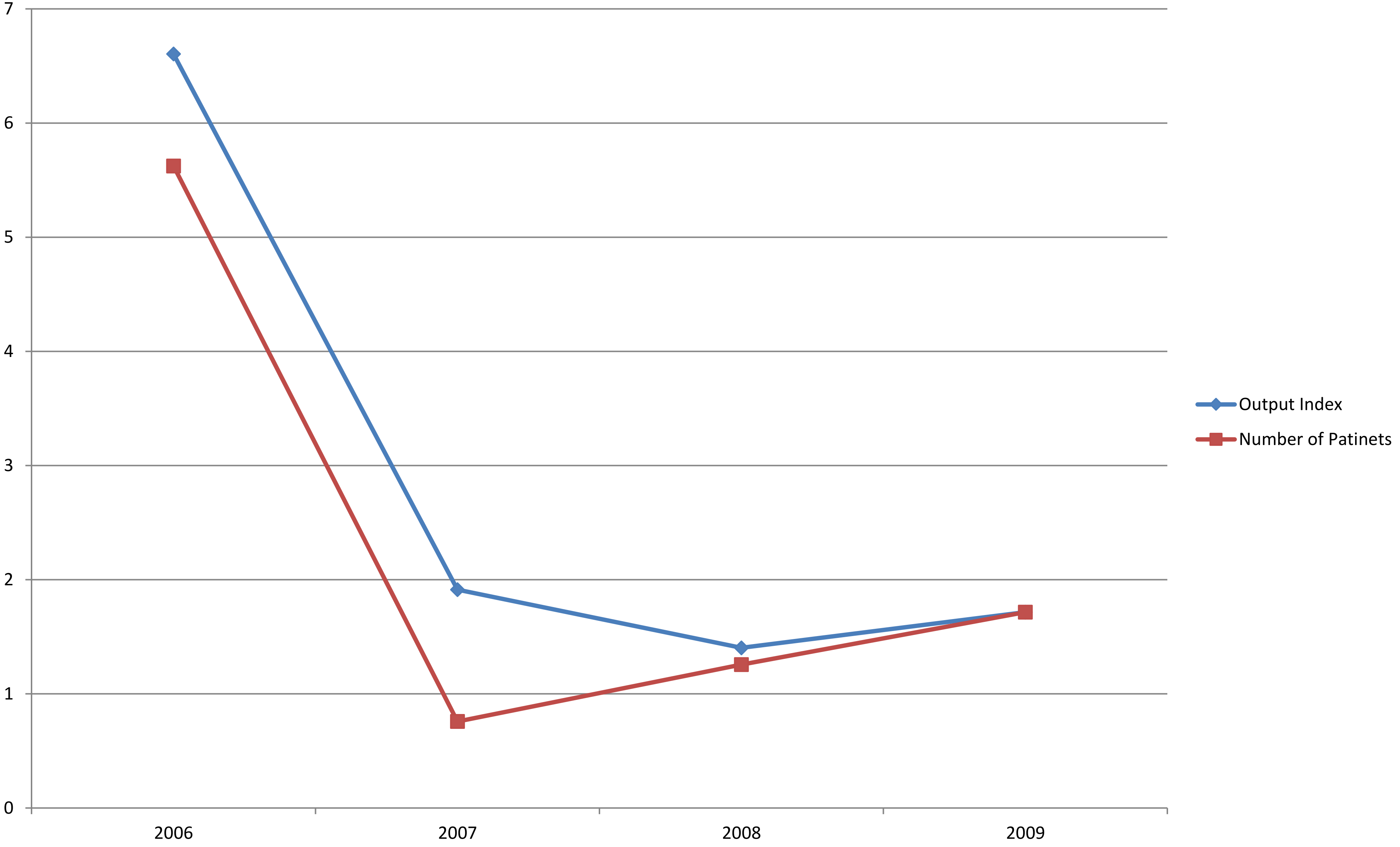
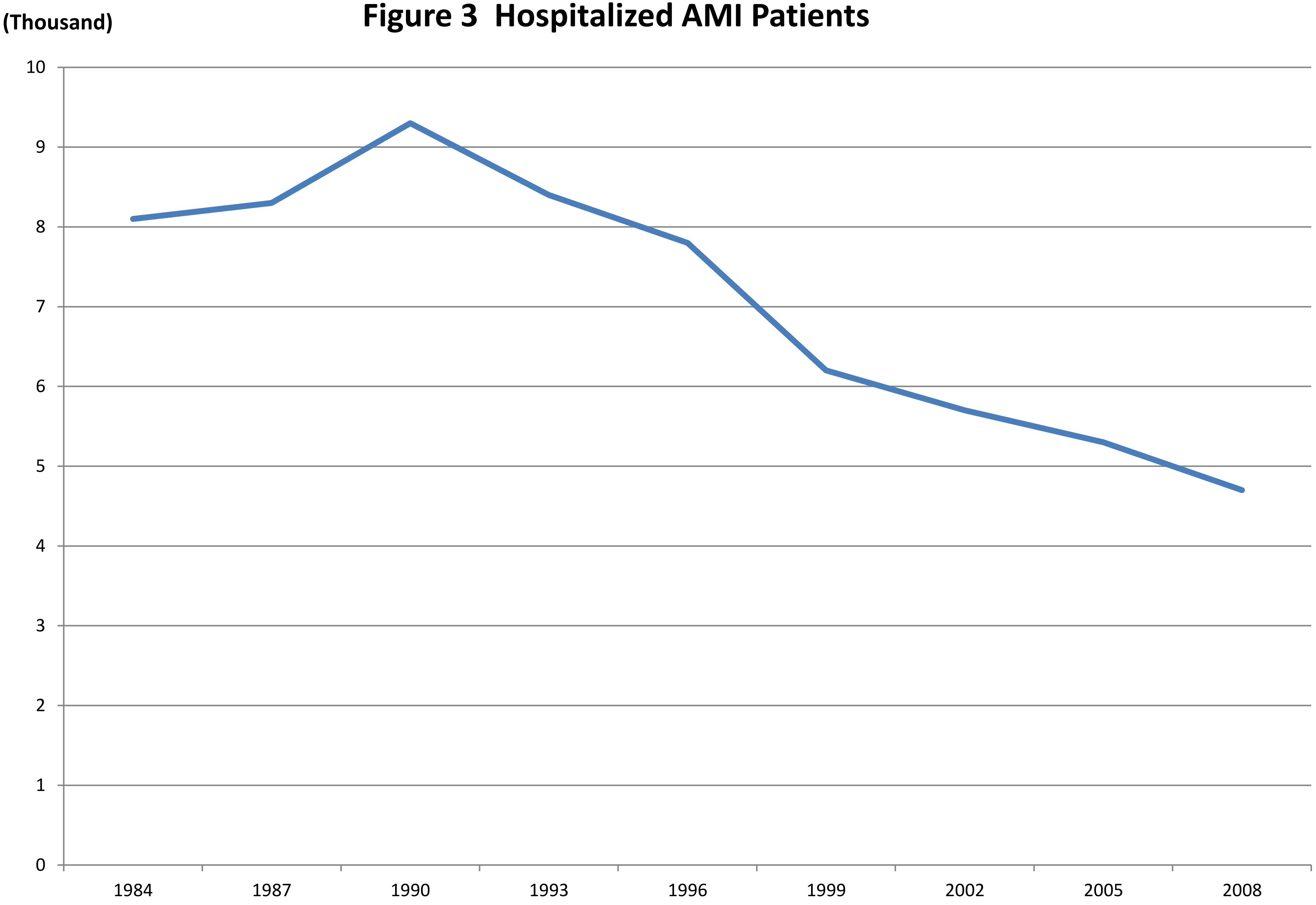


Figure 3 Hospitalized AMI Patients



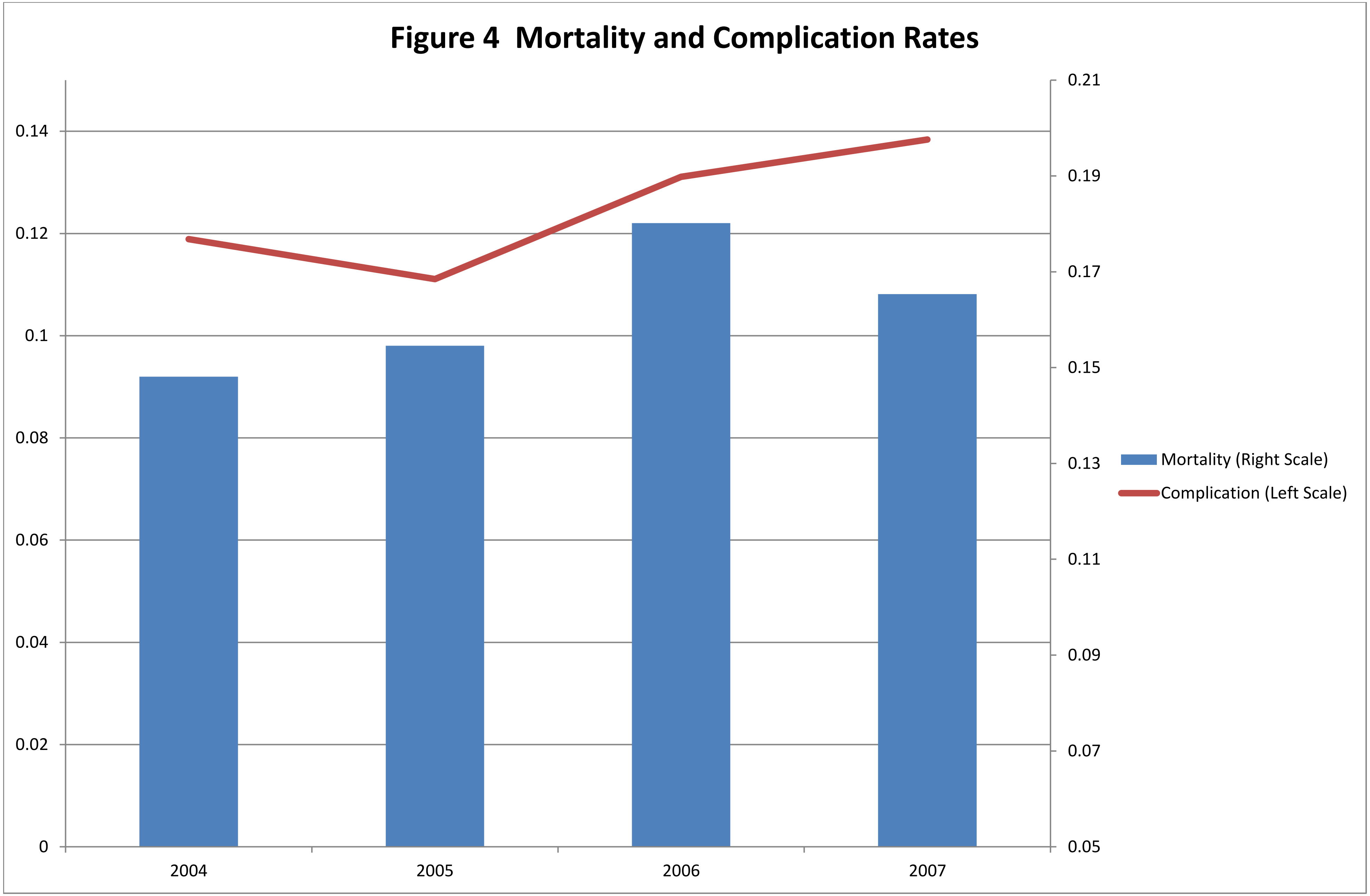
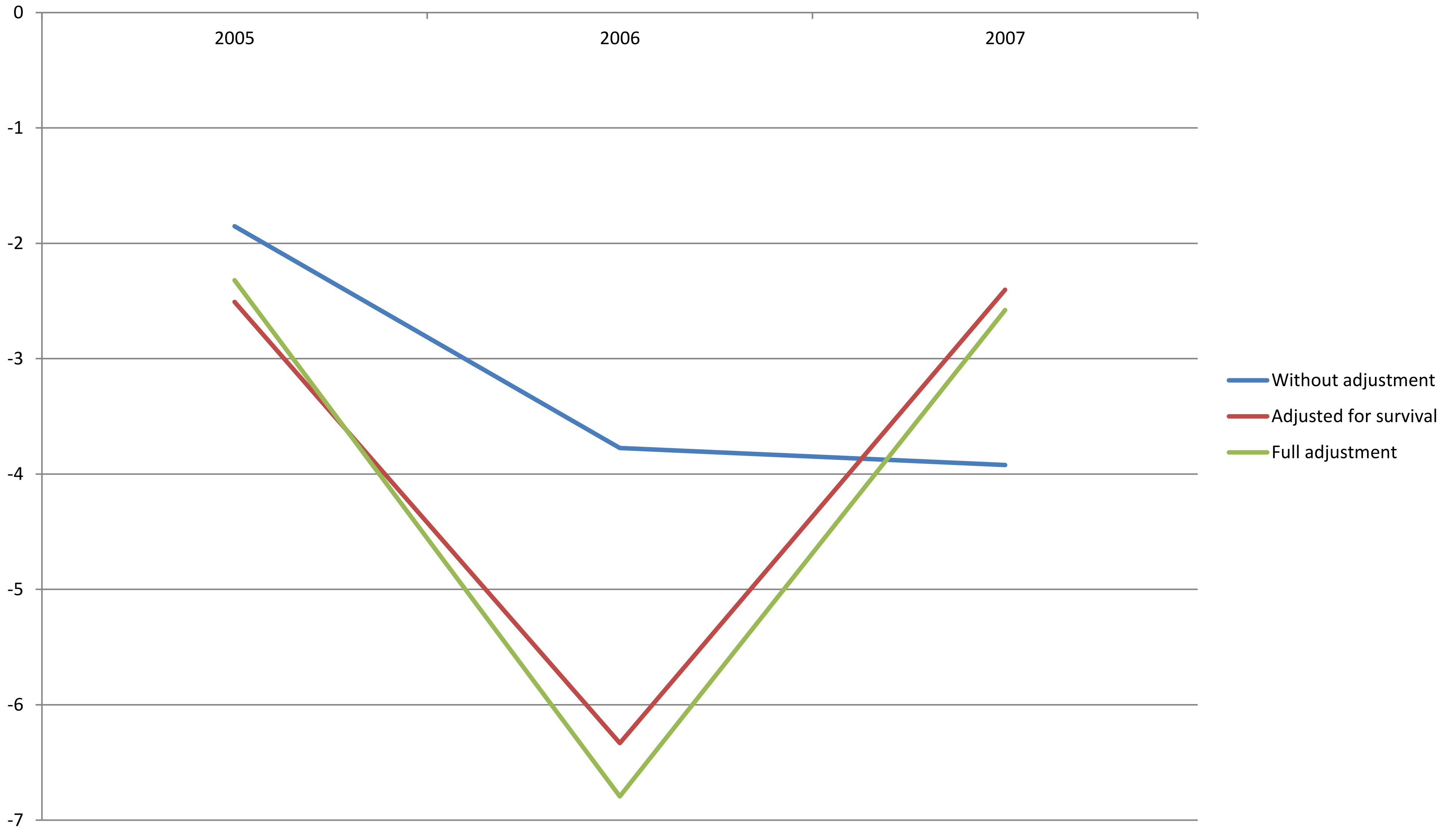


Figure 4 Mortality and Complication Rates
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0.21
0.19
0.17
0.15
0.13
0.11
0.09
0.07
0.05
2004
2005
2006
2007
Mortality (Right Scale)
Complication (Left Scale)

**Figure 5 Output Index Growth:
Adjustment by Crude Mortality & Complication Rate**



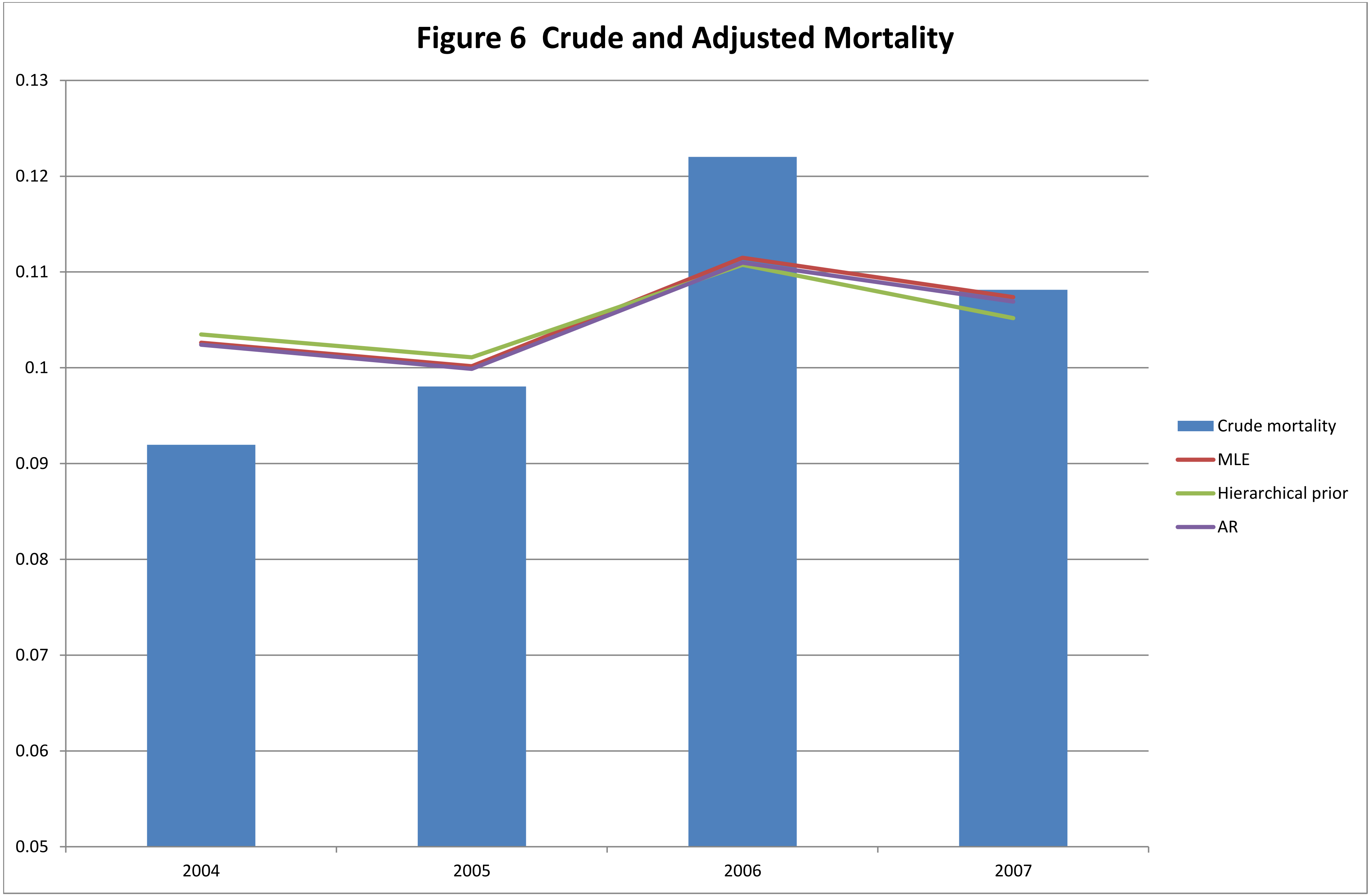
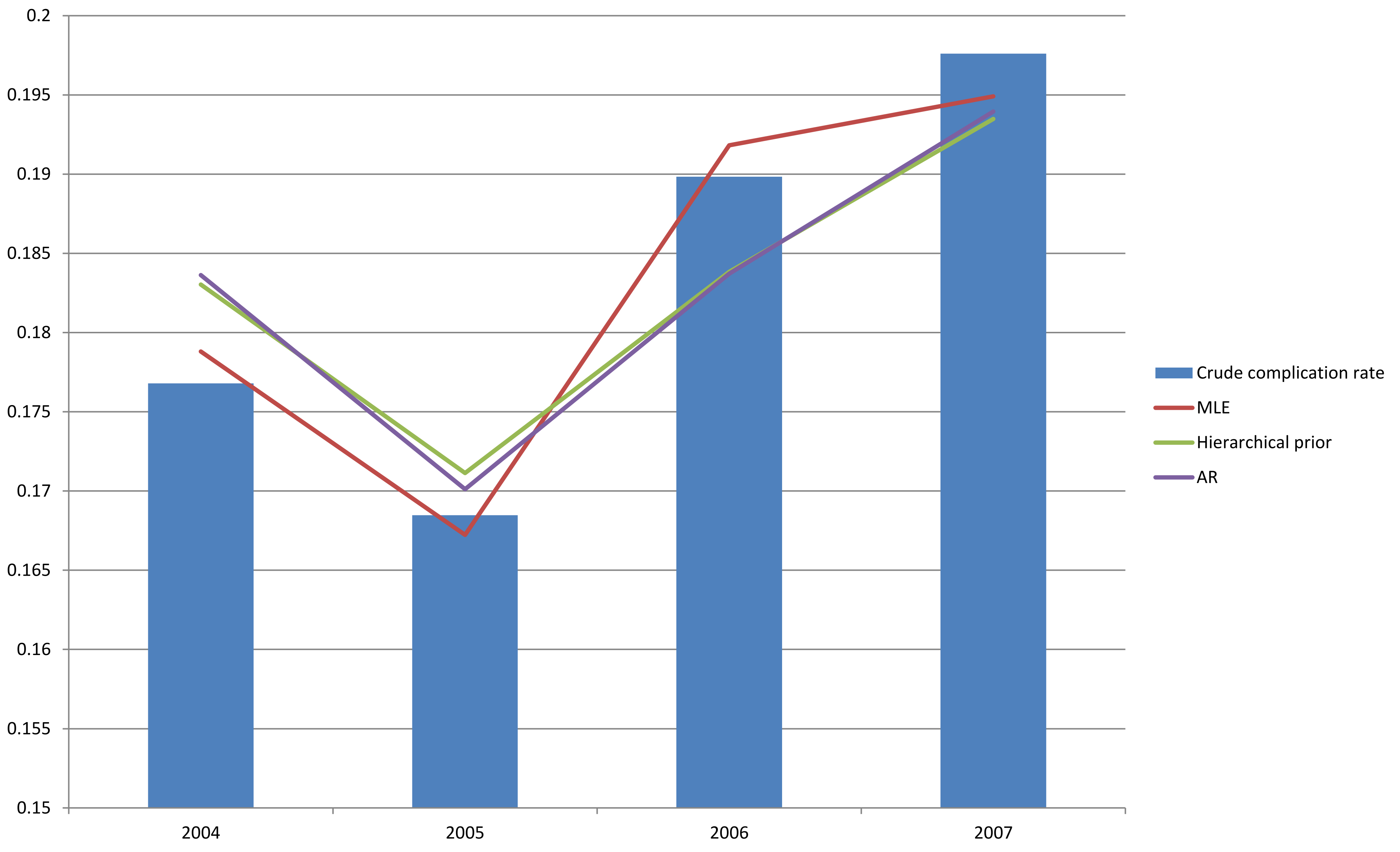


Figure 6 Crude and Adjusted Mortality
0.13
0.12
0.11
0.1
0.09
0.08
0.07
0.06
0.05
2004
2005
2006
2007
Crude mortality
MLE
Hierarchical prior
AR

Figure 7 Crude and Adjusted Complication Rate



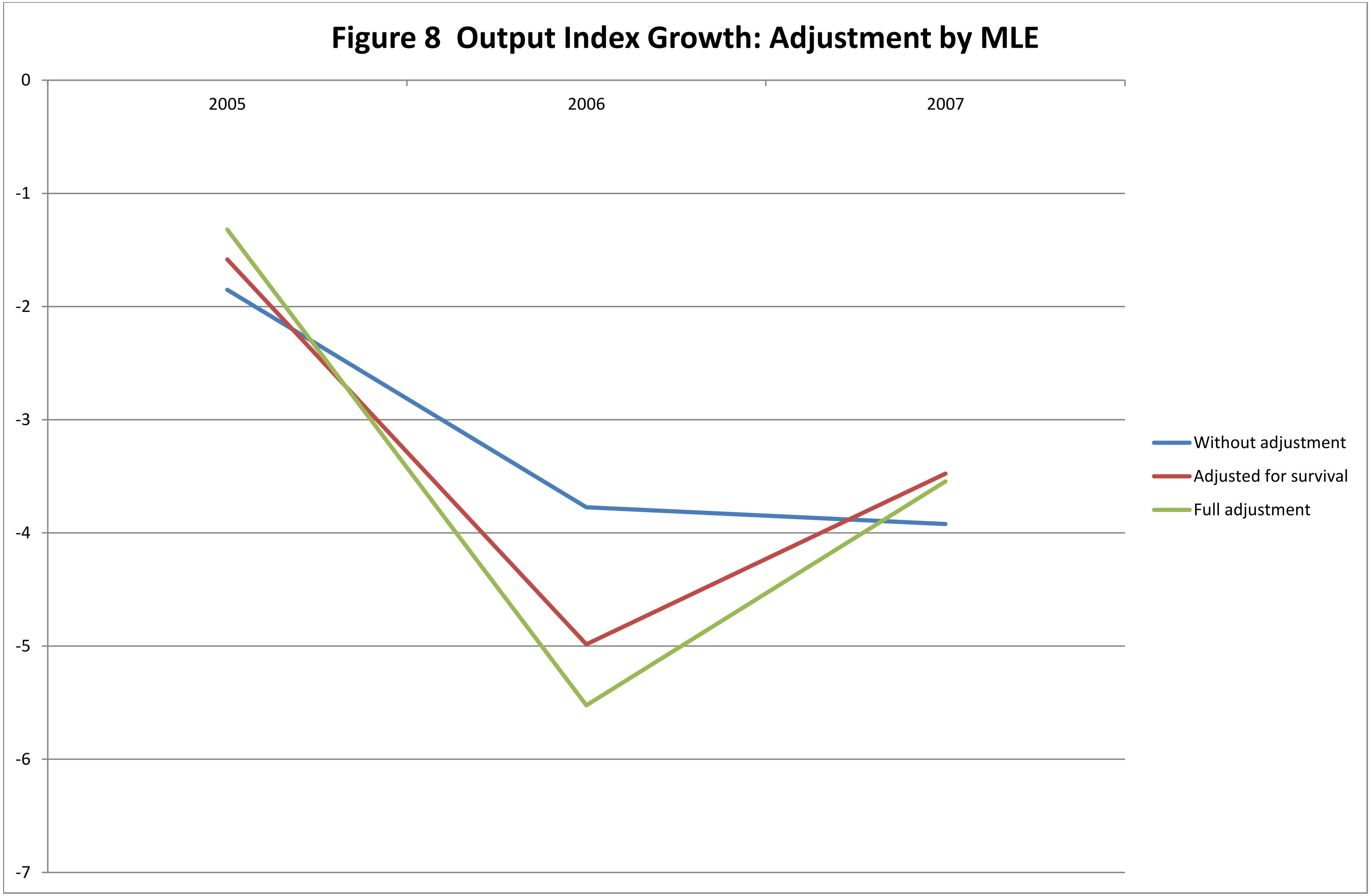
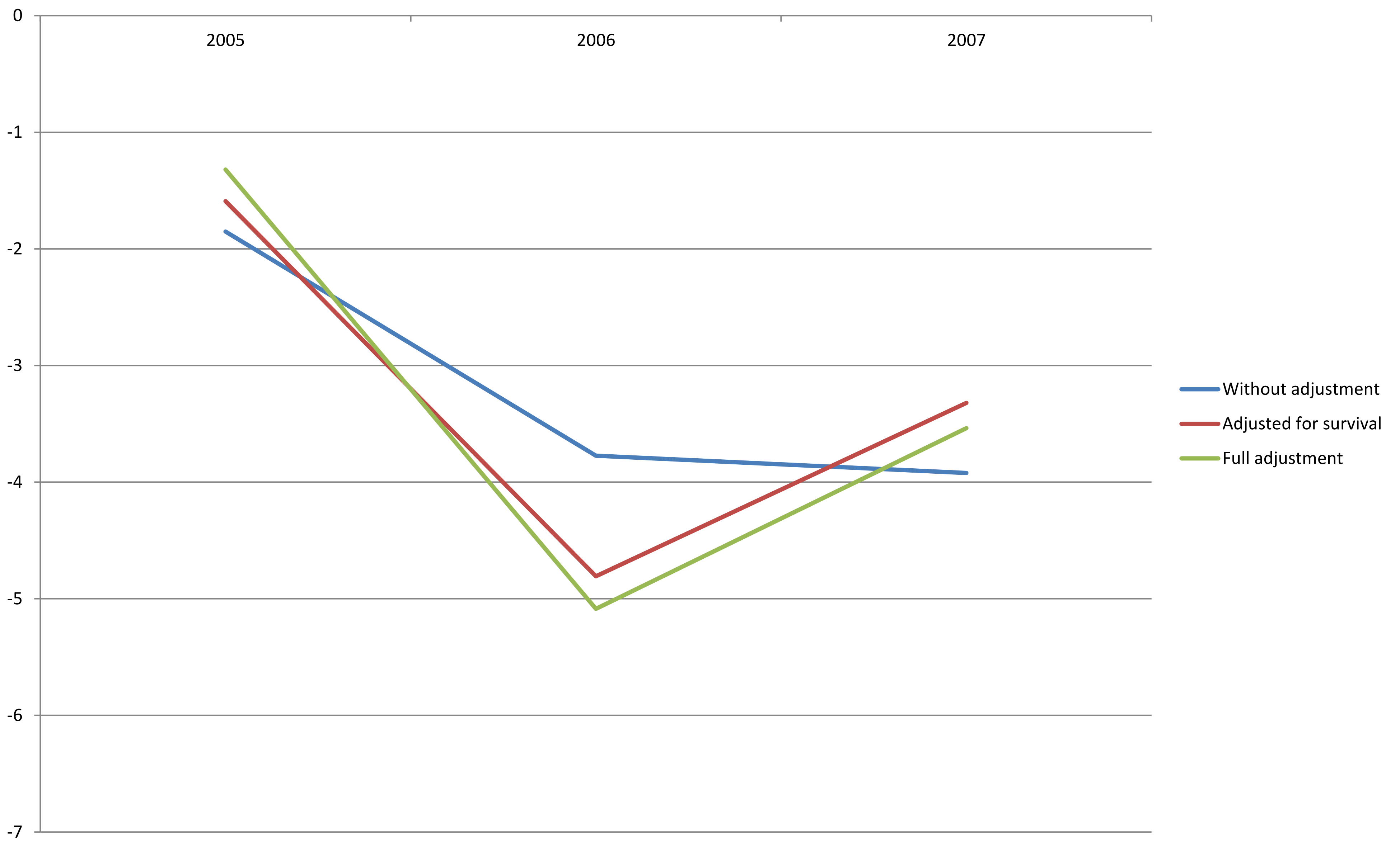


Figure 8 Output Index Growth: Adjustment by MLE
0
-1
-2
-3
-4
-5
-6
-7
2005
2006
2007
Without adjustment
Adjusted for survival
Full adjustment

Figure 9 Output Index Growth: Adjustment by Hierarchical Priors



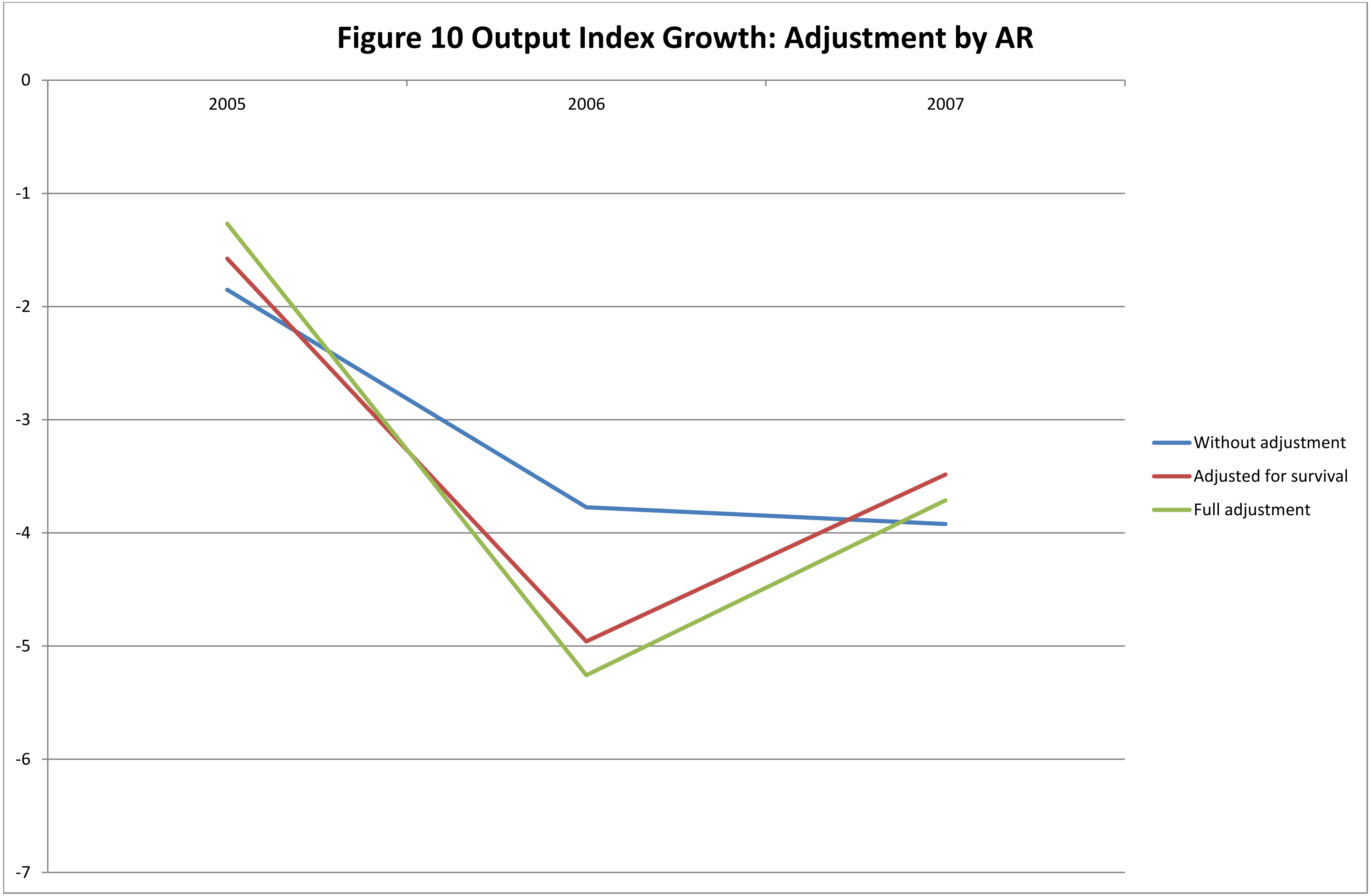


Figure 10 Output Index Growth: Adjustment by AR
0
-1
-2
-3
-4
-5
-6
-7
2005
2006
2007
Without adjustment
Adjusted for survival
Full adjustment

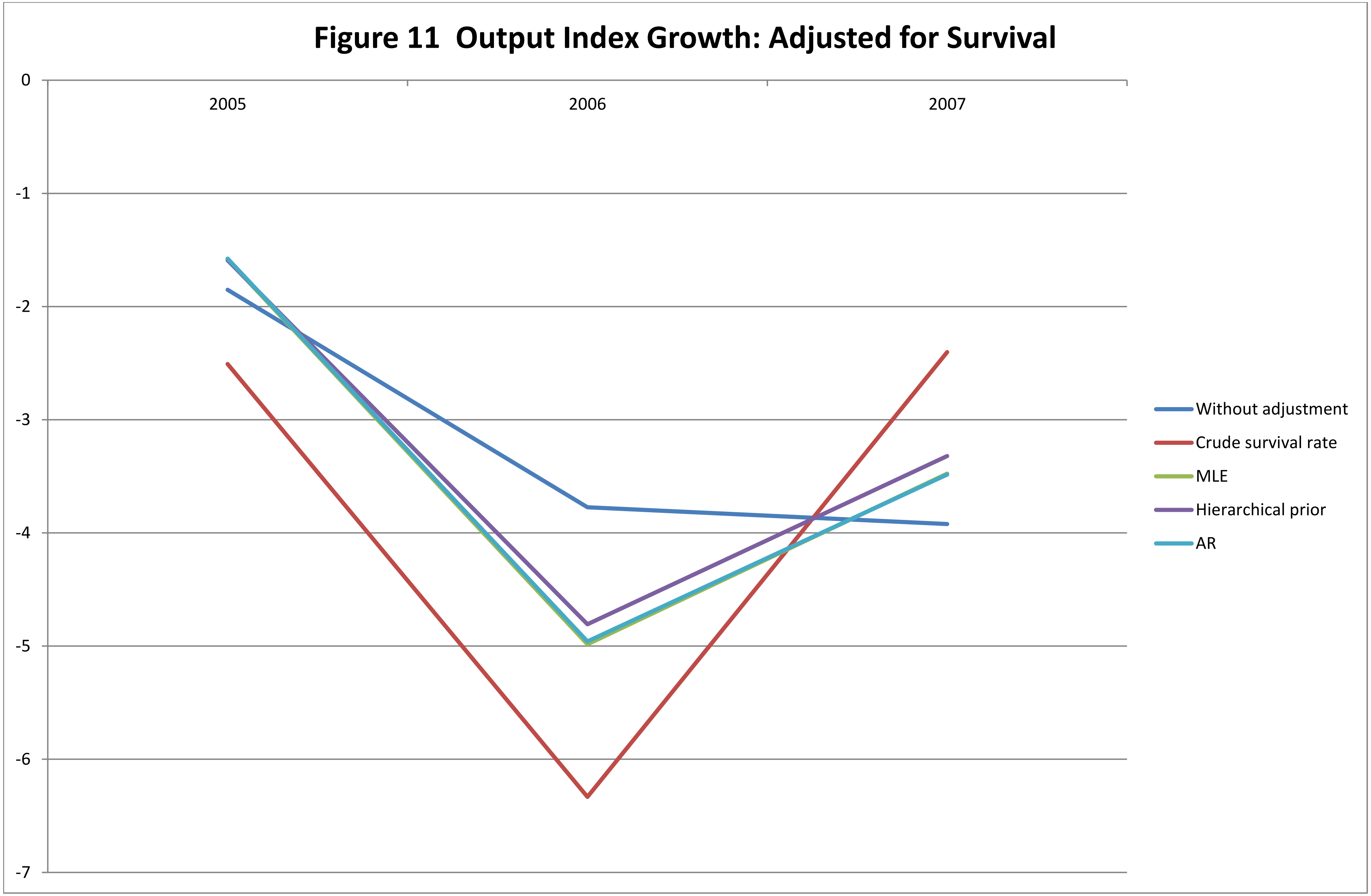
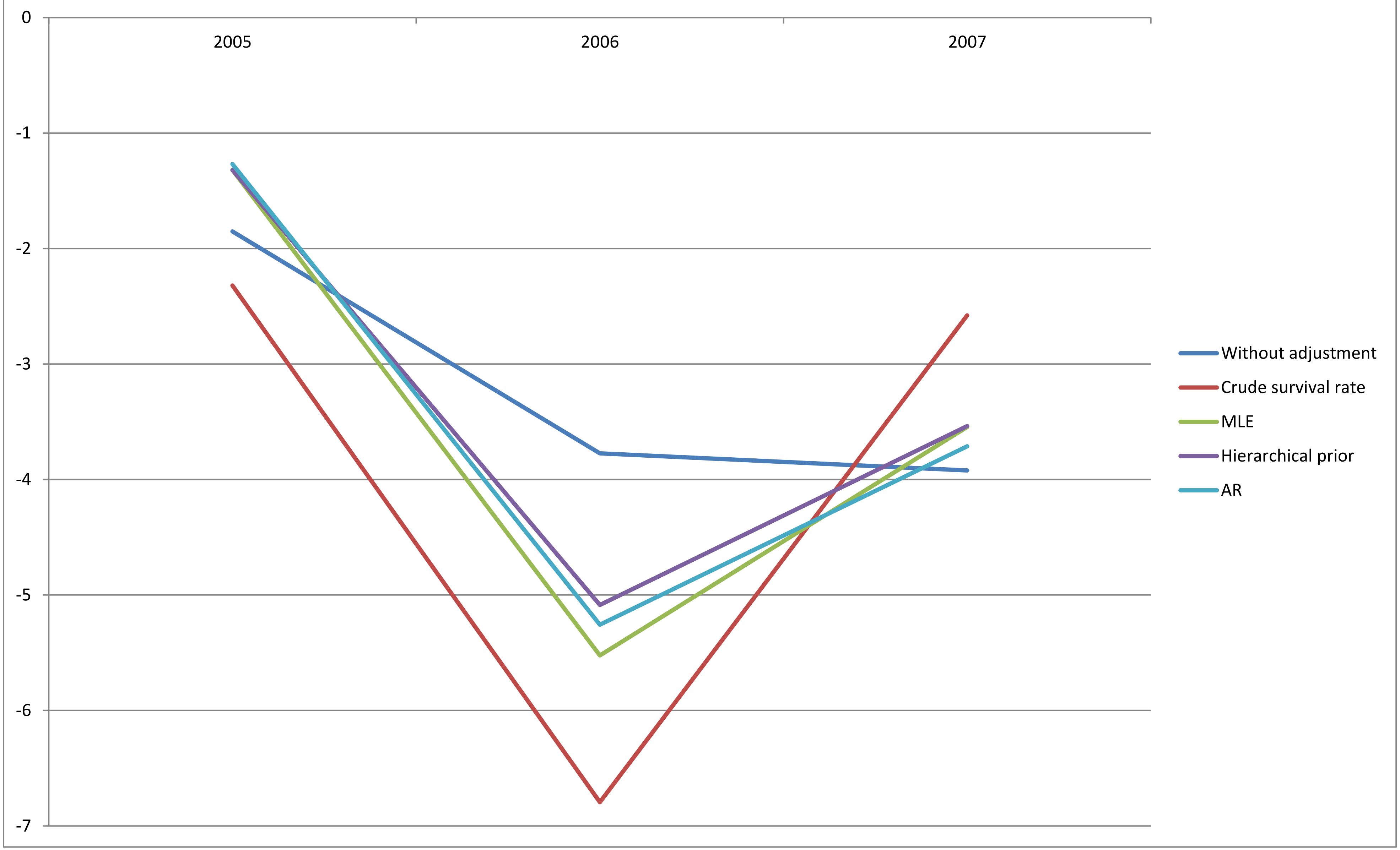


Figure 11 Output Index Growth: Adjusted for Survival
0
-1
-2
-3
-4
-5
-6
-7
2005
2006
2007
Without adjustment
Crude survival rate
MLE
Hierarchical prior
AR

Figure 12 Output Index Growth: Full Adjustment



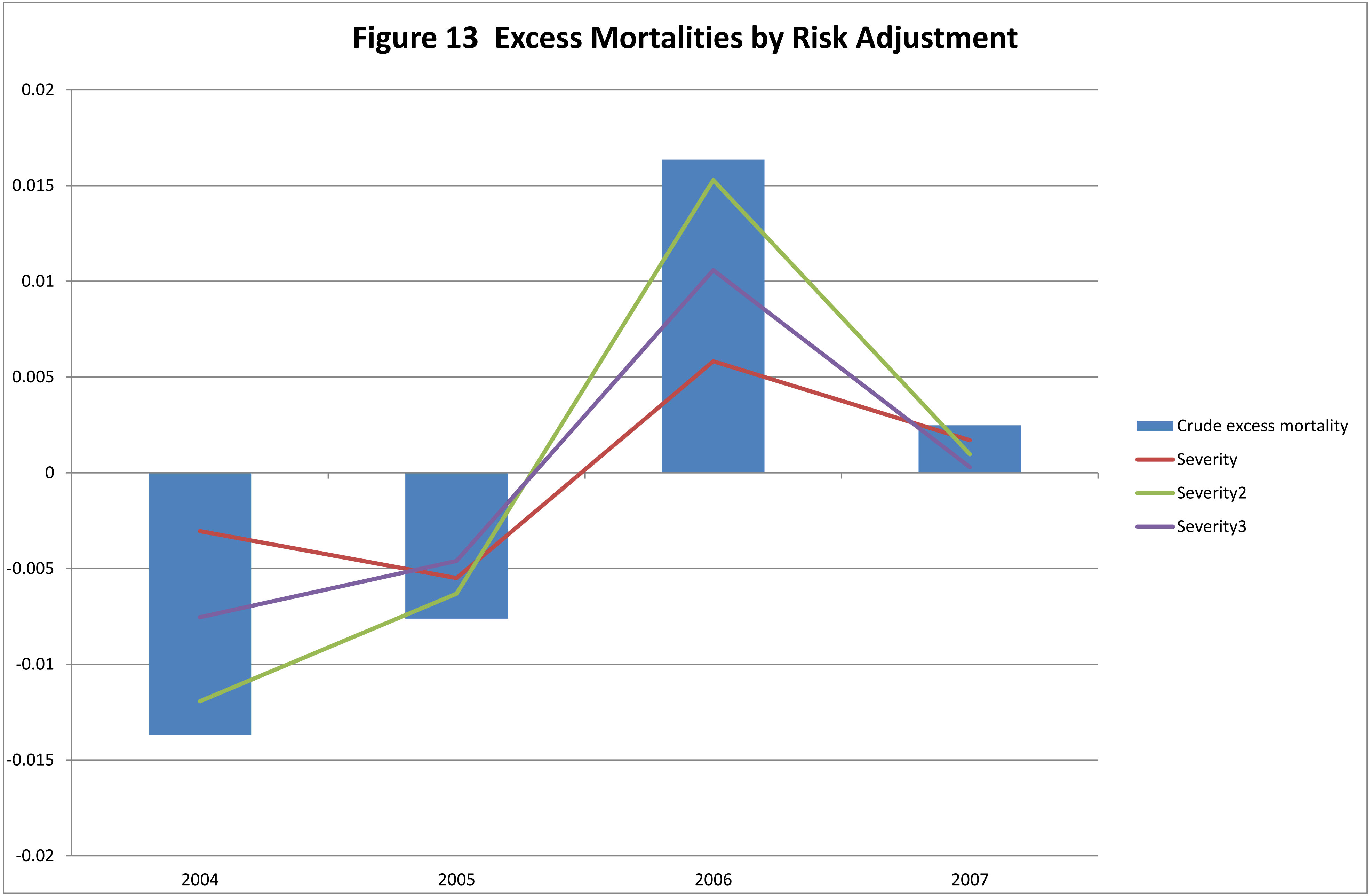


Figure 13 Excess Mortalities by Risk Adjustment
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
-0.02
2004
2005
2006
2007
Crude excess mortality
Severity
Severity2
Severity3

Appendix Table A1 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	6.5	0
Female	0.475	0.166	2.86	0.004
Killip2	1.663	0.369	4.5	0
Killip3	2.993	0.351	8.53	0
Killip4	3.668	0.355	10.33	0
Left main trunk occluded	0.230	0.278	0.83	0.408
LBBB	0.300	0.225	1.34	0.182
Ventricular fibrillation	0.965	0.251	3.85	0
Hypertension	−0.409	0.162	−2.53	0.011
Hyperlipidemia	−1.012	0.232	−4.36	0
Diabetes mellitus	0.149	0.168	0.89	0.374
Heart failure	0.040	0.230	0.17	0.861
History of myocardial infarction	0.232	0.262	0.88	0.377
History of PCI	−0.349	0.338	−1.03	0.302
History of CABG	0.901	0.494	1.82	0.068
Cancer	0.728	0.226	3.23	0.001
Bleeding	0.564	0.405	1.39	0.164
Renal failure	0.478	0.195	2.45	0.014
Cerebrovascular diseases	0.014	0.192	0.07	0.941
Aneurysm	0.574	0.372	1.54	0.123
COPD	0.435	0.407	1.07	0.285
Constant	−4.809	0.349	−13.8	0

Table A2 Mortality − MLE

2004	Logistic regression		Number of obs	=	598
	Log likelihood = −104.47098		Pseudo R2	=	0.4311

death	Coefficient	Standard Error	p−value
severity	1.179	0.143	0.000
_cons	−4.169	0.413	0.000

2005	Logistic regression		Number of obs	=	612
	Log likelihood = −114.54049		Pseudo R2	=	0.4165

death	Coefficient	Standard Error	p−value
severity	1.153	0.132	0.000
_cons	−4.141	0.385	0.000

2006	Logistic regression		Number of obs	=	672
	Log likelihood = −146.82795		Pseudo R2	=	0.4110

	Coefficient	Standard Error	p−value
severity	1.014	0.103	0.000
_cons	−3.614	0.309	0.000

2007	Logistic regression		Number of obs	=	749
	Log likelihood = −181.08996		Pseudo R2	=	0.2943

death	Coefficient	Standard Error	p−value
severity	0.804	0.084	0.000
_cons	−3.169	0.234	0.000

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

death	Coefficient	Standard Error	p−value
severity	1.000	0.054	0.000
_cons	−3.663	0.157	0.000

Table A3 Mortality – Hierarchical Priors

		mean	sd	2.50%	97.50%
2004	Constant	−4.078	0.353	−4.828	−3.439
	Severity	1.149	0.125	0.919	1.411
2005	Constant	−4.065	0.339	−4.780	−3.450
	Severity	1.129	0.119	0.909	1.377
2006	Constant	−3.673	0.287	−4.266	−3.139
	Severity	1.032	0.097	0.850	1.230
2007	Constant	−3.279	0.233	−3.751	−2.842
	Severity	0.838	0.084	0.678	1.007
Overall mean of constant		−3.767	0.486	−4.753	−2.820
Overall mean of coefficient		1.030	0.366	0.302	1.750
Correlation coefficient of constant and coefficient		−0.153	0.443	−0.871	0.735
Variance of constant		0.844	1.445	0.133	3.672
Correlation of constant and coefficient		−0.127	0.741	−1.310	0.680
Variance of coefficient		0.534	0.946	0.098	2.221
Number of observations		2631			

Table A4 Mortality – AR Restriction

		mean	sd	2.50%	97.50%
Constant	2004	−4.202	0.413	−5.068	−3.453
	2005	−4.172	0.392	−5.010	−3.465
	2006	−3.659	0.314	−4.308	−3.082
	2007	−3.196	0.239	−3.691	−2.752
Severity	2004	1.189	0.143	0.928	1.486
	2005	1.162	0.135	0.916	1.443
	2006	1.028	0.104	0.833	1.242
	2007	0.812	0.086	0.651	0.987
$\gamma_{\alpha t}$	2005	0.707	5.529	−11.220	12.280
	2006	0.446	6.531	−13.640	14.110
	2007	0.483	6.950	−14.420	14.800
$\gamma_{\beta t}$	2005	0.381	7.847	−15.780	16.270
	2006	0.278	8.126	−16.690	16.820
	2007	0.312	8.295	−17.060	17.240
$\mu_{\alpha t}$	2004	−1.500	8.012	−16.910	15.890
	2005	−2.948	23.170	−51.230	46.570
	2006	−1.850	27.240	−58.630	56.720
	2007	−1.550	22.240	−47.710	46.270
$\mu_{\beta t}$	2004	0.580	7.251	−15.200	15.720
	2005	0.450	9.347	−18.790	19.480
	2006	0.320	9.484	−19.530	19.680
	2007	0.253	6.753	−13.810	14.110
$\sigma_{\alpha t}$	2004	26.960	25.280	0.684	90.450
	2005	46.880	28.960	1.862	96.960
	2006	41.400	27.950	1.567	95.610
	2007	39.150	27.810	1.486	95.280
$\sigma_{\beta t}$	2004	20.640	22.850	0.324	85.760
	2005	41.840	29.190	1.188	96.420
	2006	31.310	26.840	0.853	93.120
	2007	28.580	26.490	0.625	92.330

Number of observations

2004	598
2005	612
2006	672
2007	749
Total	2631

Table A5 Mortality – Pooled

	mean	sd	2.50%	97.50%
Constant	−3.678	0.159	−3.997	−3.379
Severity	1.005	0.055	0.900	1.114
Overall mean of constant	−3.453	2.420	−8.033	2.181
Overall mean of coefficient	0.944	2.390	−4.406	5.928
Correlation coefficient of constant and coefficient	−0.011	0.674	−0.988	0.986
Variance of constant	139.800	19080.000	0.194	124.100
Correlation of constant and coefficient	−4.518	3783.000	−37.380	33.130
Variance of coefficient	37.300	1742.000	0.190	120.800
Number of observations	2631			

Table A6 Complication – MLE

2004 Logistic regression Number of obs = 598
Log likelihood = −286.57969 Pseudo R2 = 0.0162

complication	Coefficient	Standard Error	p–value
severity	0.150	0.049	0.002
_cons	−1.458	0.106	0.000

2005 Logistic regression Number of obs = 612
Log likelihood = −286.8045 Pseudo R2 = 0.0102

complication	Coefficient	Standard Error	p–value
severity	0.122	0.050	0.015
_cons	−1.538	0.108	0.000

2006 Logistic regression Number of obs = 672
Log likelihood = −340.90053 Pseudo R2 = 0.0009

complication	Coefficient	Standard Error	p–value
severity	0.032	0.042	0.437
_cons	−1.355	0.096	0.000

2007 Logistic regression Number of obs = 749
Log likelihood = −383.16597 Pseudo R2 = 0.0002

complication	Coefficient	Standard Error	p–value
severity	0.016	0.041	0.705
_cons	−1.336	0.090	0.000

Pooled Logistic regression Number of obs = 2631
Log likelihood = −1301.6275 Pseudo R2 = 0.0037

complication	Coefficient	Standard Error	p–value
severity	0.070	0.022	0.002
_cons	−1.410	0.049	0.000

Table A7 Complication – Hierarchical Priors

		mean	sd	2.50%	97.50%
2004	Constant	−1.504	0.111	−1.724	−1.288
	Severity	0.151	0.059	0.035	0.267
2005	Constant	−1.585	0.112	−1.809	−1.369
	Severity	0.088	0.060	−0.030	0.205
2006	Constant	−1.486	0.108	−1.702	−1.279
	Severity	−0.057	0.053	−0.162	0.045
2007	Constant	−1.420	0.098	−1.614	−1.231
	Severity	−0.027	0.049	−0.124	0.068
Overall mean of constant		−1.497	0.361	−2.213	−0.782
Overall mean of coefficient		0.032	0.351	−0.669	0.718
Correlation coefficient of constant and coefficient		−0.009	0.446	−0.816	0.806
Variance of constant		0.518	0.891	0.094	2.135
Correlation of constant and coefficient		−0.009	0.579	−0.766	0.715
Variance of coefficient		0.506	0.942	0.093	2.065
Number of observations		2353			

Table A8 Complication – AR Restriction

		mean	sd	2.50%	97.50%
Constant	2004	−1.500	0.114	−1.727	−1.281
	2005	−1.590	0.115	−1.816	−1.369
	2006	−1.487	0.110	−1.706	−1.276
	2007	−1.417	0.099	−1.616	−1.224
Severity	2004	0.151	0.059	0.035	0.268
	2005	0.081	0.060	−0.033	0.201
	2006	−0.058	0.054	−0.165	0.046
	2007	−0.027	0.049	−0.123	0.068
$\gamma_{\alpha t}$	2005	0.458	7.533	−15.270	15.770
	2006	0.384	7.740	−16.030	16.310
	2007	0.399	7.995	−16.280	16.710
$\gamma_{\beta t}$	2005	0.030	9.529	−18.850	18.670
	2006	−0.102	9.162	−18.490	18.370
	2007	0.170	9.146	−18.680	18.450
$\mu_{\alpha t}$	2004	−0.663	7.490	−16.150	15.620
	2005	−0.683	11.310	−23.570	22.970
	2006	−0.603	12.320	−25.890	25.460
	2007	−0.567	11.370	−23.910	23.240
$\mu_{\beta t}$	2004	0.124	6.593	−14.330	14.720
	2005	0.009	1.533	−3.169	3.182
	2006	−0.011	0.908	−2.004	1.967
	2007	−0.008	0.514	−1.135	1.131
$\sigma_{\alpha t}$	2004	22.100	23.500	0.402	87.170
	2005	42.370	29.230	1.266	96.460
	2006	33.160	27.040	0.948	93.710
	2007	33.080	27.080	0.972	93.580
$\sigma_{\beta t}$	2004	16.540	21.300	0.077	81.430
	2005	36.130	29.800	0.289	95.630
	2006	17.790	24.080	0.079	86.860
	2007	15.590	23.280	0.040	85.670

Number of observations

2004	543
2005	552
2006	590
2007	668
Total	2353

Table A9 Complication – Pooled

	mean	sd	2.50%	97.50%
Constant	−1.482	0.054	−1.589	−1.378
Severity	0.026	0.027	−0.027	0.080
Overall mean of constant	−1.394	2.392	−6.228	3.850
Overall mean of coefficient	0.014	2.375	−5.180	5.040
Correlation coefficient of constant and coefficient	−0.007	0.674	−0.987	0.986
Variance of constant	118.800	15980.000	0.193	120.700
Correlation of constant and coefficient	−2.279	3144.000	−35.980	33.210
Variance of coefficient	36.820	1761.000	0.191	120.400
Number of observations		2353		