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Abstract

This paper proposes a method of deriving a hospital quality performance indicator using mortality outcome measures. The method aggregates any number of mortality outcome measures observed over several years into a single indicator. We begin with the supposition that there exists an abstract quality index which drives all observed mortality outcomes in each hospital. This abstract index is not directly observable but manifested via the observed mortality outcomes, which we make use of to provide an estimate of the abstract index. The method is applied to a sample of heart disease episodes extracted from hospital administrative data from the state of Victoria, Australia. Using the quality estimates, we show that teaching hospitals and large regional hospitals perform better than other hospitals and this superior performance is related to hospital size.

1 Introduction

This paper proposes a method of deriving a mortality-based measure of hospital performance in the context of heart disease in Victoria, Australia. The method aggregates different mortality outcome measures observed over several years into a single indicator. Using the derived performance indicator, we show that teaching hospitals and large regional hospitals in Victoria perform better than other hospitals and this superior performance is related to hospital size—hospitals that handle higher number of episodes also tend to have better performance.

The empirical estimation makes use of de-identified patient-level hospital administrative data,[1] which were linked to the death registry to obtain the mortality outcome measures used in this study. The unit of observations is separations,[2] which we refer to as episodes of care in this paper.[3] We make use of four mortality outcome measures, namely in-hospital death, death within 30 days, 90 days, and 360 days after discharge. The data cover five financial years, from 2000-01 to 2004-05. This study restricts the episodes of care to selected patients with heart disease (see below).

The empirical method consists of two stages. In stage one, we perform a four-equation seemingly unrelated regression (SUR) (Zellner, 1962) where the dependent variables are mortality variables denoting the four mortality outcomes. Included in the SUR estimation is a set of hospital dummy variables, one for each hospital. We interpret the hospital-specific coefficient estimates as risk-adjusted mortality rates (RAMRs). In stage two, we implement a weighted least squares regression using RAMRs as the dependent variable, with the covariance of RAMRs as weights. The set of hospital dummy variables is also included in this regression and their coefficient estimates form the hospital performance measure we desire. We call this quality

[1] Both the patients and hospitals have been de-identified in the data set we use.

[2] A separation from a hospital occurs when a patient leaves because of death, discharge, sign-out against medical advice or transfer. A separation may also occur due to care type changes (e.g., from acute care to rehabilitative care) within a hospital. In this paper we regard transfers within the same hospital as a single episode.

[3] We also loosely refer to episodes as patients in certain situations such as when we describe the age distribution of the patients and other patient characteristics.

performance measure the two-stage aggregated risk-adjusted mortality rates (ARAMRs).

A major difficulty in modeling mortality outcomes across hospitals is the issue of self selection—patients are likely to select hospitals based on the advice of their doctors and in consideration of the severity and complexity of their conditions and the hospital's reputation. Thus hospitals that are highly regarded may attract a disproportionately large number of patients with severe and/or complex conditions. As a result unadjusted mortality outcome measures can be biased against hospitals with good quality reputation. Two common strategies have been employed to deal with adverse selection in the hospital quality literature. The first is to restrict the types of patients in the data, e.g., patients with acute myocardial infarction (AMI) are likely to be admitted to the nearest hospital rather than a hospital of choice due to the urgency of their conditions (Shen, 2003). A variant to this strategy is to account for the severity of patients' conditions in the sample using various medical status variables (Selim et al., 2002). The second strategy is to use instrumental variables. A common instrument is the distance between patients' place of residence and hospitals in the sample, e.g., Gowrisankaran and Town (1999), and Geweke et al. (2003); see Khwaja et al. (2006) for a discussion.

We attempt to remove selection bias via the first approach, i.e., by carefully restricting the sample to episodes of care that are relatively homogenous and account for the severity of conditions using variables related to the medical status of patients. By using the diagnosis information, we restrict the sample to episodes for which the patients were recorded to have one or more heart-related disease diagnosis. For each episode in the sample, we also identify the principal diagnosis by using the ICD-10 diagnosis codes.[4] By making use of data dating back to 1996/97, we are able to identify whether an episode represents the first time that the patient was diagnosed to have heart disease. In addition to diagnosis information, we also make use of the Australian Refined Diagnosis Related Group (AR-DRG) information to classify episodes into 45 Diagnosis Related Groups (DRGs). Other information we make use

[4]The International Classification of Diseases and Related Health Problems, 10th revision. Australian Modification (ICD-10-AM). Sydney: National Centre for Classification in Health, University of Sydney, 2000.

of includes comorbidity, insurance status as declared by the patient, emergency department admission, and patient characteristics such as age and gender.

By proposing a mortality-based performance measure, this paper contributes to the literature on measuring hospitals' quality performance, an important topic in health research. Besides informing policy and enhancing consumer choices, hospital quality measures are also instrumental in health-related research such as studies investigating the relationships between quality and competition, quality and case-load volume, and quality and ownership of hospitals (for-profit versus not-for-profit). All these studies require meaningful and reliable measures of quality performance. However, hospital quality is multi-dimensional in nature, covering aspects that include effectiveness of treatment, timeliness of service delivery, quality of amenities, technological sophistication, incidences of adverse outcomes and so on. Comparing and synthesizing measures across different quality dimensions are challenging topics for theoretical and applied research. The method proposed in this paper is a less ambitious attempt to synthesize different mortality measures into a single quality indicator.

In recent years there have been many attempts to make use of hospital administrative data and mortality outcomes to construct measures of hospital quality performance.[5] Different mortality outcome measures have been used, examples are in-hospital death and death within 30 days of discharge from a hospital. In principle, one can define any number of mortality measures by varying the number of days of discharge from a hospital. However, a large number of mortality measures can give rise to inconsistent and even contradicting performance information. Moreover, it is highly unlikely that all measures provide equally reliable information, the noise in some measures are likely to be higher than that in others. There is therefore a need to systematically synthesize different mortality outcome measures. To this end, this paper postulates that there exists an abstract quality index that drives all observed mortality outcomes of each hospital. This abstract quality index is not directly observable or measur-

[5] See the review articles of Romano and Mutter (2004); Iezzoni et al. (1996); and Powell et al. (2003), among others.

able but manifested via the observed mortality outcomes, which we make use of to provide an estimate of the abstract quality index. The derived quality estimate not only takes into account patient characteristics but also aggregates several mortality outcome measures observed over a number of years into a single measure. We illustrate the method using mortality measures because these are the most common outcome measures. The method, however, is straightforward to apply to other quality dimensions such as readmissions or hospital-acquired diseases or complications.

The method we propose is similar to that of McClellan and Staiger (1999), who use a two-stage method to construct hospital quality measures. However, our method differs in two respects. First, we use an SUR formulation for the stage-one episode-level regression, which allows for correlated errors across different outcome measures. Second, our method reduces several mortality outcome measures into a single measure whereas the number of measures remain unchanged using the method of McClellan and Staiger (1999).

The remainder of this paper is structured as follow. Section 2 outlines the model, Section 3 discusses the sample construction and summarizes the data. Section 4 presents the main results and Section 5 concludes.

2 Model

Suppose we have data on N_t episodes of hospital stays occurring in H hospitals at time t for $t = 1, \ldots, T$. We are interested in measuring hospitals' quality performance by exploiting the data at the episode level to provide quality information at the hospital level. As mentioned before, we regard hospital quality as a multidimensional object. Here we are interested in only one aspect—mortality. The objective is to derive a mortality-based quality estimate for each hospital from the K mortality measures across T years. We outline a two-stage approach below. First, we obtain risk-adjusted mortality rates (RAMRs) for each of the K mortality outcome measures using episode-level data. Second, we derive the quality performance esti-

mates, ϕ_h, by aggregating these RAMRs over mortality outcome measures and time.

2.1 Stage one

Let i, h and k index respectively episodes, hospitals and mortality outcome measures. Let y_{iht}^k and x_{iht}^k denote the k-th mortality outcome and patient characteristics associated with episode i that occurs in hospital h at time t and μ_{ht}^k be the kth risk-adjusted mortality rate attributed to hospital h at time t. Note that y_{iht}^k is defined at the episode level, whereas μ_{ht}^k is defined at the hospital level. Thus, for example, y_{iht}^k could be a binary variable where it takes on the value of one if the patient dies within 30 days of separation and zero otherwise, whereas μ_{ht}^k is the risk-adjusted 30-day mortality rate attributed to hospital h.

We postulate a model for the kth mortality outcome measure of episode i in hospital h at time t as

$$y_{iht}^k = x_{iht}^k \alpha_t^k + \mu_{ht}^k + \omega_{iht}^k, \tag{1}$$

where ω_{iht}^k is assumed to have mean zero and covariance matrix Σ_t^k, and is assumed to be independent across i, h and t.

Intuitively, we expect the K mortality outcome measures to share some common features or to respond to some common external shocks, such as the introduction of a new drug or the diffusion of a new technology. Hence, to account for the relationship between the K mortality outcome measures we explicitly allow the error terms to be correlated across measures for the same episode in a hospital, i.e., for $k, m = 1, \ldots, K$ and for each t,

$$E[\omega_{iht}^k \, \omega_{jlt}^m \mid X_t^k, \, X_t^m] = \begin{cases} \sigma_{km}^2 & \text{if } i = j \text{ and } h = l \\ 0 & \text{otherwise.} \end{cases}$$

With this assumption, we estimate the mortality outcome equations jointly via SUR for each

t, rather than separately for each measure. We write (1) in matrix form as

$$\begin{bmatrix} Y_t^1 \\ Y_t^2 \\ \vdots \\ Y_t^K \end{bmatrix} = \begin{bmatrix} X_t^1 & 0 & \cdots & 0 \\ 0 & X_t^2 & 0 & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \cdots & 0 & X_t^K \end{bmatrix} \begin{bmatrix} \alpha_t^1 \\ \alpha_t^2 \\ \vdots \\ \alpha_t^K \end{bmatrix} + \begin{bmatrix} D_t^1 & 0 & \cdots & 0 \\ 0 & D_t^2 & 0 & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \cdots & 0 & D_t^K \end{bmatrix} \begin{bmatrix} \mu_t^1 \\ \mu_t^2 \\ \vdots \\ \mu_t^K \end{bmatrix} + \begin{bmatrix} \omega_t^1 \\ \omega_t^2 \\ \vdots \\ \omega_t^K \end{bmatrix}, \quad (2)$$

where Y_t^k is a $(N_t H \times 1)$ vector formed by stacking the mortality outcomes of all episodes in all hospitals, X_t^k is a $(N_t H \times P)$ matrix collecting all episode/patient characteristics at time t, D_t^k is a $(N_t H \times H)$ matrix of hospital specific dummy variables, and

$$\mu_t^k = \begin{bmatrix} \mu_{1t}^k & \mu_{2t}^k & \cdots & \mu_{Ht}^k \end{bmatrix}'.$$

Let

$$\Sigma_t = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \cdots & \sigma_{1K}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 & \vdots & \sigma_{2K}^2 \\ \vdots & \ddots & & \vdots \\ \sigma_{K1}^2 & \sigma_{K2}^2 & \vdots & \sigma_{KK}^2 \end{bmatrix}.$$

The error term is

$$\begin{bmatrix} \omega_t^1 & \omega_t^2 & \cdots & \omega_t^K \end{bmatrix}',$$

which has mean zero and covariance matrix

$$\Omega_t = \Sigma_t \otimes I_{N_t}.$$

where $\otimes$ denote the Kronecker product and I_{N_t} is a $N_t \times N_t$ identity matrix. Equation (2) is estimated using the standard SUR technique. Let m_{ht}^k denote the coefficient estimate of μ_{ht}^k in the SUR estimation and W be the associated variance-covariance matrix.

2.2 Stage two

Given that m_{ht}^k is the SUR estimate of the kth risk-adjusted mortality rates, it is a random variable with mean μ_{ht}^k and variance as given by the SUR estimation. We regard each m_{ht}^k as providing a noisy snapshot of hospital h's quality performance, ϕ_h. Note that m_{ht}^k varies over

time and also across mortality measures, whereas ϕ_h is invariant with respect to k and t.[6] We postulate a fixed-effects model to capture the relationship between m_{ht}^k and ϕ_h:

$$m_{ht}^k = z_{ht}\gamma + \phi_h + \epsilon_{ht}, \tag{3}$$

where γ is a vector of unknown coefficients and ϵ_{ht} is an error term with mean zero, uncorrelated with z_{ht} and is assumed to be heteroscedasticity. Equation (3) states that the risk-adjusted mortality rates can be separated into an mean component, $z_{ht}\gamma$, and a hospital-specific component. We regard the latter as the estimate for hospital h's quality performance that is derived from mortality outcome measures.

Given the heteroscedastic assumption, (3) can be estimated efficiently using weighted least squares. Rewrite (3) in vector form as:

$$M = Z\gamma + \phi + \epsilon, \tag{4}$$

where M and Z correspond to stacking m_{ht}^k into vector form and z_{ht} into matrix form. From the SUR estimation in stage one, we have an estimate of the covariance matrix of M and which we denote as $\hat{W}$. Let $VV' = \hat{W}^{-1}$, we transform (4) using V to obtain

$$VM = VZ\gamma + V\Phi + V\epsilon, \tag{5}$$

where by construction the transformed errors are homoscedastic. Thus (5) can be estimated using ordinary least squares (OLS).[7]

Since the procedure arrives at a single estimate of ϕ_h for each h using KT estimates of μ_{ht}^k, we have in essence performed an aggregation of the estimates, where the covariance matrix $\hat{W}$ is used as weights in the aggregation. We thus called the resulting estimates of ϕ_h the aggregated risk-adjusted mortality rates (ARAMRs).

[6]The effect of time can be accounted for in the stage 2 regression below.

[7]Note that the equation is estimated without a constant term.

3 Data

The data are extracted from the Victorian Admitted Episode Dataset (VAED), a data set of admitted patient episodes reported by all public and private acute hospitals in the state of Victoria, Australia. The data set comprises demographic, clinical and administrative details for all admitted episodes of care occurring in Victorian acute hospitals. The hospital admission data were linked to the death registry via a statistical linking process developed by the Victorian Department of Human Services. Note that the data we use are de-identified with randomly assigned patient and hospital identifiers. We also affix the Australian Bureau of Statistics Socio-Economic Indexes for Areas (SEIFA) to the data by using the postcode information in the data.[8] The data set contains more than one million observations per year; not only it is computationally expensive to make use of all data in the estimation, it is also impossible to account for the high degree of heterogeneity. For our estimation, we restrict the sample to a single Major Diagnostic Categories (MDC)—MDC05 (Diseases and Disorders of the Circulatory System)—using the Australian Refined Diagnosis Related Group (AR-DRG) Classification.[9]

A major difficulty in measuring outcomes across hospitals is the issue of self selection—patients are likely to select hospitals based on the advice of their doctors and in consideration of the complexity and severity of their conditions and the hospital's reputation. Thus hospitals that are highly regarded may attract a disproportionately large number of patients with severe conditions. Mindful of this self-selection problem, we construct the sample such that

[8]SEIFA indexes consist of four different summary measures constructed from a number of variables that represent different aspects of relative socio-economic standing of residents in a geographic area. The four measures are: Index of Relative Socio-economic Disadvantage, Index of Relative Socio-economic Advantage and Disadvantage, Index of Economic Resources (IER) and Index of Education and Occupation. See ABS (2006) for details.

[9]The AR-DRG is a classification system that groups hospital episodes into clinically meaningful categories of similar levels of complexity that consume similar amounts of hospital resources. In total there are more than 400 Diagnostic Related Groups (DRGs), broadly classified into 25 Major Diagnostic Categories. In principle each hospital stay is assigned one DRG and the assignment takes into account diagnoses, medical procedures performed, patient age and sex, length of stay and other relevant factors that affect the complexity of the episode.

only relatively homogenous episodes are retained. We select the sample using the following steps.

1. We restrict the episodes to 45 four-digit DRGs in MDC05, where to the best that we can determine, these DRGs represent relatively homogenous groups of patients. The DRGs that we retain are those that end with the character code "A", "B" or "C"; those ending with the character code "Z" are omitted from the data, as the latter are often catch-all groups containing non-homogenous episodes that tend to be re-classified into other groups over time. A complete list of DRGs with the number of episodes in the sample is presented in Table A2 in Appendix A.
2. We further restrict the sample to episodes for which the patients were diagnosed to have heart disease. We identify a patient as a heart-disease patient if his or her diagnosis fields (up to 40 diagnoses were recorded in the VAED) contain one or more of the following ICD-10 codes: I05-I09 (Chronic rheumatic heart diseases), I10-I15 (Hypertensive diseases), I20-I25 (Ischaemic heart diseases), I26-I28 (Pulmonary heart disease and diseases of pulmonary circulation), and I30-I52 (Other forms of heart disease). In addition, we also identify episodes for which the patients were first diagnosed to have heart disease and included this variable as a dummy variable in the first stage regression.

In addition to restricting the sample, we also make use of several variables to account for the severity of the patient's conditions in each episode.

1. We identify the principal diagnosis of each episode and include this information as dummy variables in the estimation. The principal diagnosis of each episode is identified using the ICD-10 diagnosis code in the first diagnosis field. Approximately 92 per cent of the episodes in the sample were identified to have one of 18 ICD-10 codes as principal diagnoses. The remaining 8 per cent were episodes that have other ICD-10 codes as principal diagnoses and were classified to have "other principal diagnoses." A complete listing of the principal diagnoses is presented in Table A1 in Appendix A.
2. We construct the Charlson comorbidity index (Charlson et al., 1987) to measure comor-

bid disease status in an episode of care. The index is a good indicator of the complexity of an episode and is a strong predictor of mortality. We compute the Charlson index by making use of the diagnosis information coded in ICD-10 codes in the data and follow the method outlined in Sundararajana et al. (2004).

3. We identify whether an episode represents the first time that the patient was diagnosed to have heart disease by making use of admission episode data dating back to 1996/97. We also identify whether the patient was admitted through the emergency department.
4. Lastly, we also make use of patient characteristics to account for severity; variables that are used include age, gender and marital status.

The following criteria are used in constructing the sample from the administrative data. First, we restrict the sample to a single Major Diagnostic Categories, MDC05 (Diseases and Disorders of the Circulatory System), under the Australian Refined Diagnosis Related Group (AR-DRG) Classification. Second, we identify 48 Diagnosis Related Groups (DRGs) under the AR-DRG Classification. These DRGs are used to construct dummy variables in the episode-level regression. Third, we restrict the episodes in the sample to heart-related disease by using the ICD-10 diagnosis codes[10] so that only patients who are diagnosed to have heart disease are included. Lastly, we identify 19 principal diagnoses via the ICD-10 diagnosis fields. These principal diagnoses are used as dummy variables in controlling the severity of patients' conditions. Lastly, we account for the complexity and severity of patient conditions by making use of information on comorbidities and age.

To create a balanced panel of hospitals for the five financial years (2000/01 to 2004/05), we remove hospitals that have no observations for one or more year and the associated episodes from the sample.

The above process identifies a total of 510,765 episodes over five financial years from 2000/01 to 2004/05. However, a difficulty arises in accounting for episodes in which patients transfer

[10]The International Classification of Diseases and Related Health Problems, 10th revision. Australian Modification (ICD-10-AM). Sydney: National Centre for Classification in Health, University of Sydney, 2000.

Table 1: Episodes of care by financial years

Financial year	Episodes	Per cent	Mortality rates in-hospital	30 days	90 days	360 days
2000/01	76,130	18.2	0.030	0.052	0.082	0.153
2001/02	79,965	19.1	0.035	0.059	0.091	0.172
2002/03	83,536	20.0	0.032	0.058	0.091	0.177
2003/04	86,693	20.7	0.044	0.069	0.101	0.185
2004/05	91,898	22.0	0.037	0.060	0.093	0.127
All years	418,222	100.0	0.036	0.060	0.092	0.162

from one hospital to another. It is somewhat arbitrary to attribute patient outcomes to any hospital involved in the transfer. To avoid this problem, we identify 91,687 episodes that involve multiple hospital transfers and remove them from the sample.[11] Lastly, we also remove hospitals that registered fewer than 100 episodes in total over five years from the sample; the removal of these hospitals result in the deletion of further 856 episodes. The final sample thus contains 418,222 inpatient episodes of care handled by 146 hospitals over five financial years.

The patient mortality outcomes are in-hospital death, death within 30 days, 90 days and 360 days of separation from the hospital. Table 1 provides a breakdown of the episode counts and mortality rates over the years. As shown in Table 1, the yearly number of separations range from 76,130 in 2000/01 to 91,898 in 2004/05. In-hospital mortality rates and mortality rates within 30 days, 90 days and 360 days of separation averaged respectively 3.6 per cent, 6.0 per cent, 9.2 per cent and 16.2 per cent. These rates were stable over the years, except for the 360-day mortality which in 2004/05 registered a noticeable decline.

The 146 hospitals in the sample can be grouped into eight hospital types according to the classification scheme adopted by the Victorian Department of Human Services. We also make use of a second classification which is by ownership—hospitals in the sample are classified as public and non-public hospitals, the latter include both for-profit and not-for-profit hospi-

[11] We also implemented an alternative of assigning outcomes to the hospital in which the patient stay for the longest duration. Results were similar in terms of the regression coefficients for both stages one and two and also for the final quality performance estimates. Appendix B, available upon request from the authors, presents a summary of the results.

Table 2: Hospitals and episodes of care by hospital types

Hospital type	Hospitals		Sample episodes	
	Number	Per cent	Number	Per cent
A1 Large Teaching	8	5.3	116,468	26.4
A2 Other Teaching	10	7.1	95,776	22.9
B Large Regional Base & Suburban	21	14.4	69,572	16.2
C Regional General Hospitals	14	9.6	13,412	3.2
D Area Hospitals	22	15.2	14,309	3.5
E Local Hospitals	15	10.6	3,312	1.1
M Multi Purpose Services	4	2.9	1,795	0.4
Z Ungrouped Agencies*	51	34.8	103,578	26.3
Public hospitals	104	71.2	316,207	75.6
Non-public hospitals	42	28.8	102,015	24.4
Total	146	100.0	418,222	100.0

*Included in Ungrouped agencies are mostly non-public hospitals.

tals.[12] Table 2 presents the number of sample episodes handled by different types of hospitals. Not surprisingly, large teaching hospitals, although few in number, handle the most number of episodes of care in our sample. Ungrouped agencies, which include mostly non-public hospitals, consist of the highest number of hospitals and together handle almost the same number of episodes of care as large teaching hospitals. Table 2 also shows that public hospitals account for approximately 71 per cent of all hospitals in Victoria and approximately three-quarter of all episodes of care in our sample during the five year period.

Table 3 presents some statistics on patient characteristics, these variables appear in the stage one episode-level regression from which RAMRs are derived. We distinguish three types of variables, namely variables denoting medical conditions, insurance status and personal characteristics.

The Charlson comorbidity index is used as an indicator of the complexity, and hence severity, of patients' conditions.[13] From this index, two further related variables are derived, the first

[12] Since we are not able to identify the non-public hospitals, we are not able to separate for-profit from not-for-profit hospitals among the non-public hospitals.

[13] Strictly speaking, the complexity of a patient's condition is distinct from its severity. Charlson comorbidity index measures the complication that was brought about by other diseases that the patient may have. It does,

is an indicator of no comorbidity, which is a binary variable taking the value of unity if the Charlson index is zero. The second indicator is also a binary variable with a value of one indicating the presence of high comorbidities, i.e., the Charlson index is above 6 in value. Table 3 shows that the Charlson index is highly skewed, almost 47 per cent of the episodes have no comorbidity, and only about 2 per cent of the episodes have high comorbidities.

Table 3: Patient characteristics of episodes of care

Variable	Mean / Prop.	Std. dev.
Medical conditions		
Charlson comorbidity index	1.1022	1.5464
No comorbidity (Charlson index $= 0$)	0.4684	0.4990
High comorbidity (Charlson index ≥ 6)	0.0216	0.1452
First-time heart disease diagnosis	0.5625	0.4961
Emergency department admission	0.6082	0.4882
Same-day separation	0.2026	0.4020
Hospital Insurance status		
With private hospital insurance	0.3047	0.4603
Private insurance billing account	0.2469	0.4312
DVA billing account	0.0946	0.2927
Personal characteristics		
Age	70.6	14.5
Male	0.5500	0.4975
Married	0.5702	0.4951
Divorced	0.0657	0.2477
Australian born	0.6284	0.4832

In addition to comorbidities, other characteristics related to patient conditions are whether the patient was diagnosed to have heart disease for the first time, whether it was an emergency department admission, and whether it was a same-day separation, i.e., admission and separation occurs on the same day.[14] An episode is a first-time heart disease episode if the patient was not diagnosed to have heart disease in the patient's prior hospitalization records dating

however, capture some aspect of severity in the sense that, other things equal, a patient with high number of comorbidities will be more difficult to treat than one without any comorbidity.

[14]To be sure, the empirical specification omits some important factors. The impact of primary care, ambulance response and emergency department care are important factors that may play an important role in explaining mortality rates, but until we have data linking hospital episodes with outpatient and emergency department care, we can only delegate these factors to the error terms of the model.

back to 1996/97. Table 3 shows that the sample consists of approximately 56 per cent first-time heart disease patients, about 61 per cent of all episodes were admitted via the emergency department, and about 20 per cent were same-day separation.

On hospital insurance status, Table 3 shows that about 30 per cent of patients in the sample declared to have private hospital insurance. However, not all patients with private insurance elected to bill their private insurance funds; of the 30 per cent who had private insurance, 25 per cent chose to do so.[15] There is also a small proportion of about 9 per cent of patients who had Department of Veteran Affairs (DVA) insurance and billed the DVA for their hospital stays.

On personal characteristics of patients, the sample contains approximately 55 per cent male patients. Table 3 shows that 57 per cent of the patients were married, 6 per cent were divorced, and the others were single. Further, about 63 per cent of all patients in the sample were Australian born.

4 Results

We perform the stage-one episode-level SUR estimation year by year. Included in the regressions are a set of hospital dummy variables, one for each hospital in the sample. Since we include all hospital dummies in the estimation, the SUR equations are estimated without a constant term. Thus the coefficient estimates on these hospital dummies are absolute rather than relative levels. We interpret these coefficient estimates as hospitals' risk-adjusted mortality rates (RAMRs), a summary of which is presented in Table 4. The year-by-year SUR coefficient estimates are presented in Table A3 in Appendix A.

The RAMRs presented in Table 4 are on average loosely tracking the unadjusted mortality rates, although there appears to be large fluctuations both within and across financial years.

[15] It is also possible that, for various reasons, some patients chose not to declare their private insurance status when admitted as public patients in public hospitals.

Table 4: Risk-adjusted mortality rates by financial years

Financial year	Risk-adjusted mortality rates							
	In-hospital		30 days		90 days		360 days	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
2000/01	0.064	0.0681	0.085	0.0802	0.108	0.0747	0.208	0.1042
2001/02	0.023	0.0837	0.058	0.0815	0.048	0.0903	0.114	0.1093
2002/03	0.067	0.1278	0.072	0.1343	0.128	0.1396	0.135	0.1240
2003/04	0.148	0.1040	0.131	0.1025	0.188	0.1065	0.239	0.1288
2004/05	0.019	0.1150	-0.017	0.1309	0.030	0.1291	0.015	0.1248
All years	0.064	0.1118	0.066	0.1183	0.100	0.1243	0.142	0.1419

Table 5: Risk-adjusted mortality rates by hospital types

Hospital type	Risk-adjusted mortality rates							
	In-hospital		30 days		90 days		360 days	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
A1 Large Teaching Hospitals	0.026	0.0534	0.028	0.0729	0.061	0.0852	0.112	0.1090
A2 Other Teaching Hospitals	0.044	0.0565	0.044	0.0553	0.080	0.0636	0.131	0.1108
B Large Regional Base & Suburban	0.075	0.1476	0.068	0.1402	0.102	0.1335	0.145	0.1293
C Regional General Hospitals	0.065	0.0792	0.075	0.0976	0.111	0.1021	0.158	0.1184
D Area Hospitals	0.051	0.0537	0.056	0.0669	0.095	0.0767	0.132	0.1090
E Local Hospitals	0.042	0.0656	0.053	0.1012	0.094	0.1271	0.131	0.1500
M Multi Purpose Services	0.061	0.0579	0.070	0.0662	0.108	0.0735	0.155	0.1057
Z Un-grouped Agencies#	0.083	0.1433	0.080	0.1489	0.111	0.1552	0.151	0.1726
All hospitals	0.064	0.1118	0.066	0.1183	0.100	0.1243	0.142	0.1419

#Ungrouped agencies mostly include non-public hospitals.

The notable decline of the unadjusted 360-day mortality rates in 2004/05 is also reflected in the RAMRs, although the decline is now across all adjusted measures. Table 5 further summarizes RAMRs by hospital types. Among the different groups of hospitals, large teaching hospitals have the lowest average RAMRs in all four adjusted mortality measures, while large regional and ungrouped agencies tend to have higher average RAMRs than other hospital groups.

To perform the stage-two hospital-level weighted regression, we extract the RAMRs and their covariance matrix from the stage-one SUR estimation in order to perform the stage-two weighted least squares estimation. The coefficient estimates of the weighted least squares are presented in Table 6. We have only made use of the year dummy variables in aggregating the RAMRs, variables denoting hospital characteristics are not used in the aggregation since

Table 6: Stage two hospital-level regression

Independent Variable	Coefficient estimate	Standard error
Year 2 (dummy, 1 = 2001/02)	-.0307**	.0032
Year 3 (dummy, 1 = 2002/03)	-.0063**	.0031
Year 4 (dummy, 1 = 2003/04)	.0817**	.0031
Year 5 (dummy, 1 = 2004/05)	-.0569**	.0030
N	2,920	
R^2	0.380	

Note: included in the regression are dummy variables denoting the 146 hospitals in the sample.
The R^2 value is computed using the untransformed values of the dependent and independent variables.
**: significant at 1% level

we want to relate the resulting aggregated mortality rates to hospital characteristics.[16]

Given that there are four mortality measures observed over five years for each hospital, we thus have 20 observations per hospital and in total we have 2,920 hospital-level mortality outcome estimates. We interpret the coefficient estimates for the hospital dummies as a measure of hospitals' quality performance and we refer to this measure as the two-stage aggregated risk-adjusted mortality rates (ARAMRs).

Table 7 summarizes the two-stage ARAMRs by hospital types. Ungrouped agencies, which are a mixed group consisting of mostly non-public hospitals and health-care facilities, register the highest average value of ARAMRs at 8.6 per cent; they are followed by large regional and suburban hospitals, whose average ARAMRs value stands at 7.1 per cent. However, the standard deviations of both groups of hospitals are also large, suggesting that large variations in ARAMRs exist between hospitals in these two groups. At the other extreme, other teaching hospitals and local hospitals have had the lowest average ARAMRs at respectively 2.6 per cent and 3.2 per cent; and not far behind is large teaching hospital with an average ARAMRs of 3.3 per cent.

Based on the two-stage ARAMR estimates, we are able to construct a ranking of hospitals—

[16]See Table 9 below.

Table 7: Two-stage aggregated risk-adjusted mortality rates by hospital types

Hospital type	mean	std. dev.	min	max
A1 Large Teaching	0.0333	0.0227	-0.0173	0.0522
A2 Other Teaching	0.0263	0.0574	-0.1360	0.0569
B Large Regional & Suburban	0.0705	0.1410	-0.0821	0.6535
C Regional General Hospitals	0.0640	0.0241	0.0424	0.1389
D Area Hospitals	0.0539	0.0143	0.0293	0.0880
E Local Hospitals	0.0319	0.0388	-0.0486	0.1196
M Multi Purpose Services	0.0598	0.0165	0.0472	0.0841
Z Ungrouped Agencies	0.0857	0.1191	0.0074	0.6573
All hospitals	0.0634	0.0922	-0.1360	0.6573

Note: standard deviations measure the dispersion of the computed ARAMRs.

the best performing hospital is ranked 1 and the worst is ranked 146. Table 8 presents the average ranks and a summary of the top and bottom 25 hospitals according to the ARAMR ranking. The percentage figures are computed with the total number of hospitals in the respective group as the denominator. As expected, large teaching hospitals perform well in the ranking, with the lowest average rank of 52.1 and 37.5 per cent are ranked in the top 25. Local hospitals also perform well with an average rank of 49.1 and 33 per cent of the hospitals ranked in the top 25. In terms of average ranks, regional general hospitals and multi purpose services are the two worst performing groups. However, looking at the bottom 25 hospitals, we find ungrouped agencies to be the worse performer with 30.8 per cent of the hospitals in this group among the bottom 25. It should, however, be noted that ungrouped agencies are well represented in both the top and bottom 25 hospitals, suggesting a high degree heterogeneity among hospitals in this group. In terms of hospital ownership, public hospitals have an average rank of 78.4, as compared to 61.4 of non-public hospitals. Public hospitals also do not perform as well in terms of the top 25 hospitals, only 12.5 per cent of public hospitals are ranked in the top 25, compared to 28.6 per cent of non-public hospitals. However, there are proportionately fewer public hospitals among the bottom 25 hospitals—16.3 per cent of public hospitals are found in the bottom 25, compared to 19 per cent of non-public hospitals.

We next relate the ARAMRs to hospital characteristics, which are constructed using data of

Table 8: Hospital rankings by aggregated risk-adjusted mortality rates

Hospital type	Total numb.	Average rank	Top 25 Numb.	Top 25 Within group Per cent	Bottom 25 Numb.	Bottom 25 Within group Per cent
A1 Large Teaching	8	52.1	3	37.5	0	0.0
A2 Other Teaching	10	60.3	1	10.0	0	0.0
B Large Regional & Suburban	20	67.6	2	10.0	2	10.0
C Regional General Hospitals	14	101.4	0	0.0	3	21.4
D Area Hospitals	23	88.6	1	4.3	2	8.7
E Local Hospitals	15	49.1	5	33.3	1	6.7
M Multi Purpose Services	4	100.3	0	0.0	1	25.0
Z Ungrouped Agencies	52	72.4	13	25.0	16	30.8
Public hospitals	104	78.4	13	12.5	17	16.3
Non-public hospitals	42	61.4	12	28.6	8	19.0

all episodes handled by the hospitals in the sample over the five year period. The hospital characteristics are: hospital size, as measured by the total number of episodes handled by the hospital over the five year period, proportion of heart-disease episodes to all episodes, proportion of episodes with high Charlson index to all episodes, proportion of episodes for which the patients were 86 years old or older, and proportion of episodes for which patients had private hospital insurance to all episodes. We also group the hospitals into five groups, namely teaching hospitals, large regional hospitals, area hospitals, local hospitals and others. However, since hospital groups and size are highly correlated, we do not include both sets of variables in a single regression. Instead, we estimate two regression models, the first model includes hospital group dummies but not hospital size, while the second replace the hospital group dummies with hospital size variable. Both regression models were estimated with weighted least squares, where the weights are formed using the variance-covariance matrix of the ARAMRs. Table 9 presents the estimation results.

The coefficient estimates of both regression models are within expectations. The results of Model I show that teaching hospitals and large regional hospitals tend to have lower ARARMs than other hospitals. The results of Model II further show that larger hospitals have lower ARARMs than smaller hospitals. Taken together, these two results suggest that teaching hospitals and large regional hospitals perform better than other hospitals, and this superior perfor-

Table 9: Aggregated risk-adjusted mortality rates and hospital characteristics

Dependent variable: ARAMRs				
	Regression I		Regression II	
Indep. variables	Coeff.	Std. err.	Coeff.	Std. err.
Total episodes of care handled	–	–	-5.2$\times 10^{-8*}$	2.6$\times 10^{-8}$
Proportion heart-disease episodes	-0.0690	0.0485	-0.0865†	0.0474
Proportion episodes via emergency admissions	-0.0374†	0.0217	-0.0406*	0.0205
Proportion episodes with high Charlson index	0.2703**	0.0600	0.2271**	0.0593
Proportion patients aged 86 or older	0.3347**	0.0918	0.3614**	0.0804
Proportion privately insured patients	-0.0466**	0.0150	-0.0264**	0.0095
Dummy: teaching hospitals	-0.0230*	0.0112	–	–
Dummy: large regional hospitals	-0.0226*	0.0112	–	–
Dummy: area hospitals	-0.0125	0.0151	–	–
Dummy: local hospitals	-0.0284	0.0248	–	–
Constant	0.0676**	0.0137	0.0563**	0.0102
R^2	0.213		0.180	
Number observations	146		146	

Note: The R^2 values are computed using the untransformed values of the dependent and independent variables.
Significance levels: †: 10% *: 5% **: 1%

mance is positively related to size—there exists a size advantage so far as their mortality-based quality performance is concerned.

Table 9 also shows that the proportion of episodes for which patients are privately insured is associated with lower ARARMs and this relationship is highly statistically significant in both models. Hospitals with a larger proportion of privately insured patients tend to have lower mortality following hospitalisation for cardiac events. However, it is not possible to pinpoint factors that are responsible for this result. We offer four conjectures which will be investigated in follow-up studies. Firstly, perhaps privately insured patients are healthier than non-insured patients to begin with. This better health of private patients could be income related since it is known that private health insurance take-up in Australia is closely linked to income (Palangkaraya and Yong, 2005; Palangkaraya et al., 2008). Secondly, privately insured patients may receive more treatment than patients without private insurance. These treatments could take the form of, for example, expensive technologies and newer drugs.[17]

[17]In a study using Victorian hospital data, Robertson and Richardson (2000) show that AMI patients were more likely to undergo more invasive procedures in private hospitals.

Thirdly, perhaps an increased proportion of private patients is related to an incentive structure closely tied to hospital ownership—hospitals with disproportionately more private patients are likely to be non-public hospitals and these hospitals may have greater incentives to provide higher intensity of care.[18] Lastly, patients who use their private insurance may be cared for by the same specialist in the hospital and outpatient setting, leading to greater continuity of care, which is known to result in better health outcomes.

5 Conclusion

This paper proposes a method of deriving an indicator for hospitals' quality performance using several mortality outcome measures observed over a number of years. The method is implemented using hospital administrative records from the state of Victoria, Australia. Four mortality outcome measures are used: in-hospital death, death within 30 days, 90 days, and 360 days of separation. A two-stage estimation procedure yields a performance estimate for each of the 146 hospitals in the sample. This estimate is used to assess the quality performance of different groups of hospitals. We find that teaching hospitals and large regional hospitals tend to perform better than other hospitals, and this superior performance is related to hospital size.

We emphasize that the ranking of hospitals is based on a single quality dimension, namely mortality. It does not provide a complete picture of the quality performance of hospitals. To do so one would not only need information on other outcome measures such as readmissions, but also on process measures that are clinically based (Romano and Mutter, 2004). A possible extension to our work is to further restrict the sample to patients with a particular condition such as Acute Myocardial Infarction (or heart attack). Doing so will further alleviate the consequence of self selection. In addition, as argued by Mukamel et al. (2002), hospitals have different areas of expertise and their competency in treating one condition may reveal little

[18] See, for example, Harper et al. (2000).

about their competency in treating another. For this reason it may be desirable to provide quality performance rankings for hospital treatment of different conditions.

Appendix A

Table A1: Sample distribution of principal diagnoses by ICD-10 codes

ICD-10 diagnosis	Freq.	%	ICD-10 definition
E11	9,821	2.35	Non-insulin-dependent diabetes mellitus
I10	9,453	2.26	Essential (primary) hypertension
I20	84,019	20.09	Angina pectoris
I21	34,456	8.24	Acute myocardial infarction
I25	22,176	5.30	Chronic ischaemic heart disease
I35	6,750	1.61	Nonrheumatic aortic valve disorders
I47	11,618	2.78	Paroxysmal tachycardia
I48	46,721	11.17	Atrial fibrillation and flutter
I49	4,745	1.13	Other cardiac arrhythmias
I50	76,110	18.20	Heart failure
I70	13,739	3.29	Atherosclerosis
I71	5,041	1.21	Aortic aneurysm and dissection
I80	6,810	1.63	Phlebitis and thrombophlebitis
I95	7,437	1.78	Hypotension
R00	4,915	1.18	Abnormalities of heart beat
R07	7,261	1.74	Pain in throat and chest
R55	21,583	5.16	Syncope and collapse
T82	13,003	3.11	Complications of cardiac & vascular prosthetic devices, implants & grafts
Others	32,564	7.79	Other ICD-10 diagnosis codes not listed above
Total	418,222	100.00	

Note: VAED data contain up to 40 diagnosis fields, primary diagnoses are marked with a prefix “P” and recorded as the first diagnosis field, although in some cases a patient may have two or more primary diagnoses. The primary diagnoses presented in this table and elsewhere in the paper are those recorded in the first diagnosis field.

Table A2: Sample distribution of DRGs

DRG	Freq.	%	DRG definition
F04A	4,981	1.19	Cardiac Valve Proc W CPB Pump W/O Invasive Cardiac Inves W Cat CC
F04B	1,384	0.33	Cardiac Valve Proc W CPB Pump W/O Invasive Cardiac Inves W/O Cat CC
F05A	2,404	0.57	Coronary Bypass W Invasive Cardiac Inves W Catastrophic CC
F05B	1,637	0.39	Coronary Bypass W Invasive Cardiac Inves W/O Catastrophic CC
F06A	10,262	2.45	Coronary Bypass W/O Invasive Cardiac Inves W Catastrophic or Severe CC
F06B	2,515	0.60	Coronary Bypass W/O Invasive Cardiac Inves W/O Catastrophic or Severe CC
F08A	3,737	0.89	Major Reconstruct Vascular Procedures W/O CPB Pump W Catastrophic CC
F08B	5,292	1.27	Major Reconstruct Vascular Procedures W/O CPB Pump W/O Catastrophic CC
F11A	861	0.21	Amputation for Circ System Except Upper Limb and Toe W Catastrophic CC
F11B	478	0.11	Amputation for Circ System Except Upper Limb and Toe W/O Catastrophic CC
F14A	2,557	0.61	Vascular Procs Except Major Reconstruction W/O CPB Pump W Cat CC
F14B	3,335	0.80	Vascular Procs Except Major Reconstruction W/O CPB Pump W Sev CC
F14C	9,556	2.28	Vascular Procs Except Major Reconstruction W/O CPB Pump W/O Cat or Sev CC
F21A	2,504	0.60	Other Circulatory System O.R. Procedures W Catastrophic CC
F21B	2,029	0.49	Other Circulatory System O.R. Procedures W/O Catastrophic CC
F41A	2,889	0.69	Circ. Disorders W AMI W Invasive Cardiac Inves Proc W Cat or Sev CC
F41B	3,538	0.85	Circ. Disorders W AMI W Invasive Cardiac Inves Proc W/O Cat or Sev CC
F42A	16,582	3.96	Circ. Disorders W/O AMI W Invasive Cardiac Inves Proc W Complex DX/Pr
F42B	38,957	9.31	Circ. Disorders W/O AMI W Invasive Cardiac Inves Proc W/O Complex DX/Pr
F60A	11,688	2.79	Circ. Disorders W AMI W/O Invasive Cardiac Inves Proc W Cat or Sev CC
F60B	11,299	2.70	Circ. Disorders W AMI W/O Invasive Cardiac Inves Proc W/O Cat or Sev CC
F60C	3,193	0.76	Circ. Disorders W AMI W/O Invasive Cardiac Inves Proc, Died
F62A	21,707	5.19	Heart Failure and Shock W Catastrophic CC
F62B	53,381	12.76	Heart Failure and Shock W/O Catastrophic CC
F63A	2,106	0.50	Venous Thrombosis W Catastrophic or Severe CC
F63B	4,871	1.16	Venous Thrombosis W/O Catastrophic or Severe CC
F65A	4,151	0.99	Peripheral Vascular Disorders W Catastrophic or Severe CC
F65B	12,268	2.93	Peripheral Vascular Disorders W/O Catastrophic or Severe CC
F66A	7,215	1.73	Coronary Atherosclerosis W CC
F66B	15,410	3.68	Coronary Atherosclerosis W/O CC
F67A	3,465	0.83	Hypertension W CC
F67B	6,147	1.47	Hypertension W/O CC
F69A	944	0.23	Valvular Disorders W Catastrophic or Severe CC
F69B	5,696	1.36	Valvular Disorders W/O Catastrophic or Severe CC
F70A	1,638	0.39	Major Arrhythmia and Cardiac Arrest W Catastrophic or Severe CC
F70B	3,339	0.80	Major Arrhythmia and Cardiac Arrest W/O Catastrophic or Severe CC
F71A	11,449	2.74	Non-Major Arrhythmia and Conduction Disorders W Catastrophic or Severe CC
F71B	44,713	10.69	Non-Major Arrhythmia and Conduction Disorders W/O Catastrophic or Severe CC
F72A	7,978	1.91	Unstable Angina W Catastrophic or Severe CC
F72B	28,069	6.71	Unstable Angina W/O Catastrophic or Severe CC
F73A	6,899	1.65	Syncope and Collapse W Catastrophic or Severe CC
F73B	17,899	4.28	Syncope and Collapse W/O Catastrophic or Severe CC
F75A	2,364	0.57	Other Circulatory System Diagnoses W Catastrophic CC
F75B	4,031	0.96	Other Circulatory System Diagnoses W Severe CC
F75C	10,804	2.58	Other Circulatory System Diagnoses W/O Catastrophic or Severe CC
Total	418,222	100.00	

Table A3: Stage 1 SUR coefficient estimates and standard errors

Dep. variable:	In-hospital mortality		30-day mortality		90-day mortality		360-day mortality	
	Coeff. est.	Std. err.	Coeff. est.	Std. err.	Coeff. est.	Std. err.	Coeff. est.	Std. err.
2000/01								
Conditions								
Charlson index	0.0114**	0.0005	0.0190**	0.0007	0.0305**	0.0008	0.0470**	0.0011
Emergency admission	-0.0025	0.0017	-2.6×10^{-5}	0.0023	-0.0034	0.0029	0.0084*	0.0037
First heart diagnosis	-0.0005	0.0011	-0.0002	0.0015	-0.0064**	0.0019	-0.0318**	0.0024
Same-day separation	-0.0093**	0.0016	-0.0041†	0.0022	-0.0030	0.0027	0.0048	0.0035
ICU hours	0.0003**	3.3×10^{-5}	0.0002**	4.5×10^{-5}	0.0001	0.0001	-4.1×10^{-5}	0.0001
Length of stay	0.0001	0.0001	0.0003**	0.0001	0.0008**	0.0001	0.0018**	0.0001
Insurance status								
Privately insured	0.0020	0.0017	0.0034	0.0025	0.0043	0.0032	0.0033	0.0036
Private insurance billing	–		-0.0040	0.0026	-0.0051	0.0033	–	
DVA billing	-0.0015	0.0020	-0.0059*	0.0029	0.0035	0.0036	-0.0010	0.0044
Personal characteristics								
Age	-0.0029**	0.0003	-0.0046**	0.0003	-0.0072**	0.0004	-0.0110**	0.0006
$(\text{Age})^2$	2.9×10^{-5}**	2×10^{-6}	4.7×10^{-5}**	2.7×10^{-6}	0.0001**	3.4×10^{-6}	0.0001**	4.4×10^{-6}
Male	0.0032**	0.0012	0.0073**	0.0016	0.0157**	0.0020	0.0340**	0.0025
Married	0.0051**	0.0012	0.0092**	0.0017	0.0090**	0.0021	0.0070*	0.0028
Divorced	–		0.0027	0.0023	0.0199**	0.0034	0.0081†	0.0049
Australian born	-0.0005	0.0012	0.0057**	0.0016	0.0072**	0.0020	0.0090**	0.0026
Area characteristics								
ln(population)	0.0005	0.0006	-0.0021**	0.0006	–		-0.0006	0.0012
Disadvantage index	0.0151	0.0146	0.0270*	0.0106	–		-0.0410	0.0296
Educ.-occup. index	0.0048	0.0121	–		0.0038	0.0158	–	
Economic resource index	-0.0049	0.0154	–		0.0166	0.0200	0.0037	0.0326
N	76,130							
Degrees of freedom	900							
Log-likelihood	108,533.3							
2001/02								
Conditions								
Charlson index	0.0115**	0.0005	0.0187**	0.0006	0.0267**	0.0008	0.0451**	0.0010
Emergency admission	-0.0024	0.0018	0.0054*	0.0024	0.0073*	0.0029	0.0007	0.0038
First heart diagnosis	-0.0017	0.0012	-0.0065**	0.0015	-0.0109**	0.0019	-0.0291**	0.0025
Same-day separation	-0.0111**	0.0016	0.0017	0.0021	0.0028	0.0026	0.0019	0.0034
ICU hours	0.0002**	3.7×10^{-5}	0.0002**	4.9×10^{-5}	0.0001†	0.0001	4.1×10^{-5}	0.0001
Length of stay	-2×10^{-5}	0.0001	0.0005**	0.0001	0.0013**	0.0001	0.0017**	0.0001
Insurance status								
Privately insured	0.0102**	0.0017	0.0117**	0.0025	0.0101**	0.0031	0.0024	0.0035
Private insurance billing	–		-0.0018	0.0025	0.0024	0.0033	–	
DVA billing	-0.0015	0.0021	-0.0044	0.0029	-0.0101**	0.0036	-0.0113*	0.0045
Personal characteristics								
Age	-0.0028**	0.0003	-0.0042**	0.0003	-0.0062**	0.0004	-0.0107**	0.0006
$(\text{Age})^2$	2.8×10^{-5}**	2×10^{-6}	4.2×10^{-5}**	2.7×10^{-6}	0.0001**	3.3×10^{-6}	0.0001**	4.3×10^{-6}
Male	0.0026*	0.0012	0.0099**	0.0016	0.0217**	0.0020	0.0394**	0.0026
Married	0.0029*	0.0012	-0.0002	0.0017	0.0035	0.0021	0.0062*	0.0028
Divorced	–		-0.0019	0.0024	0.0009	0.0036	0.0152**	0.0051
Australian born	0.0082**	0.0013	0.0112**	0.0017	0.0142**	0.0021	0.0145**	0.0027
Area characteristics								
ln(population)	0.0018**	0.0006	0.0009	0.0006	–		0.0022†	0.0012
Disadvantage index	0.0146	0.0149	0.0168	0.0108	–		-0.0089	0.0305
Educ.-occup. index	-0.0035	0.0124	–		0.0026	0.0161	–	
Economic resource index	0.0145	0.0160	–		0.0454*	0.0204	0.0378	0.0337
N	79,965							
Degrees of freedom	900							
Log-likelihood	97,525.2							
2002/03								
Conditions								

continued on next page. . .

Dep. variable:	In-hospital mortality		30-day mortality		90-day mortality		360-day mortality	
	Coeff. est.	Std. err.	Coeff. est.	Std. err.	Coeff. est.	Std. err.	Coeff. est.	Std. err.
Charlson index	0.0080**	0.0004	0.0173**	0.0006	0.0280**	0.0008	0.0475**	0.0010
Emergency admission	0.0029†	0.0017	0.0110**	0.0023	0.0055†	0.0029	0.0117**	0.0037
First heart diagnosis	-0.0027*	0.0011	-0.0086**	0.0015	-0.0137**	0.0019	-0.0371**	0.0025
Same-day separation	-0.0095**	0.0015	-0.0014	0.0021	-0.0014	0.0026	0.0088**	0.0033
ICU hours	0.0002**	3.3×10^{-5}	0.0002**	4.5×10^{-5}	0.0002**	0.0001	0.0001	0.0001
Length of stay	0.0001†	0.0001	0.0012**	0.0001	0.0020**	0.0001	0.0027**	0.0002
Insurance status								
Privately insured	0.0036*	0.0016	0.0096**	0.0024	0.0097**	0.0030	0.0082*	0.0035
Private insurance billing	–		-0.0073**	0.0025	0.0102**	0.0032	–	
DVA billing	0.0019	0.0020	-0.0068*	0.0029	-0.0025	0.0036	-0.0232**	0.0044
Personal characteristics								
Age	-0.0029**	0.0002	-0.0047**	0.0003	-0.0067**	0.0004	-0.0100**	0.0005
$(\text{Age})^2$	2.8×10^{-5}**	1.9×10^{-6}	4.6×10^{-5}**	2.6×10^{-6}	0.0001**	3.2×10^{-6}	0.0001**	4.2×10^{-6}
Male	0.0040**	0.0011	0.0110**	0.0016	0.0175**	0.0019	0.0389**	0.0025
Married	0.0047**	0.0012	0.0071**	0.0017	0.0133**	0.0021	0.0069*	0.0028
Divorced	–		0.0030	0.0024	0.0146**	0.0035	0.0131**	0.0051
Australian born	0.0060**	0.0012	0.0095**	0.0016	0.0127**	0.0020	0.0181**	0.0026
Area characteristics								
ln(population)	0.0030**	0.0006	0.0039**	0.0006	–		0.0063**	0.0012
Disadvantage index	0.0110	0.0145	0.0096	0.0106	–		-0.0758*	0.0308
Educ.-occup. index	-0.0187	0.0121	–		-0.0634**	0.0159	–	-
Economic resource index	0.0129	0.0156	–		0.0334†	0.0200	0.0006	0.0336
N	83,536							
Degrees of freedom	900							
Log-likelihood	100,347							
2003/04								
Conditions								
Charlson index	0.0112**	0.0005	0.0171**	0.0006	0.0248**	0.0007	0.0355**	0.0010
Emergency admission	-0.0134**	0.0018	-0.0074**	0.0024	-0.0081**	0.0029	0.0012–	0.0037
First heart diagnosis	-0.0017	0.0012	-0.0001	0.0016	-0.0036†	0.0019	-0.0256**	0.0024
Same-day separation	-0.0087**	0.0016	0.0056**	0.0021	0.0077**	0.0026	0.0070*	0.0033
ICU hours	-0.0001	4.2×10^{-5}	-0.0002**	0.0001	-0.0002**	0.0001	-0.0006**	0.0001
Length of stay	0.0003**	0.0001	0.0017**	0.0001	0.0024**	0.0001	0.0031**	0.0002
Insurance status								
Privately insured	0.0034†	0.0017	0.0077**	0.0026	0.0203**	0.0032	0.0228**	0.0036
Private insurance billing	–		-0.0005	0.0025	-0.0098**	0.0032	–	
DVA billing	-0.0064**	0.0022	-0.0107**	0.0030	-0.0033	0.0037	-0.0034	0.0045
Personal characteristics								
Age	-0.0021**	0.0003	-0.0035**	0.0003	-0.0065**	0.0004	-0.0100**	0.0005
$(\text{Age})^2$	2.2×10^{-5}**	2×10^{-6}	3.8×10^{-5}**	2.6×10^{-6}	0.0001**	3.2×10^{-6}	0.0001**	4.2×10^{-6}
Male	0.0077**	0.0012	0.0095**	0.0016	0.0213**	0.0019	0.0438**	0.0025
Married	-0.0084**	0.0013	-0.0058**	0.0017	-0.0003	0.0021	-0.0050†	0.0028
Divorced	–		-0.0006	0.0023	0.0051	0.0034	0.0068	0.0048
Australian born	0.0021	0.0013	0.0037*	0.0017	0.0018	0.0020	0.0008	0.0026
Area characteristics								
ln(population)	-0.0032**	0.0006	-0.0019**	0.0006	–		0.0041**	0.0012
Disadvantage index	-0.0523**	0.0154	0.0007	0.0109	–		0.1176**	0.0302
Educ.-occup. index	-0.0248*	0.0125	–		0.0286†	0.0156	–	
Economic resource index	0.0576**	0.0159	–		-0.0205	0.0197	-0.2040**	0.0331
N	86,693							
Degrees of freedom	900							
Log-likelihood	96,425.3							
2004/05								
Conditions								
Charlson index	0.0095**	0.0004	0.0158**	0.0005	0.0244**	0.0006	0.0286**	0.0007
Emergency admission	-0.0079**	0.0017	-0.0067**	0.0022	-0.0190**	0.0027	-0.0163**	0.0032
First heart diagnosis	-0.0011	0.0011	0.0015	0.0015	0.0059**	0.0018	-0.0067**	0.0021
Same-day separation	-0.0116**	0.0015	-0.0024	0.0019	-0.0040†	0.0024	-0.0112**	0.0027

continued on next page. . .

Dep. variable:	In-hospital mortality		30-day mortality		90-day mortality		360-day mortality	
	Coeff. est.	Std. err.	Coeff. est.	Std. err.	Coeff. est.	Std. err.	Coeff. est.	Std. err.
ICU hours	0.0007**	2.8×10^{-5}	0.0006**	3.7×10^{-5}	0.0005**	4.6×10^{-5}	0.0004**	0.0001
Length of stay	-0.0004**	0.0001	0.0002*	0.0001	0.0005**	0.0001	0.0005**	0.0001
Insurance status								
Privately insured	0.0086**	0.0015	0.0084**	0.0024	0.0124**	0.0028	0.0066*	0.0029
Private insurance billing	–		0.0056*	0.0023	-0.0063*	0.0025	–	
DVA billing	0.0040†	0.0021	-0.0009	0.0029	-0.0022–	0.0035	-0.0031	0.0040
Personal characteristics								
Age	-0.0029**	0.0002	-0.0043**	0.0003	-0.0053**	0.0004	-0.0064**	0.0005
$(\text{Age})^2$	3×10^{-5}**	1.9×10^{-6}	4.5×10^{-5}**	2.5×10^{-6}	0.0001**	3×10^{-6}	0.0001**	3.5×10^{-6}
Male	0.0039**	0.0011	0.0134**	0.0015	0.0140**	0.0018	0.0120**	0.0021
Married	-0.0015	0.0011	-0.0012	0.0016	-0.0009–	0.0020	0.0001–	0.0023
Divorced	–		-0.0005	0.0021	-0.0113**	0.0031	0.0102**	0.0038
Australian born	0.0020†	0.0012	0.0054**	0.0016	0.0107**	0.0019	0.0144**	0.0022
Area characteristics								
ln(population)	-0.0020**	0.0006	-0.0008	0.0006	–		0.0050**	0.0008
Disadvantage index	0.0227	0.0141	0.0809**	0.0101	–		0.1501**	0.0199
Educ.-occup. index	-0.0240*	0.0114	–		0.0514**	0.0125	–	
Economic resource index	0.0542**	0.0147	–		0.0362*	0.0172	-0.0816**	0.0237
N	91,898							
Degrees of freedom	900							
Log-likelihood	151,242.9							

Notes: 1. Included in each SUR estimation are dummies for each 45 DRGs, 19 principal diagnoses and 146 hospitals.
2. Insurance status of a patient is not necessarily identical to the billing account; a patient with private hospital insurance is permitted to choose to be billed as a public patient.
3. Significance levels: †: 10% *: 5% **: 1%

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