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Summary

This paper investigates whether there are differences in patient outcomes across different types of hospitals using patient-level data on re-admission and mortality associated with acute myocardial infarction (AMI). Hospitals are grouped according to their ownership status (private, teaching, non-teaching) and their location (metropolitan, country and remote country). Using data collected from 130 Victorian hospitals on 19,000 patients admitted to a hospital with their first AMI between January 2001 and December 2003, we consider how treatment affects the likelihood of various outcomes based on unplanned re-admission and mortality. A hazard rate model is used to assess the effect of hospital type on patient outcome. Control variables included in the estimating model are patient-level characteristics such as age, gender, co-morbidity, country of birth, and indigenous, marital and socio-economic status. We find that there are significant differences across hospital types in the outcomes observed for patients presenting with their first AMI – private hospitals persistently outperform teaching, non-teaching and country hospitals. Interestingly, we find that result is that the impact of hospital type is quite robust to the definition of "patient outcomes" that we adopt and our attribution strategy, but not to whether we include multiple-hospital patients.

Keywords mortality; acute myocardial infarction; hospital performance; hazard model

1 Introduction

A substantial empirical literature has emerged which examines variations in hospital performance. Although there are many ways to measure hospital performance, the most commonly used relate to patient outcomes following medical procedures (e.g. Aron *et al*. 1998), readmission rates (e.g. Cooper *et al.* 1999) or risk-adjusted in-hospital mortality rates (e.g. DesHarnais *et al.* 1988, Iezzoni *et al.* 1996).[1] The empirical evidence suggests that hospital performance is highly sensitive to the choice of outcome metric (McClellan and Staiger 1999). However, due to data constraints, most studies are able to evaluate hospital performance in terms of only one metric (e.g. in-hospital mortality) or another (e.g. hospital readmission) (Shen 2002 is a notable exception).

In this paper, we contribute to this literature on heterogeneity of hospital performance by examining the robustness of the relationship between hospital type and performance on a range of different performance measures and attribution assumptions.[2] Our ability to examine this relationship is aided by the availability of a dataset which links individual patients in Victoria, Australia with a range of outcomes including in-hospital mortality, unplanned hospital readmission, out-of hospital mortality and (right-censored) survival. We define performance in terms of *patient health* outcomes rather than *economic* outcomes, and we compare the performance of different *types* of hospitals rather than comparing performance of individual hospitals. For example, we examine whether performance varies across hospital status (private/public teaching/public non-teaching) and location (metropolitan/country/remote country).[3] We argue that public and private hospitals operate under different budget constraints and that private hospitals' access to high-tech equipment, innovative surgical techniques and costly treatments could be associated with observed differences in patient outcomes.

Like many studies on the relationship between hospital type and patient outcomes, we focus on one specific condition – acute myocardial infarction (AMI) – in order to minimise

[1] There is also a large literature examining the performance of hospitals in terms of economic indicators such as technical efficiency, productivity or profit margins (see Grosskopf and Valdmanis 1987; Ehreth 1994).
[2] Other studies have considered heterogeneity in the performance of the type of hospital (for example, see Baker *et al.* 2000).
[3] There is a mix of public, private and non-profit hospitals in Victoria (not all private hospitals are for-profit). There are also teaching hospitals, which are all public institutions.

the effects of selection bias (see Allison *et al.* 1999, Milcent 2005, Farsi and Ridder 2006). To control for patient history, our dataset only includes patients (19,000 observations) who presented with their *first* AMI in one of 130 Victorian hospitals during 2001 to 2003.[4] Since we know whether patients are transferred from one hospital to another hospital, we also consider the effect of different "attribution decisions" – that is, whether the patient outcome is attributed to the initial-admitting hospital, the final-treating hospital or whether multiple-hospital patients are excluded from the analysis.[5] All of our estimates are conditioned on the type of AMI, a set of patient-level characteristics, and a set of hospital-level characteristics such as its cardiac capacity, ownership status, teaching status, and location. Using these data, we estimate the likelihood of patient failure which we define six combinations of in-hospital and out-of-hospital mortality and/or unplanned AMI re-admission.

The paper is organized as follows: Section 2 synthesises previous research findings and presents the key empirical difficulties in examining the hospital-patient outcome relationship. In Section 3, we present the empirical model, while the data and variable construction are presented in Section 4. Following this, we analyse the results of the estimations in Section 5 and provide some conclusions in Section 6.

2 Background

Use of patient outcome data to assess hospital performance is becoming increasingly widespread as policymakers search for ways to evaluate quality of care. Our objective here is not to contribute to the debate on the merits of hospital report cards, but to examine the robustness of the relationship between patient outcomes and performance of different hospital types by taking an in-depth look at the performance of hospitals with respect to their treatment of AMI patients. Our analysis of hospital type performance, therefore, is not

[4] Any individuals we observe having an AMI in the years 2001-03 who have also had an AMI in the period 1996-2000 are removed from the analysis. In addition, we exclude all AMI admissions observed in the period 2001-03 which are classified as "planned".

[5] A "multiple-hospital patient" is someone who is either transferred from one hospital to another, or someone who has an initial AMI which is treated by Hospital A while a subsequent AMI is treated by Hospital B.

a comprehensive hospital-wide analysis of performance but rather a narrow analysis based on only one specific condition.[6]

A large variety of studies have used AMI outcomes to compare hospital types. Generally, the results support the conclusion that hospitals which are better equipped, have more specialists and higher patient volumes, are associated with better patient outcomes. In other words, hospital resources affect patient outcomes. Hospitals with more resources (or weaker budget constraints) are more likely to have successful patient outcomes, *ceteris paribus*. In addition, location has been shown to be an important determinant of patient outcomes. Metropolitan hospitals have largely been found to have higher survival rates following an AMI episode than rural hospitals (Vu *et al.* 2000).

Better outcomes were also related to differences in the processes of care, highlighted by the fact that metropolitan hospitals provide cardiac procedures significantly more often than rural hospitals (Heller *et al.* 2000). For-profit hospitals were found to have higher mortality rates than not-for-profit hospitals, and teaching hospitals had lower mortality than not-for-profit hospitals, but more generally, this was related to a strong negative relationship between volume and mortality (McClellan and Staiger 1999). Hospitals that were "top-ranked" (as defined by the *US News & World Report*) were also found to have lower mortality rates compared to not top-ranked, similarly equipped hospitals (Chen *et al.* 1999).

In Australia, there is a mixed healthcare system – that is, a private health care sector exists alongside the larger public health care sector. Consequently, patients can choose whether to be treated in public or private hospitals. If treated in the former as a public patient, all costs are covered by Medicare, Australia's publicly-funded universal health insurance scheme. If treated in a private hospital, patients need to either have private health insurance to cover their costs, or pay for their treatment out-of-pocket. Patients can also choose to be treated privately in a public hospital as well, in which case Medicare pays only part of the hospital stay, the rest being covered by private health insurance or out-of-pocket payments. The benefits of private health insurance include more choice, for example regarding the specialist patients want to see, and shorter waiting lists for some procedures.

[6] Hospital performance is difficult to generalize across all departments of a hospital, because, while one indicator (for example, outcomes of AMI patients) might predict high quality care, another (for example, hospital-acquired pneumonia) may not (Jha *et al.* 2005).

Specialists often work in both sectors; in the public sector they are paid by Medicare, while in the private sector they can charge their own (higher) fees.

Hospital status – private, public teaching, public non-teaching – is indicative of different budget constraints, administrative arrangements and the likely presence of economies of scope. Private hospitals, which may be either for-profit or not-for-profit, can access funding from several sources and are considered to be less financially constrained than public hospitals.[7] By contrast, public hospitals depend mainly on government grants. Private hospitals are administered as independent organisations while public hospitals are subject to an additional higher tier of ex-hospital administration. Teaching hospitals are more likely than non-teaching hospitals to offer a broad range of medical and surgical capabilities which affords them economies of scope. Other than these apparent differences, the three types of hospital may differ according to the quality of medical, nursing and general staff; the calibre of equipment; patient:staff ratios; patient:equipment ratios; and the use of costly new innovative surgical procedures.

In the following sections, we provide some background on the issues associated with empirical models including how the literature has treated important issues such as patient outcome measurement, selection bias, referral (or discharge) bias, attribution decisions, patient history and severity of AMI.

2.1 Selection bias

There are three reasons why we (and most other studies) focus specifically on one condition like AMI. First, it is important to consider single conditions because the relationship between mortality and covariates is disease-specific (Milcent 2005). Second, AMI is a commonly-observed condition whose treatment and outcomes are relatively easy to observe. Third, and perhaps more importantly, the effect of selection bias is minimised when using AMI data because patients require urgent attention and are thus normally taken to the nearest hospital. Other studies have also noted that the likelihood of selection bias is minimised when using AMI patients (Shen 2002).

[7] Public hospitals treating public patients are funded directly from state governments using a case-mix formula while private hospitals are funded through private health insurance companies and the government run Medicare scheme. Over and above this, private hospitals may charge patients a fee which is only limited by what the market will bear.

Although it is true that selection bias is minimised when using AMI patients, it is hard to rule out the fact that AMI severity is correlated with specific hospital types – such as large (or teaching) hospitals which may be more able to treat severe AMI cases – since some diagnosis is probably done in the ambulance on the way to the hospital and such diagnoses (and any in-field triage) are typically unobserved. For instance, anecdotal evidence suggests that ambulance officers may recognise when a patient is having a severe heart attack and bypass a small, private hospital and go straight to a larger, teaching hospital. To the extent that the hospital of first admission is non-random with respect to AMI severity, we most likely under-estimate the performance of large or teaching hospitals.

2.2 Outcome measurement

Like most health outcomes, measuring the outcomes of treatment for AMI is non-trivial (although it is easier for AMI than for many other conditions). Most studies in the literature focus on in-hospital mortality rates since such data is commonly available. However, it only captures short-term effects, much of which may be determined by severity of the AMI rather than by hospital-treatment effects. What is of more interest to doctors, epidemiologists and policymakers are the long-term effects of hospital treatment. Many studies using in-house mortality can conflate the effects of hospital-treatment with length of stay since serious patients may simply be transferred to other hospitals. One way around this problem is to collect (or estimate) out-of-hospital mortality (as done by Farsi and Ridder 2006), which provides a longer-term perspective depending on whether you analyse 30-day, 60-day, 90-day mortality or time-unrestricted mortality (that is, mortality at any time in the future).[8] Compounding this problem is the fact that use of mortality rates is a noisy indicator of hospital performance if it captures mortality through any event, rather than mortality due to AMI-related events.

A complementary outcome metric is readmission (or re-hospitalisation)[9] since poor initial treatment of an AMI may lead to a secondary AMI sometime in the future. Many of the same problems encountered in mortality indicators apply to readmission indicators. For instance, time is an important dimension of readmission indicators and it is common for

[8] Although Garnick *et al.* (1995) show that there is no difference between using 30-day and 180-day AMI mortality rates as an indicator of performance.

[9] See Cooper *et al.* (1999) for more on the complementarity between mortality and readmission to intensive care units.

researchers to focus on 14-day, 1-month, 3-month or 6-month readmission rates. Some studies use data on readmission for any condition (e.g. Farsi and Ridder 2006), while others focus on readmission for any cardiac-related complaint secondary AMI, angina and congestive heart failure (e.g. Tu *et al.* 2003). Most of these indicators have been widely used to compare provider quality (for example, by the Agency for Healthcare Research and Quality (AHRQ)) and have been statistically validated (across hospitals) in Scott *et al.* (2004).

2.3 Hospital attribution

In addition to problems associated with measuring outcomes, the relationship between hospital type and patient outcomes is complicated by the fact that patients are often treated by multiple hospitals. That is, an individual patient can have multiple episodes and be treated in a different hospital each time. Or a patient could have one episode but be treated by two hospitals (i.e. if they are transferred from one to the other). Any statistical analysis of the relationship between hospital and patient outcomes must account for these possibilities and have some way of attributing outcomes to a specific hospital.

There are three different approaches adopted in the literature: i) to attribute all outcomes to the initial-admitting hospital; ii) to drop all patients who enter more than one hospital; and iii) to attribute outcomes to the final-treating hospital. The most common approach is to attribute outcome to the initial-admitting hospital (see Shen 2002; Thiemann *et al.* 2000). The rationale for attributing all outcomes to the initial-admitting hospital is that most damage to the heart from an AMI is caused in the period immediately after the AMI occurs. Thus, the treatments and referrals given by the initial-admitting hospital are crucial and all subsequent outcomes may depend on this initial treatment. Attributing outcomes to the initial-admitting hospital effectively tests how successfully the hospital which first treated the patient dispensed timely and appropriate diagnoses and made effective referrals to other facilities for planned follow-up treatments.

One of the problems with attributing outcomes to the initial-admitting hospital is that poor treatments provided by a hospital several years after the initial AMI event are attributed to the initial-admitting hospital. Thus, the longer the time period between the first AMI and subsequent treatments by other hospitals, the noisier is the relationship between initial-admitting hospital performance and patient outcomes. This may suggest that attributing outcomes to the final-treating hospital is a better way to proceed. One obvious difficulty with this approach is that you must control for patient history.

Another approach which is often used in the literature is to exclude transferred patients from the analysis (Allison *et al.* 2000, Farsi and Ridder 2006). This avoids problems associated with how to treat patients who attend more than one hospital, but care must be given in case patients that are referred have different mortality rates from those that are not (the evidence presented by Thiemann *et al.* 2000 suggests that referred patients do have different mortality rates). This is particularly important in instances where outcome is measured by in-house mortality since it is possible that hospitals simply transfer patients who are chronically ill leading to a "referral" or "discharge" bias.

2.4 Therapeutic treatment

Another important issue is how to treat the administration of therapeutic drugs since there is much evidence suggesting that the use of beta blockers, aspirin or other forms of therapy administration improves AMI health outcomes (Heller *et al.* 2000; Vu *et al.* 2000; Lim *et al.* 1999). However, there is an issue as to whether the administration of therapeutic drugs is endogenous to the severity of the heart attack – perhaps less severe heart attacks are treated in this way and if so this may bias any mortality estimates. Other studies have treated the administration of drugs as exogenous and have accordingly included it as an explanatory variable in their regression analysis (see Allison *et al.* 2000). However, this is only justifiable if you can identify which patients were correctly administered the drugs and which weren't (Allison *et al*. 2000 attempt to address this issue using the approach of identifying "ideal candidates").

2.5 Other issues

There are a number of other issues that must be addressed in empirical estimations of the hospital-outcome relationship including:

i) *Age*. Patients above a certain age (say 95 years of age) are often excluded because of the likelihood of death no matter what the treatment (Farsi and Ridder 2006).

ii) *Insurance*. Patients below a certain age (say 65) are sometimes excluded because of the fact that those under 65 can be turned away from hospitals if they aren't insured. This is less of an issue in countries like Australia and France where there is comprehensive public insurance (Milcent 2005).

iii) *Patient history*. It is important to control for a patient's history in some way since the inclusion of patients who have had several previous AMIs would seriously bias any estimates of mortality rates. Very few studies filter out those patients who have previously had an AMI (Allison *et al.* 2000 is an exception).

iv) *Hospital size*. Some studies (e.g. Milcent 2005) exclude hospitals which do less than 30 AMIs per year, while other studies simply include a continuous variable to control for the effects of hospital volume, which Bach *et al.* (2001) have shown to be positively associated with survival rates.

v) *AMI severity*. This is difficult to measure directly but there is evidence that it is correlated with AMI type – for example, that subendocardial infarctions have the highest mortality rate. Patients who enter the emergency department and die within a few hours should be removed from the analysis on the grounds that the AMI is severe. However, few studies do this.

3 Empirical model

Our approach to modelling hospital type and patient outcomes addresses all of the issues raised above. Specifically, we include different measures of patient outcomes based on both in-hospital and out-of-hospital mortality and readmission, and we consider short-term (30-day mortality or 6-month readmission) and long-term (mortality or readmission at any future time) effects. We also consider a range of different attribution decisions in order to understand the sensitivity of our results to whether patient outcomes are attributed to the initial-admitting or final-treating hospital and whether multiple-hospital patients are included. Although we can't directly control for selection bias effects,[10] we do mitigate its potential effect by filtering out patients who have previously had an AMI, who die on the same day as admission and by including a dummy variable according to the patient's private insurance status. Finally, we do not include the type of treatment the patient receives either during their first admission or subsequently since, in our estimation, this is endogenous to the severity of the AMI. Since our research question is partly testing the appropriateness of the hospitals' prescribed treatment, it would be incorrect to control for it.[11]

[10] Ideally, we would like to model the ambulance trip separately. However, decisions made by ambulance officers on the way to hospitals are unobserved in our dataset, as is the time elapsed between initial ambulance encounter and entry into a hospital emergency department.

[11] If the objective of the paper were to isolate the unobservable hospital-type qualities, such as counselling and quick response, that are not apparent from formal records, then treatments should be included in the specification of the hazard function. However, this is not the issue under consideration in this paper.

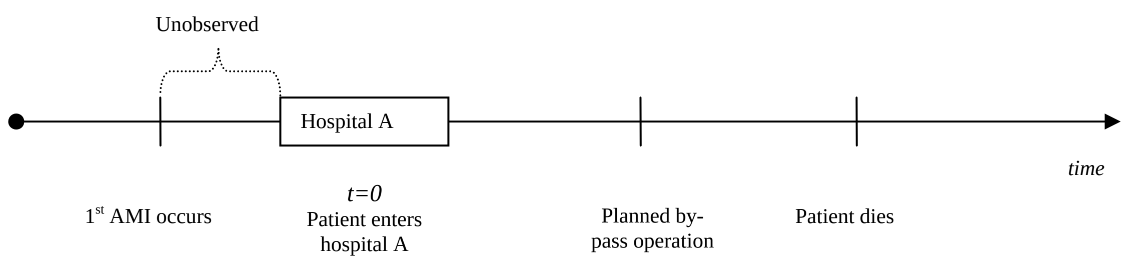
We use a hazard rate function to compare differences in patient outcomes following AMI episodes across different types of hospitals. The hazard, or the probability of failure for patient i in period t conditional on having survived up to that point, is denoted as $h_i(t|\mathbf{x})$, and can be written as:

$$h_i(t \mid \mathbf{x}) = h_0(t)\exp(\mathbf{x}_i{}'\boldsymbol{\beta}) \qquad (1)$$

where $h_0(t)$ is the baseline-hazard function, $\mathbf{x}_i$ is a vector of explanatory variables which impose a proportional characteristic-specific shift on the baseline hazard. Since the failure rate is defined with respect to time, h_0 is written as an unspecified function of time. We choose a Cox specification for our baseline hazard since it is a flexible specification that avoids potential mis-specification bias resulting from choosing an inappropriate parametric specification for the baseline hazard. Time since the first AMI (in days) is the unit of time-analysis. To isolate the hospital effect, we include a set of patient-specific characteristics.

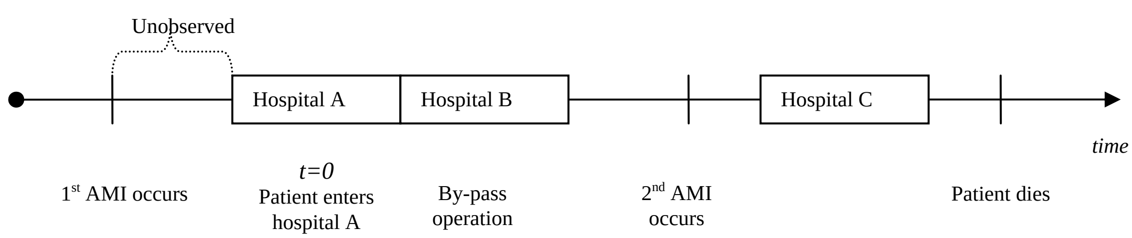
To clarify the structure of our empirical models, consider the hospitalisation history timeline in Figure 1 which outlines the simple case of a patient who has his/her 1st AMI, is treated by one hospital (a coronary by-pass operation is undertaken) and dies shortly thereafter. The period of analysis starts at time $t=0$ when the patient first enters the emergency room of a hospital. All of our analysis is conditioned on the patient entering the emergency room in a reasonable state – patients who are clinically dead (or almost) on arrival are not included in the analysis. And any treatments given by the ambulance/paramedics on the way to the emergency room – including other factors which occur prior to $t=0$ such as the time taken to reach the emergency room – are unobserved. In this case, identifying the relationship between hospital type and patient outcomes is straightforward.

Figure 1: Timeline for a simple hospitalisation history



As we have explained earlier, there are many instances where the relationship between hospital performance and patient outcome is more complex than that outlined in Figure 1: that is, where there are multiple AMIs and multiple hospitals. In Figure 2, a more complex scenario is outlined where a patient has a 1st AMI, enters hospital A and is then transferred to Hospital B for a coronary by-pass operation and then 2 years later has a 2nd AMI, enters Hospital C and dies shortly thereafter. In this complex scenario, it is not clear how to attribute the final outcome (death): should it be attributed to Hospital C which was the last hospital to treat the patient or should it be attributed to Hospital A which made the initial diagnosis and referral?[12]

Figure 2: Timeline for a complex hospitalisation history



A third possible attribution strategy we consider in this paper is where all multiple-hospital patients are removed from the analysis. This simplifies the hospital-patient outcome relationship because it only includes patients who i) have one hospital admission (as in Figure 1); or ii) have multiple admissions *to the same hospital*. Thus, patients who are referred from one hospital to another are excluded as are those who have one (or more) admission to two (or more) different hospitals.

4 Data and variable construction

Our primary data source is the Victorian Admitted Episodes Dataset (VAED) from 1996–2005. This dataset links individual patient records to the death registry to include information about whether or not the patient died, and if so, when.[13] Since the VAED does not include information on lifestyle and socio-demographic background, we have linked

[12] An alternative strategy - which we don't explore here – would be to attribute outcomes to Hospital B.
[13] For more details on the construction of the VAED, see Sundararajan *et al.* (2002).

patients' records to an index of the socio-economic status of their residential post code thereby taking advantage of some conjectures that associate socio-economic status with lifestyle and health.[14]

Since VAED includes data on all admissions for patients since fiscal year 1996/1997, we exclude those patients who we observe having an AMI in the period 1996-2000. Included in our final sample, then, are only those patients who (apparently) have their *first* AMI during the period 2001-03.[15] We also excluded interstate or overseas residents and any deaths that occur on the same day as first AMI admission. The latter may represent cases that were dead-on-arrival and beyond the assistance of the hospital. Unlike other studies, we don't exclude any patients for reasons associated with age (see Farsi and Ridder 2006, for example).[16] In a significant minority of cases, patients were separated and then admitted on the same day. This was treated as a single continuous admission with the assigned hospital being the first hospital. Our time horizon for outcomes extends to June 2005.

4.1 Dependent variable

In our hazard model, we define failure in the following manner: following a person's first AMI, failure is either an unplanned hospital readmission due to the occurrence of another spontaneous AMI, or death. More specifically, failure is defined according to the following different definitions of patient outcomes:

a. Mortality within 30 days of admission to hospital;
b. Unplanned readmission for a subsequent AMI within 6 months of separation from hospital;

[14] Lifestyle and socio-economic background have been found to be an important contributing factor to AMI: Dobson *et al.* (1999) found declines in the death and nonfatal myocardial infarction rates in New South Wales, Australia, and were able to fully explain average annual reductions in these rates by decreases in smoking, diastolic blood pressure and total cholesterol, and by increased aspirin use for both men and women. Less than half of the average annual reductions in case fatality rates in their data could be explained by use of aspirin, beta-blockers, fibrinolytic therapy, and ACE inhibitors. Taylor *et al.* (1999) found that risk for AMI admissions and congestive heart disease (CHD) mortality is significantly higher in lower socio-economic status (SES) populations.

[15] Five years since a previous AMI is also regarded clinically as the 'first' AMI.

[16] Studies that exclude patients under 65, such as Farsi and Ridder (2006), do so because elderly patients are covered by Medicare and are thus less likely to be rejected by a hospital. However, this is not a problem in Australia where *everyone* is covered by public health insurance of some sort.

c. Mortality within 30 days or unplanned readmission for a subsequent AMI within 6 months.

Since we cannot identify the cause of a patient's death, mortality as defined here includes death *from any cause* (i.e. AMI-related and non AMI-related deaths are included). Unplanned readmission, however, is only for patients who re-enter any hospital with a subsequent AMI.[17] Given that the time constraints (30 days, 6 months) we impose in this model are somewhat arbitrary,[18] we also conduct a separate set of analyses which are not time-restricted. That is, we re-estimate the following more general models:

d. Mortality;

e. Unplanned readmission for a subsequent AMI;

f. Mortality or unplanned readmission for a subsequent AMI.

In these models (a-f), all of the outcomes are right-censored – the observed outcome can occur at any time up to the end of our period of analysis, June 2005. This enables us to compare short-term and long-term patient outcomes. In order to understand the effects of the attribution decision, we also run exactly the same set of analyses attributing outcomes to the initial-admitting hospital and also when multi-hospital patients are excluded (see Thiemann *et al.* (2000) and Allison *et al.* (2000) in reply for a discussion of this issue).

4.2 Patient-level control variables

The empirical literature identifies a number of patient-specific factors affecting the survival and successful recovery from an AMI. These are related to the type of the original AMI, the patient's co-morbidities, the patient's demographic characteristics and their life-style behaviours as proxied by the socio-economic conditions of the area in which they reside.

[17] Planned readmissions do not affect the coding of the dependent variable. That is, planned follow-up treatments are not included in our analysis. Also excluded are patients who re-enter hospital for other cardiac-related complaints such as angina.

[18] However, since we include deaths from *all* causes, it is true that the shorter is the time restriction the greater is the likelihood that the death is related to the observed AMI. This is perhaps a strong reason to examine patient outcomes in the period immediately after treatment. On the other hand, it is the patient's long-term health outcomes that are of most interest.

These form the basis of our time-invariant control variables which are described in more detail below.[19]

Type of the original AMI

Six types of AMI are distinguished in the data (based on ICD-10 codes): acute transmural myocardial infarction of anterior wall (I210); acute transmural myocardial infarction of inferior wall (I211); acute transmural myocardial infarction of other sites (I212); acute transmural myocardial infarction of unspecified site (I213); acute subendocardial infarction (I214); and acute myocardial infarction of unspecified site (I219). Although these diagnoses are not mutually exclusive, the overwhelming majority of patients have only one diagnosis. Ideally, we would like to convert these diagnoses into a severity index, however inclusion of the two 'unspecified' diagnoses prevents this and so we have included the type of AMI as six dummy variables. However, there is a strong correlation between type of AMI and mortality rates.[20] In addition, information on whether the patient was intended to stay overnight or longer (Intended to stay overnight) was included as an indicator of the severity of the disease.

Co-morbidities

Two main types of pre-conditions are relevant for our purpose: those that may complicate the underlying heart condition and make its treatment more intractable and those that may contribute to a non-heart related death. To reduce the extensive list of co-morbidities to meaningful aggregates we use the Charlson co-morbidity index (Charlson *et al.* 1987).

Demographics

Data on gender, country of birth and indigenous status (ATSI) have been used to control for genetic factors that may affect recovery rates following the first AMI. We also controlled for marital status, but since we found that all other states apart from married or de facto had the same effects, we reduced this to a single dummy variable.

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[19] Correlations between the explanatory variables were very low, with almost all correlations being below |0.2|. In particular, the correlations between AMI type, intended stay overnight, and hospital type varied from 0.01 to 0.11.

[20] The medical literature suggests that non-transmural (subendocardial) infarctions, followed by those with an infarction of the anterior wall, have the poorest prognosis (Hutter, *et al.* 1981; Szklo *et al.* 1978; Cannom *et al.* 1976). Nonetheless, there is also presumably a spectrum of severity within non-transmural infarctions which we are unable to observe.

Socio-economic characteristics

Existing medical studies demonstrate that eating, exercise and recreational habits have a considerable bearing on a person's cardio-vascular condition. To indirectly control for some of these factors we used an index of socio-economic status of all Australian residents grouped by post code. This is the 2001 ABS SEIFA Index of Advantage/Disadvantage which is composed of the proportion of families with high incomes, people with a tertiary education and employees in skilled occupations.[21]

4.3 Hospital-level explanatory variables

Three hospital characteristics are under investigation for the purposes of this study. The first is hospital status which can be private, public teaching or public non-teaching. As discussed in the background, this does not translate into a for-profit versus not-for-profit distinction but is indicative of different budget constraints, different administrative arrangements and the presence of economies of scope. The second relates to the location of the hospital which can be metropolitan, country or remote country.[22] The third characteristics relates to the capacity of the hospital to perform cardio-vascular services, which is a continuous variable based on the number of all cardiac services provided by the hospital (e.g. heart failure, AMI, angina, aneurysm) regardless of whether they are planned or unplanned. This variable is time invariant and is calculated as the total number of cardiac patients per hospital over the period 2001-04. This variable has been separated into quartiles to permit us to model a flexible relation between cardiac volume and patient outcome.

5 Results and analysis

Table 1 shows that there were between 6,031 and 6,900 first AMI admissions per year over the period 2001-03. Almost two thirds of these people were men and the majority are over the age of 70 years. Less than one per cent were identified as from an indigenous heritage, while 57.4 per cent were born in Australia and substantial minorities came from the UK and

[21] For further details, see 2039.0.55.001-Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), Australia - Technical Paper, 2001.

[22] Australian postcodes file can be downloaded from http://www1.auspost.com.au/download/pc-full.zip.

Southern Europe. Compared with the 2001 Australian population (over 65 years of age), this represents a disproportionately high number of people born in Southern Europe and low proportion of people born in Australia.

Table 1: Personal characteristics of AMI patients

Characteristic	Frequency	Per cent
Year of first AMI		
2001	6,031	31.1
2002	6,458	33.3
2003	6,900	35.6
Gender		
Male	12,484	64.4
Female	6,905	35.6
Age (years)		
0-19	3	0.0
20-29	34	0.2
30-39	375	1.9
40-49	1,691	8.7
50-59	3,259	16.8
60-69	3,962	20.4
70-79	5,180	26.7
80-89	4,004	20.7
90+	881	4.5
Country of birth		
Australia	11,148	57.5
UK	1,729	8.9
Southern Europe	2,530	13.1
Eastern Europe	711	3.7
Western Europe	599	3.1
South East Asia	218	1.1
Other	2,454	12.7
Primary diagnosis at first admission		
Acute transmural myocardial infarction of anterior wall	3,686	19.0
Acute transmural myocardial infarction of inferior wall	4,664	24.1
Acute transmural myocardial infarction of other sites	611	3.2
Acute transmural myocardial infarction of unspecified	149	0.8
Acute subendocardial infarction	6,147	31.7
Acute myocardial infarction of unspecified site	4,255	22.0
Number of admissions to June 2005		
1	17,798	91.8
2	1,404	7.2
3-8	187	1.0
Died before June 2005	4,648	24.0
TOTAL	19,389	100.0

There are six reported types of AMI in our dataset. The most frequent type of AMI (31.7 per cent) was acute subendocardial infarction, followed by acute transmural myocardial infarction of inferior wall (24.1 per cent), acute myocardial infarction of unspecified site (22.0 per cent) and acute transmural myocardial infarction of anterior wall

(19.0 per cent). Overall, 91.8 per cent of patients only experienced one AMI admission during our reference period while 7.2 per cent had a second AMI admission and 1.0 per cent experienced more than 2 AMIs. In addition, 24.0 per cent of the patients in our sample died, from any cause, before June 2005.

Table 2 presents data on the number of interventions and cardiac admissions per hospital according to hospital type. It shows that, on average, the 19 public teaching hospitals conduct the largest number of bypass, PCI and angioplasty interventions and have over 37,000 cardiac admissions a year. The average private hospital performs fewer than half the number of bypass and PCI operations than the average public teaching hospital, but about three quarters of the total number of angioplasties. By contrast, public non-teaching hospitals undertake much fewer interventions. If hospitals are disaggregated by location we find that the average number of interventions (and patients) declines the further is the hospital from the metropolitan region.

Table 2: Number of hospitals, mean number of interventions per hospital by type, 2001-04

Hospital type	Frequency (%)	Bypass	PCI	Angioplasty	Number of cardiac admissions per year
Private	30 (23.1)	46.2	88.7	262.8	9488.6
Public teaching	19 (14.6)	107.4	175.4	358.8	37084.1
Public non-teaching	81 (62.3)	0.3	0.3	5.2	4571.2
Metropolitan	47 (36.2)	66.4	121.4	267.9	20924.0
Country	11 (8.4)	29.3	26.8	229.7	17419.2
Remote country	72 (55.4)	0.2	0.3	0.03	2562.2
Mean annual AMI admissions	103.2				
TOTAL	130				

While Table 2 presents the average number of interventions per hospital, Table 3 presents the average number of interventions per 1000 cardiac patient admissions. These data reveal that while public teaching hospitals undertake a significantly larger volume of interventions (per hospital), they are considerably less likely to undertake an intervention on a given patient than private hospitals. The intervention rate in the private system for bypasses and PCIs in the private system is double that for public teaching hospitals and for angioplasties, it is triple.[23] With the exception of angioplasties, metropolitan hospitals are

[23] Similarly, Robertson and Richardson (2000) found that private patients in private hospitals were 2.17 times more likely to undergo coronary angiography; 2.87 times more likely to undergo coronary artery

more likely than country and remote country hospitals to undertake an intervention. While these gross data do not control for patient selection, it is suggestive of major differences between the private and public systems.

Table 3: Number of interventions per 1000 cardiac admissions by hospital type, 2001-04

Hospital type	Bypass	PCI	Angioplasty
Private	4.87	9.35	27.70
Public teaching	2.90	4.73	9.68
Public non-teaching	0.08	0.07	1.14
Metropolitan	3.17	5.80	12.81
Country	1.68	1.54	13.19
Remote country	0.08	0.11	0.01
TOTAL	2.54	4.43	11.12

Tables 4, 5 and 6 present the hazard estimates when outcomes are attributed to the initial-admitting hospital; final-treating hospital; and when multiple-hospital patients are excluded respectively. The coefficients on the control variables, which we do not report, are fairly stable and have the expected signs across all 18 models. Briefly, we find that age significantly increases the probability of failure across all definitions, as does the Charlson co-morbidity index and lack of 'Intent to stay overnight'. Being female either gave no advantage or was negative in a few cases. Birthplace gave somewhat mixed results, but there were overall poorer outcomes for Aboriginal and Torres Strait Island people. Being married or de facto significantly decreases the likelihood of failure in most models. Having private health insurance was insignificant except for two occasions when it was marginally positive, and finally, the advantage/disadvantage index was mostly positive and significant.

In Table 4, we present hazard estimates when outcomes are attributed to the initial-admitting hospital. The first column defines failure as 30-day mortality only. This estimation indicates that the failure rate is significantly lower for private hospitals, *ceteris paribus* (public non-teaching hospitals are the base category). When failure is defined as readmission within 6 months (second column of Table 4) or as 30-day mortality or 6-month readmission (third column of Table 4), again only private hospitals have significantly lower failure rates. The effect of hospital cardiac volume is irregular. While larger volumes are associated with a higher probability of death, it is also associated with a lower probability

revascularization procedures; 1.95 times more likely to undergo coronary artery bypass graft; and 3.05 times more likely to undergo coronary artery angioplasty than public patients in public hospitals.

of re-admission, *ceteris paribus*. Looking at columns 4-6, where outcomes are time-unrestricted, private hospitals still have significantly lower failure rates across all three definitions. In addition, teaching hospitals have significantly lower mortality rates (column 4, Table 4), and mortality or readmission rates (column 6, Table 4), country hospitals have significantly lower mortality rates, and remote country hospitals have significantly higher readmission rates (metropolitan is the base category).[24] Again the results for hospital cardiac volumes are difficult to interpret and the main conclusion is that medium-large hospitals have the worst outcomes, *ceteris paribus* (1st quartile is the base category).

Table 4: Hazard results for initial-admitting hospital

Independent variables	30-day mortality (a)	6-month unplanned readmission (b)	(a) or (b)	Mortality before June 2005 (d)	Unplanned readmission before June 2005 (e)	(d) or (e)
Initial-admitting Hospital						
Private	-0.340**	-0.828**	-0.501**	-0.226**	-0.484**	-0.278**
	(2.73)	(4.56)	(4.93)	(3.03)	(3.35)	(4.21)
Public teaching	-0.039	-0.107	-0.073	-0.105+	-0.099	-0.101+
	(0.39)	(0.82)	(0.91)	(1.71)	(0.92)	(1.90)
Country	-0.129	0.121	-0.035	-0.093+	0.146	-0.037
	(1.45)	(1.03)	(0.50)	(1.70)	(1.48)	(0.77)
Remote country	0.107	0.127	0.116	0.067	0.266+	0.105
	(0.83)	(0.78)	(1.15)	(0.86)	(1.89)	(1.53)
Cardiac admissions						
2nd quartile	0.140	-0.083	0.065	0.143*	0.121	0.129*
	(1.40)	(0.67)	(0.84)	(2.42)	(1.12)	(2.51)
3rd quartile	0.268*	-0.257+	0.085	0.206**	-0.047	0.143*
	(2.37)	(1.71)	(0.95)	(3.04)	(0.37)	(2.39)
4th quartile	0.223+	-0.413**	-0.004	0.162*	-0.193	0.08
	(1.86)	(2.63)	(0.04)	(2.24)	(1.46)	(1.26)
Observations	24606	24607	24608	25264	25264	25264

Notes: i) Time of analysis is time since first AMI. †, *, ** significant at the 10, 5 and 1 per cent respectively.
ii) Control variables included: AMI Type, Age, Overnight stay, Charlson co-morbidity index, Gender, Country of birth, Aboriginal or TSI, Married/de facto, Health insurance status, SEIFA index.
iii) Base categories are public non-teaching hospitals, metropolitan hospitals and 1st quartile of cardiac admissions.

In Table 5, we present the results when we attribute patient outcomes to the final-treating hospitals. Here, the results changed only very slightly. In the time-unrestricted analysis, teaching hospitals no longer had significantly lower mortality rates, and remote

[24] To test whether these results were sensitive to very young or very old patients, we repeated these estimations first, by excluding patients under 50 and secondly, by excluding patients over 80. The results were essentially the same as when all patients were included, and thus are not illustrated separately in this paper.

country hospitals no longer had significantly higher unplanned readmission rates. The pattern of all other hospital-type variables remained the same.

Table 5: Hazard results for final-treating hospital

Independent variables	30-day mortality (a)	6-month unplanned readmission (b)	(a) or (b)	Mortality before June 2005 (d)	Unplanned readmission before June 2005 (e)	(d) or (e)
Final-treating Hospital						
Private	-0.349**	-0.821**	-0.504**	-0.218**	-0.543**	-0.280**
	(2.79)	(4.56)	(4.97)	(2.94)	(3.77)	(4.26)
Public teaching	-0.043	-0.099	-0.069	-0.101	-0.137	-0.104+
	(0.42)	(0.76)	(0.87)	(1.64)	(1.27)	(1.95)
Country	-0.128	0.104	-0.037	-0.092+	0.134	-0.035
	(1.44)	(0.88)	(0.52)	(1.68)	(1.37)	(0.73)
Remote country	0.12	0.079	0.108	0.08	0.195	0.107
	(0.93)	(0.49)	(1.07)	(1.03)	(1.43)	(1.58)
Cardiac admissions						
2nd quartile	0.146	-0.119	0.057	0.136*	0.067	0.128*
	(1.47)	(0.96)	(0.74)	(2.31)	(0.64)	(2.50)
3rd quartile	0.272*	-0.295*	0.073	0.211**	-0.088	0.140*
	(2.40)	(1.97)	(0.81)	(3.11)	(0.71)	(2.36)
4th quartile	0.232+	-0.436**	-0.01	0.178*	-0.231+	0.085
	(1.94)	(2.79)	(0.11)	(2.47)	(1.77)	(1.36)
Observations	24605	24607	24608	25264	25264	25264

Notes: i) Time of analysis is time since first AMI. †, *, ** significant at the 10, 5 and 1 per cent respectively.
ii) Control variables included: AMI Type, Age, Overnight stay, Charlson co-morbidity index, Gender, Country of birth, Aboriginal or TSI, Married/de facto, Health insurance status, SEIFA index.
iii) Base categories are public non-teaching hospitals, metropolitan hospitals and 1st quartile of cardiac admissions.

Table 6 presents the results when we excluded all multi-hospital patients. In total, 515 patients present at multiple hospitals. Typically, they are uninsured, non-teaching, country hospital patients who transfer to a metropolitan, teaching hospital. They have low mortality rates – only 9 of the 515 died prior to June 2005. Omitting this small group of people affected the results, particularly the coefficients on the country and remote country hospitals. Country hospitals had significantly lower 30-day mortality rates, significantly higher 6-month readmission and readmission rates, and no longer exhibited any advantage in the time-unrestricted mortality model. Remote country hospitals, in addition to the significantly higher readmission rates found in the previous analyses, were also found to have significantly higher 6-month readmission, 30-day mortality or 6-month readmission, and mortality or readmission rates. On the other hand, the coefficients for private hospitals continued to have significantly lower failure rates across all models (except for 6-month readmission, which became insignificant). Teaching hospitals continued to enjoy a marginally significant advantage over non-teaching hospitals. The effect of hospital cardiac volume also changes and suggests that the smallest (1st quartile) hospitals have the best outcomes overall and the medium-large (3rd quartile) hospitals have the worst.

At first glance, the results from Table 6 seem to be inconsistent with the initial-admitting hospital and final-treating hospital results. The results suggest that country and remote country hospitals are making an appropriate decision to transfer patients who appear, from their low mortality rates, to benefit from treatment at the metropolitan teaching hospital (hence the performance of country and remote country hospitals falls when transfer patients are excluded). The lack of effect of this on the teaching coefficient in the final-treatment results is probably due to the small magnitude of multi-hospital patients relative to all patients who are treated at a teaching hospital.

Table 6: Hazard results for single-hospital patients only

Independent variables	30-day mortality (a)	6-month unplanned readmission (b)	(a) or (b)	Mortality before June 2005 (d)	Unplanned readmission before June 2005 (e)	(d) or (e)
Single Hospital						
Private	-0.232**	-0.27	-0.230**	-0.356**	-0.451*	-0.396**
	(3.06)	(1.49)	(3.30)	(2.84)	(2.00)	(3.64)
Public teaching	-0.111+	-0.132	-0.120*	-0.033	-0.172	-0.08
	(1.77)	(0.98)	(2.12)	(0.32)	(1.06)	(0.93)
Country	-0.091+	0.430**	0.005	-0.137	0.408**	0.018
	(1.66)	(3.71)	(0.09)	(1.53)	(2.90)	(0.24)
Remote country	0.064	0.616**	0.149*	0.105	0.561*	0.212+
	(0.80)	(3.34)	(2.03)	(0.81)	(2.55)	(1.90)
Cardiac admissions						
2nd quartile	0.139*	0.464**	0.199**	0.130	0.408*	0.203*
	(2.31)	(3.26)	(3.60)	(1.30)	(2.39)	(2.37)
3rd quartile	0.217**	0.441**	0.263**	0.253*	0.355+	0.272**
	(3.14)	(2.71)	(4.14)	(2.23)	(1.79)	(2.77)
4th quartile	0.172*	0.322+	0.205**	0.207+	0.266	0.208*
	(2.33)	(1.88)	(3.04)	(1.72)	(1.28)	(2.00)
Observations	23749	23749	23749	23292	23291	23290

Notes: i) Time of analysis is time since first AMI. †, *, ** significant at the 10, 5 and 1 per cent respectively.
ii) Control variables included: AMI Type, Age, Overnight stay, Charlson co-morbidity index, Gender, Country of birth, Aboriginal or TSI, Married/de facto, Health insurance status, SEIFA index.
iii) Base categories are public non-teaching hospitals, metropolitan hospitals and 1st quartile of cardiac admissions.

6 Conclusions and limitations

Our results suggest the following. First, we find substantial variation in performance across hospital types with regard to health outcomes for AMI patients: private hospitals consistently perform better than teaching hospitals in that the likelihood of failure (unplanned readmission or mortality) is lower across almost all model specifications. Second, we find that the relative performance ranking by hospital type is quite robust to the definition of heath outcomes. However, teaching hospitals seem to perform better if outcomes are defined by mortality rather than readmission, while private hospitals generally perform well on both mortality and readmission measures. Third, the choice of attribution strategy doesn't appear to play a major role in shaping hospital performance results. Country and remote country hospitals do, however, appear to perform worse when multiple-hospital patients are excluded from the analysis. Finally, higher mortality rates but lower readmission rates are generally found among hospitals with higher volumes of cardiac procedures. The benefit of size in improving readmission rates is reversed when multiple-hospital patients are excluded from the analysis which is indicative that these patients may have lower mortality rates than single-hospital patients.

From a methodological perspective, our analysis has shown that (1) when attributing outcomes to the initial-admitting hospital, the results are very similar to those when attributing outcomes to the final-treating hospital, and (2) excluding multiple-hospital patients has a substantial effect on the results. With respect to (1), the results may be idiosyncratic to our dataset since if there are not many transfer patients, it is not surprising that the attribution does not change very much between the two sets of analyses. With respect to (2), we can hypothesize that while the number of multiple-hospital patients are large enough relative to the number of country and remote country patients to affect the country and remote country hospital coefficients, they are not large enough to affect the teaching hospital coefficients.

In terms of hospital type, our results show that quite clearly private hospitals have better survival rates than other types of hospitals. The significantly lower failure rates of private hospitals persist across all six definitions in both the time-restricted and time-unrestricted analyses, the one exception being 6-month readmission in the single hospital patient analyses. These lower failure rates may be explained by the rate at which interventions are performed. In our data, we found that private hospitals perform PCIs, angiographs and bypasses significantly more often given patient volumes than public hospitals, which may explain out findings since other studies have shown that cardiac procedures contribute to better patient outcomes (Heller *et al*. 2000; Hand *et al*. 1996). We also found that teaching hospitals perform these same procedures significantly more often than non-teaching hospitals, which may explain why these have some lower failure rates than non-teaching hospitals, though not to the extent of private hospitals.

This finding raises the question of why private hospitals exhibit superior performance. We have earlier indicated that the main differences arising from hospital status relate to their financial constraints, administrative structure and economies of scope. Private hospitals, by and large, have greater access to new (and expensive) treatments and equipment and have less demand for bed space than public hospitals. For instance, Harper *et al.* (2000) found that private hospitals have higher pharmaceutical costs due to the more frequent use of abciximab (an antiplatelet agent that costs A$1,593 per use). They attributed the difference in administration directly to the funding of the drug: in private hospitals, abciximab is paid by the Federal Government because it is listed on the Pharmaceuticals Benefits Scheme (PBS). In public hospitals, the hospital pays for abciximab out of its pharmaceutical budget. Thus, cardiologists are more careful in administering abciximab in public hospitals, and usually reserve it for patients with clear signs of needing it.

While we cannot test for the effects of these attributes directly, our data on the number of interventions per admission hints at the fact that resources maybe at the core of our results. One might argue that private hospitals have an incentive to over-service their patients (i.e. there is a moral hazard problem), but the fact that the level of intervention provided by private hospitals *increases* survival rates suggests that this is not the case.[25] It is important to note that it is not the profit motive which is driving the result since private hospitals in our sample are both for-profit and non-profit organisations. Rather, it is the different budget constraints faced by public and private hospitals that are influencing patient outcomes.

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[25] If the level of service provided by private hospitals was higher than for public hospitals, but there was no corresponding difference in survival rates, the case for the existence of moral hazard would be strong.

At this point, some caveats should be noted. One is that the choice of hospital may not be random, as we assumed, but that there is selection bias which results in some hospital types receiving more severe AMI patients. This is plausible since ambulance drivers likely make decisions en route to take more serious cases to larger hospitals. To the extent this selection bias exists, our findings will likely overstate the failure rate in large hospitals. Additionally, we were not able to control for some important individual-specific determinants that clearly affect outcomes, since this information was not available in the data set. These range from medical details, such as patients' blood pressure upon presentation, to lifestyle variables that are known to affect cardiac health, such as whether patients smoke. We have attempted to indirectly capture some of these by linking a SEIFA index to each patient, but this is obviously not as good as direct observation.

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