Author/s:
Palangkaraya, A;Yong, J

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Effects of Competition on Hospital Quality: An Examination Using Hospital Administrative Data

by

Alfons Palangkaraya and Jongsay Yong

Melbourne Institute of Applied Economic & Social Research

The University of Melbourne

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Send correspondence to: Jongsay Yong
Level 7, 161 Barry Street
MIAESR
The University of Melbourne
Parkville
Victoria 3010
Australia
email: jongsay@unimelb.edu.au

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Abstract

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This paper investigates the effects of competition on hospital quality using hospital administration data from the State of Victoria, Australia. Hospital quality is measured by 30-day mortality rates and 30-day unplanned readmission rates. Competition is measured by Herfindahl-Hirschman Index (HHI) and the numbers of competing public and private hospitals. The paper finds that hospitals facing higher competition have lower unplanned admission rates. However, competition is negatively related to hospital quality when measured by mortality, albeit the effects are weak and barely statistically significant. The paper also finds that the positive effect of competition on quality as measured by unplanned readmission differs greatly depending on whether the hospital is publicly or privately owned.

Keywords: Hospital Competition; Hospital Quality, Hospital markets.

JEL Codes: I11, D24.

1 Introduction

This paper investigates the effect of competition on hospital quality using hospital administrative data of patients with heart diseases from the state of Victoria, Australia. Two quality indicators are used in the investigation: mortality and unplanned readmission, both within 30 days of discharge. We define hospital markets using the notion of catchment areas (Melnick and Zwanziger, 1988; Zwanziger and Melnick, 1988) and measure hospital competition using both the Herfindahl-Hirschman index (*HHI*) and the number of competing hospitals in the market.

The question of how competition affects hospital quality has been a long-standing issue in health economics and policy discussion. Its policy relevance is obvious since health care markets are heavily regulated, and government policies often have profound implications on the competition and concentration of the hospital sector. The effect of competition on quality is not only of relevance for health policymaking but also for competition authority monitoring the competitiveness of the hospital industry.

This paper contributes to the literature in two ways. First, it provides evidence alongside previous studies which are predominantly US-based studies (e.g., Mutter et al., 2008) that found hospital competition to have a mixed effect on quality. This paper finds a mixed effect in the context of Australia in which, when compared to the U.S., public hospitals play a more dominant role than private hospitals. Specifically, an increase in competition appears to be associated with lower hospital quality in one dimension (higher mortality) but higher quality in another dimension (lower unplanned readmissions). Further, we also find that the latter effect of competition on quality are relatively more significant, statistically and in magnitude, than the former effect.

The second contribution of the paper is in the evaluation of the competition-quality relationship in terms of the ownership of hospitals in the form of public versus private hospitals. First, we investigate if the relationship depends on whether the competitors are public or private hospitals. Second, we investigate how the relationship between competition and quality may vary between public and private hospitals and between other types of hospitals (e.g., teaching, large regional, or local hospitals). For the first case, we find that the positive link between hospital competition and quality as measured by unplanned readmissions depends on whether the competitors are public or private hospitals. On average, hospitals competing with a large number of public hospitals appear to have higher unplanned readmission rates than those facing competition mostly from private hospitals. We also find that competition affects unplanned readmission in a substantially different way for private and public hospitals—the quality-improving effect for private hospitals is less than half of those for public hospitals. No such patterns, however, are observed on the effect of competition on mortality; the quality-lowering effect is about the same for both private and public hospitals.

In standard economic theory, competition almost invariably leads to higher quality, especially if prices are fixed; see for examples, Kessler and McClellan (2000); Brekke et al. (2006); Karlsson (2007) and the review by Gaynor (2006).[1] However, the empirical literature on this topic in relation to the health care sector gives a rather mixed picture. For examples, Kessler and McClellan (2000), Sari (2002), Tay (2003), Cooper et al. (2010) find a positive relationship between competition and quality (when prices are fixed), Gowrisankaran and Town (2003) and Mukamel et al. (2002) find a negative relationship, Shen (2003) and Mutter et al. (2008) find a positive relationship for some quality indicators, negative or no relationship for others, while Mukamel et al. (2001) find no relationship between competition and quality.

Recently, (e.g., Mutter et al., 2008; Propper et al., 2008) have suggested that hospitals, when faced with increased competition, may rationalise by shifting resources to improve quality dimensions that are easily observed and understood by consumers. The end result is thus mixed—some quality dimensions improve while others deteriorate as competition

[1] However, in a recent theoretical contribution that incorporates semi-altruistic care providers, Brekke et al. (2009) show that an ambiguous relationship exists between competition and quality.

intensifies. However, as pointed out by Mutter et al. (2008), the evidence is by no means strong. Thus, an empirical study of the competition-quality relationship based on Australian data can provide valuable insights into the debate since the data allow for comparisons of public and private hospitals (i.e., whether or not prices are fixed) and the use of different measures of quality which are not easily observed by consumers. It is in this context that our results add to the empirical literature.

The structure of the rest of this paper is as follows. In Section 2 we briefly discuss the relevant literature and the settings for Australian hospitals. In section 3 we discuss the data and how we measure hospital competition and estimate the effects of competition on hospital quality with a random-intercept logistic model. In Section 4 we present the estimation results and analyse their implications as well as the robustness of the estimates. Finally, in Section 5 we provide some concluding remarks.

2 Related Literature and Background

2.1 Related literature

Standard microeconomic models almost invariably predict that higher hospital competition leads to higher hospital service quality. Gaynor and Town (2011), for example, compare cases when prices are determined by regulators and by market forces.[2]. The first case applies for public hospitals in the UK, Australia, and in part of the US health system under the Medicare programs. Under this case competition would lead to higher quality; however, although it is not clear if it would result in too much quality. In contrast, when hospitals compete in both quality and prices, competition leads to higher quality only if demand is not price elastic (such as if patients are covered by private health insurance). In other words, hospitals' bargaining power vis-a-vis private health insurers becomes an important factor. Also, a separate recent theoretical study shows that an ambiguous

[2]See also Kessler and McClellan (2000); Brekke et al. (2006); Karlsson (2007) and the review by Gaynor (2006).

relationship between hospital competition and quality may result if care providers are semi-altruistic Brekke et al. (2009).

The empirical evidence also exhibits inconsistency depending on study period, geographical area, types of diseases, types of payers, and specific quality and competition measures used (Gaynor and Town, 2011). For examples, for the case of regulated prices, studies using *HHI* and data of all-, heart attack-, and AMI-Medicare patients in the US in different periods found higher hospital competition to be associated both with lower and higher mortality rates (Kessler and McClellan, 2000; Gowrisankaran and Town, 2003; Kessler and Geppert, 2005). Further, Tay (2003) used demand elasticity instead of *HHI* and found higher competition to be associated with higher quality (lower mortality); whereas Shen (2003) and Mutter et al. (2008) found a positive relationship for some quality indicators, negative or no relationship for others. Moreover, in certain periods and US regions, there is no apparent relationship between the two (Mukamel et al., 2001). On the other hand, studies based on UK data on heart attack and all patients with different measures of competition appear to be relatively consistent in finding a positive relationship between competition and quality, where the latter is measured by mortality.

Similarly mixed evidence has also been found for the case when prices are not exogenously fixed but determined by the market. Studies based on data from patients in various US states showed that higher competition (measured by *HHI*) might lead to either lower or higher mortality, or no significant effect at all (Gowrisankaran and Town, 2003; Sari, 2002; Escarce et al., 2006; Rogowski et al., 2007). The findings of studies using UK data (e.g., Propper et al., 2008), different measures of competition (hospital merger, deregulation, number of competitors, entrant's market share), and/or quality (patient safety, quality indicator, quantity of output) under this setting are also inconclusive (Sohn and Rathouz, 2003; Encinosa and Bernard, 2005; Ho, 2002; Capps, 2005; Volpp et al., 2003; Howard, 2005; Abraham et al., 2007; Cutler et al., 2010).

Two interesting studies (e.g., Mutter et al., 2008; Propper et al., 2008) suggested that hospitals, when faced with increased competition, might rationalise by shifting resources to improve quality dimensions that were easily observed and understood by consumers. This would result in an observation where some quality dimensions improve while others deteriorate as competition intensifies. However, as pointed out by Mutter et al. (2008), while there is empirical evidence supporting this hypothesis, the evidence is by no means strong; there are also empirical results that contradict the hypothesis.

The mixed evidence notwithstanding, an important limitation in making any policy inference from the above-mentioned studies—which are extensively reviewed in Gaynor and Town (2011)—is they are mainly based on either US (majority) or UK data. Evidence from other developed countries, many of which have health care systems that differ in fundamental ways from the US and UK, is scant. Thus studies from countries with different health care systems can provide valuable additions to the knowledge base on the effects of competition. An example is a series of studies on the recent pro-competition health care reform in the Netherlands (Bijlsma et al., 2011; Custers et al., 2007). The Dutch system, with its mandatory private health insurance and the nonexistence of for-profit private hospitals (Enthoven and van de Ven, 2007), is both similar to (in terms of insurers-driven competition) and different from (in terms of the lack of a private hospital sector) the US system.

Similarly, the experience of Australia, which has implemented various major pro-competition reforms in the past two decades, will also prove valuable. Unlike the Dutch system, the Australian system appears to be similar to the US system so far as the presence of both public and (not-for-profit and for-profit) private hospitals is concerned. However, there are subtle differences in the relative importance of the private hospital sector and the relationship between insurers and hospitals. Unlike in the US and the Netherlands (Halbersma et al., 2011), private health insurers in Australia play a relatively passive role in determining the prices that private hospitals charge. To our knowledge, how hospital competition affects quality in Australia's unique setting has never been explored, although the role of quality as an endogenous variable was investigated in a study of hospital efficiency in Chua et al. (2011).

2.2 The Australian health care system

The Australian hospital system is a complex mixed public-private system consisting of a large public hospital sector and a smaller but by no means insignificant private hospital sector. Australians generally have a number of options when it comes to hospital care. They can choose to be admitted as a public patient (in any public hospital) and receive treatment without any co-payments. They can also choose to be admitted as a private patient in a public hospital (currently around 9 per cent of admissions in public hospitals are of this type). In addition, they can choose to be admitted into private hospitals as a private patient. In the last two cases, patients or their private health insurer may have to pay for the 'gap' between the amount covered by the government via the Medicare scheme and the amount hospitals charge. The main benefits of being a private patient is a greater choice of surgeon, shorter waiting lists, and better amenities (O'Hara and Brook, 1996; Sundararajan et al., 2004).

Public hospitals are mainly funded by the federal and state governments, with the latter also responsible for managing the service provision.[3] The main objective for public hospital service provision is to ensure access equity by providing free hospital treatment—the expenses are covered by a universal, tax funded, public health insurance scheme known as Medicare—to public patients, although in recent years improving efficiency in service delivery has increasingly received greater emphasis. In addition, large public hospitals also provide emergency services and perform clinical teaching and research duties. Due to their equity objective and funding arrangement, the business operational strategy of public hospitals is driven by the desire to manage demand under a given budget constraint. As such, non-price factors such as elective surgery waiting lists often become a strategic choice variable.

[3] The discussion in this paragraph is mainly based on Productivity Commission (2009).

In contrast to the operation of public hospitals, management of private hospitals enjoys more discretionary power as there are less restrictive service delivery provision and more freedom in managing funding sources. As a result, (for-profit) private hospitals tend to focus on elective procedures and avoid providing less profitable services (Deber, 2005). Private hospitals also face fewer constraints than public hospitals in charging for prescription costs because such costs are usually covered by private health insurance. There is thus little surprise that private patients have better access than public patients to newer and often more expensive treatment options, as illustrated by their higher use of an expensive antiplatelet agent, abciximab, for AMI.[4]

In terms of market share, private hospitals accounted for around 30 per cent of all hospital admissions across Australia. This share stays relatively constant in the last two decades and is roughly similar in the State of Victoria where the hospital data for this study are drawn. However, private hospitals admissions are concentrated in surgeries and other clinical procedures (accounting around 60 per cent of all surgeries and 70 per cent of all other clinical procedures in 2007-08). Furthermore, private hospitals tend to specialise on certain types of services provision and patients. Around two-thirds of elective surgeries but only five per cent of outpatient occasions service (including emergency) are accounted for by private hospitals. Private patients are more likely to come from higher socioeconomic and the middle age groups (35-64 years old). They are less likely to have complex medical conditions (Productivity Commission, 2009). These observations have led to allegations of private hospitals cherry picking their patients thus adding to the burden of public hospitals (O'Loughlin, 2002).

Within the private hospital sector, there are significant variations in market shares which may affect the competitive behaviour of hospitals. Based on ownership, there are four type of private hospitals: (i) for-profit independent hospitals, mostly owned by doctors; (ii) for-profit group hospitals or chain hospitals (mostly owned by private or public investors); (iii) not-for-profit hospitals owned by religious (mostly Catholic) and charitable

[4]see Harper et al. (2000) as cited in Jensen et al. (2009).

organisations (some may belong to a group); and, (iv) other not-for-profit hospitals; e.g., bush nursing, community and memorial hospitals. Between 1991/92 and 1999/2000, for-profit hospitals experienced the fastest growth with a growth rate of 107 per cent over the period (O'Loughlin, 2002). Since 2002, there have been eleven for-profit hospital groups, four of them own around 80 per cent of the for-profit hospitals. The market share of the largest group is approximately 25%; the next largest group has approximately a 10% share. There have been few entries and exits from the industry; this phenomenon, and the increasingly higher market concentration of for-profit private hospitals, are likely a result of the high entry costs of setting up a new hospital. Thus acquisitions rather than green field investment have been the most feasible mode of entry into the industry (Perrot and Hughes, 2005).

Beside the increasing concentration of for-profit private hospitals, a number of developments that took place in the last two decades may also have important bearing on the extent of hospital competition in Australia. First, the private health insurance reforms that took place in 1999–2001 resulted in the proportion of population covered increasing from 31 per cent in 1998 to 45 per cent in 2001 and maintaining thereafter (Sundararajan et al., 2004). Second, funding arrangements reforms which greatly increased the number of co-locations (commercial arrangements between public and private hospitals which allow a private hospital to be located on the same site at or near to a public hospital). Finally, the move from per-diem reimbursement by private health insurance funds to per-episode reimbursement which has shifted some of the risks from private health funds to the hospitals.

3 Data and empirical framework

3.1 Data

The primary source of data for this study is hospital administrative data from the State of Victoria, Australia. The database, known as the Victorian Admitted Episode Dataset (VAED), contains detailed information on admitted patient episodes reported by all public and private acute hospitals in Victoria. The data include 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. The data we use are de-identified at two levels. At the patient level, patient identifiers have been randomly generated; and at the hospital level, the identity and location of private hospitals are not revealed.

In this paper, we use a sample of minor heart disease related admission episodes over a five-year period, from 2000/01 to 2004/05. The admission episodes were identified from seven three-digit DRG codes.[5] We choose minor, nonsurgical, heart episodes because of two important reasons. First, most hospitals could provide the required treatment for these specific episodes and thus we expect a greater degree of competition among hospitals than in other heart-related episodes such as open-heart surgeries. Second, there is evidence that measures of quality such as unplanned readmissions are less noisy when the comparison across hospitals is restricted to specific episodes (Benbassat and Taragin, 2000).

In addition, we use episode level data—which may contain multiple related separations because of transfers between hospitals—rather than simply separation-level data in order to account for transfers across hospitals for the same episode of illness. The final sample

[5]The DRG classification follows that of the Australian Refined Diagnosis Related Groups (AR-DRGs) version 5.1. These seven DRG codes are: F65 (Peripheral Vascular Disorders), F66 (Coronary Atherosclerosis), F67 (Hypertension), F69 (Valvular Disorder), F71 (Non-Major Arrhythmia and Conduction Disorders), F72 (Unstable Angina), F73 (Syncope and Collapse).

contains slightly over 30,000 admission episodes each year, for a total of 157,427 episodes. Patients in the sample resided in some 800 postcodes; most patients were residents of Victoria but there were also sizeable number of patients from the neighbouring states (i.e., New South Wales and South Australia). The number of hospitals in the sample range from 174 in 2004/05 to 183 in 2000/01.

To investigate the relationship between hospital competition and quality we use two quality indicators: death and unplanned readmission, both within 30 days of discharge. The first measure is a common quality indicator used throughout the literature. The second indicator—which includes readmissions in either the same or another hospital—is used because of its many advantages in measuring quality (Benbassat and Taragin, 2000); (Gorodeski et al., 2010) argues that it captures significantly different quality dimensions from mortality.

In terms of the construction of the quality measures, our use of episode-level rather than separation-level unit requires us to take into account the possibility of a patient admitted to Hospital A for some days, transferred to Hospital B for some additional days and then discharged and died or readmitted within 30 days. In that case, unless one has detailed clinical assessment about the care the patient received from both hospitals, it is difficult to attribute the patient's mortality or readmission outcome: Should it be Hospitals A or B? Of the 157,427 admission episodes in the sample, approximately 2.6 per cent involved transfers between two or more hospitals. Given that there is no natural way of assigning the outcome for these episodes, we have arbitrarily assigned the outcome to the hospital in which the patient stayed for the longest time.

To control for the effects of patient and hospital characteristics on mortality and unplanned readmission, we include a number of covariates in the regression models. Table 1 lists the variables used in the regression (except concentration measures, which were reported in Table 2), also reported were the respective sample mean and standard deviation.

Included in the regression as explanatory variables are episode- and hospital-level covariates. The former include clinical-type variables that are designed to capture the severity and/or complexity of the admission episode as well as personal characteristics of the patient such as age, gender, and whether the patient had private hospital insurance cover. Covariates of a clinical nature include the Charlson Comorbidity index,[6] whether the patient was diagnosed to have heart disease for the first time, whether the patient was admitted via the emergency department, whether it was a same-day episode, whether the episode involved transfers between hospitals, and whether there were complexities and complications as identified in the DRG code. In addition to admission episode-level variables, we also construct hospital-level characteristics using all admissions the hospitals handled in each year (i.e., the entire annual case-load volume, not just restricted to the heart-disease DRGs we used to construct the sample). These hospital-level variables include total annual case-load volume, proportion of admission episodes with no comorbidity, proportion of admission episodes with no ICU stay, proportion of admission episodes with private hospital insurance, and teaching hospital status. These variables are intended to capture respectively scale effects, complexity of cases handled, hospital resources and teaching hospital effect.

3.2 Measuring Competition

To construct measures of hospital competition, we first define hospital markets using the notion of catchment areas (Melnick and Zwanziger, 1988; Zwanziger and Melnick, 1988). This approach seeks to first identify the catchment area of a hospital using quantity flow information (number of admission episodes from a given region) and then identify other hospitals that serve the same catchment area as competitors. Usual measures of market concentration include the *HHI* and the number of competing hospitals. We use this approach rather than adopting a distance-based approach primarily because, for confiden-

[6] A measure of the complexity of an episode, the Charson Comorbidity index(Charlson et al., 1987) is a good indicator of the complexity of an episode and is a strong predictor of mortality. We compute the Charlson Comorbidity index by making use of the diagnosis information coded in ICD-10 codes in the data and follow the procedure outlined in Sundararajana et al. (2004).

tiality reasons, hospitals in the data have been de-identified. Without knowledge of the location of these hospitals, a distance-based approach is ruled out.[7]

The geographical unit we work with is postcode. For each hospital j, we compute the proportion of hospital admissions from each postcode. As per Zwanziger and Melnick (1988), we specify two conditions. First, we identify postcodes that contribute more than three per cent of the total admissions of hospital j. Second, sorting the postcodes from the largest to the smallest contribution proportions, we identify the first K postcodes that make up 40 per cent or more of hospital j's admissions, where K is such that the admissions from the first $(K-1)$ postcodes account for strictly less than 40 per cent of hospital j's total admissions. A postcode that satisfies at least one of the two conditions is said to be in the catchment area of hospital j.

A hospital is said to be a competitor of hospital j if the two hospitals' catchment areas overlap. Specifically, if a postcode is included in the catchment areas of two hospitals, we say that the two hospitals are competitors in that postcode. The *HHI* of a hospital is simply the sum of the squared market shares of all competing hospitals serving the catchment area, which may consist of one or several postcodes. In addition, as suggested by Wong et al. (2005), the number of competing hospitals in a catchment area is also used as a measure of competition. In enumerating competing hospitals, we also distinguish between private and public hospitals, on the belief that ownership could make a difference in so far as how hospitals respond to competition.

In defining the market for each hospital and by each financial year, after finding the catchment areas in terms of postcodes, we compute the *HHI* and number of competing public and private hospitals. Table 2 provides some basic statistics about the sample and the competition measures we computed. Note that in line with common practice the *HHI* figures were multiplied by 10,000. Thus a monopoly market would be indicated by a *HHI* of 10,000, while at the other extreme a perfectly competitive market would give a

[7] Although distance-based approaches of defining hospital markets are considerably more popular than other approaches, they are not without problems; see Propper et al. (2004) for a discussion.

HHI of close to zero.

The computed competition measures suggest that hospitals were on average highly concentrated, with mean *HHI* of around 5,000. A typical hospital faced on average 11 competitors, of which six were private and five public hospitals. The standard deviation of *HHI* is roughly more than half of the mean *HHI*, indicating high variability across hospitals. We also see a large difference in mean *HHI*s between private and public hospitals—the mean *HHI*s are respectively 3,670 and 5,651, suggesting that private hospitals operate in substantially more competitive or less concentrated environment than public hospitals. This is not surprising, given that private hospitals tend to locate in urban areas where the population base is large and hence with a greater concentration of hospitals.

Table 3 summarises each of the competition measures by type of hospitals. Relying on the official classification, we group hospitals in the sample as "Teaching," "Large Regional," "Regional," "Area," "Local" and "Private" hospitals. There is also a residual group that does not fall into the above categories, we refer to these as "Others" and it includes mainly multi-purposes health services facilities that are typically located in remote rural areas.

The pattern of concentration in Table 3 is within expectations. Teaching hospitals and private hospitals tend to locate in urban areas with a large population base, hence faced the most competition not only in terms of *HHI* but also by the number of competing hospitals. At the other extreme, regional general hospitals appear to be the most concentrated in terms of *HHI*, while local and area hospitals, which typically are located in rural areas, faced the least number of competing hospitals.

3.3 Models of Hospital Quality

This section outlines a random-intercept logistic model that exploits the nested structure of the data. Since our main variables of interest—the competition measures—are hospital-level variables that do not vary across admission episodes for a given hospital, a hospital

Table 1: List of variables and summary statistics

Variable name	Remark	Mean	Std dev
	Dependent variables		
m30	30-day mortality	0.043	0.105
unplan	30-day unplanned readmission	0.048	0.071
	Patient characteristics		
charlson	Charlson comorbidity index	0.481	1.049
fheart	dummy, 1=first-time heart diagnosis	0.266	0.442
emerg	dummy, 1=admitted via emergency dept.	0.736	0.441
sameday	dummy, 1=same-day separation	0.305	0.460
transf	dummy, 1=transfers between hospitals	0.026	0.159
cc	dummy, 1=with complexities & complications	0.198	0.399
age	Age in years	69.622	14.757
male	dummy, 1=male	0.523	0.499
auborn	dummy, 1=Australian born	0.657	0.475
insur	dummy, 1=with private hospital insurance	0.309	0.462
	Hospital characteristics #		
volume	Hospital overall caseload volume (100,000)	0.091	0.138
pch0	Prop. of admissions with no comorbidity	0.693	0.168
picu0	Prop. of admissions with no ICU stay	0.769	0.422
pinsur	Prop. of admissions with private insurance	0.355	0.369
teach	dummy, 1=teaching hospital	0.118	0.322

#Hospital characteristics are based on annual total caseload volume of hospitals.
Also included as covariates are time trend and its square, 7 principal diagnosis dummies and 5 ARDRG dummies.

Table 2: Descriptive statistics and hospital concentration measures

	Financial Year					All
	2000/01	2001/02	2002/03	2003/04	2004/05	Years
Number hospitals	183	178	181	176	174	892
Number postcodes	779	796	784	787	794	3,940
Number admission episodes	30,476	31,871	32,637	31,578	30,865	157,427
Mean HHI—All hospitals	4,525	5,126	5,116	4,891	5,078	4,945
	(2,538)	(2,677)	(2,761)	(2,638)	(2,671)	(2,661)
Mean HHI—Private hospitals	3,241	3,753	3,650	3,771	3,983	3,670
	(2,106)	(2,421)	(2,327)	(2,304)	(2,606)	(2,351)
Mean HHI—Public hospitals	5,285	5,896	5,917	5,501	5,653	5,651
	(2,473)	(2,508)	(2,656)	(2,616)	(2,530)	(2,560)
Means no. competing hospitals	12.6	11.1	10.4	10.7	10.5	11.1
	(12.6)	(11.8)	(10.5)	(10.4)	(10.1)	(11.1)
Mean no. competing private hospitals	7.1	6.3	5.6	5.4	5.2	5.9
	(8.6)	(8.1)	(6.5)	(6.5)	(6.0)	(7.3)
Mean no. competing public hospitals	5.5	4.8	4.9	5.3	5.4	5.2
	(4.4)	(4.2)	(4.3)	(4.4)	(4.6)	(4.4)

Note: Figures in parentheses are sample standard deviations.

fixed-effects approach will not separately identify the effect of competition; rather it would capture all hospital-level effects that are invariant to admission episodes, e.g., hospital teaching status and rurality. To capture the effect of competition on quality, we apply the random-intercept logistic model.

Since admission episodes are nested within hospitals, we can specify a two-level random-intercept logistic model. We adopt a latent-response formulation. The basic idea is that for each admission episode there exists an unobserved health measure, or more precisely, morbidity index whose value depends on the health of the patient as well as the quality of treatment the patient received. Among the factors that may influence the latter are the intensity of competition faced by the hospital.

Let there be H hospitals ($h = 1, \ldots, K$) and for each hospital h there are N_h admission episodes indexed by $i = 1, \ldots, N_h$. Let y^*_{iht} denote the (unobserved) morbidity of the patient in admission episode i at hospital h in year t. The way y^*_{iht} relates to hospital characteristics is specified as:

$$y^*_{iht} = X_{iht}\beta + \eta^*_{ht} + \varepsilon_{iht}, \tag{1}$$

where X_{iht} is a vector containing patient demographic and morbidity characteristics such as age, gender, co-morbidity, principal diagnosis and so on, η^*_{ht} represents the (unobserved) hospital quality index, and ε_{iht} is an independently and identically distributed error term.

The latent hospital quality index is assumed to depend on market competition and hospital characteristics in a linear way:

$$\eta^*_{ht} = \gamma_0 + Z_{ht}\gamma + \zeta_{ht}, \tag{2}$$

where Z_{ht} is a vector containing hospital-level variables that do not vary across admission episodes; in our context it contains competition variables and other hospital characteristics such as caseload volume and the teaching status of the hospital. The random term ζ_{ht} captures the effect of unobserved hospital-specific characteristics that cause some hospitals to have higher or lower than average patient outcome than others. We assume ζ_{ht} is normally distributed with mean zero and constant variance ψ, and uncorrelated with ε_{iht} .

Substituting (2) into (1) yields the main estimating equation:

$$y^*_{iht} = X_{iht}\beta + Z_{ht}\gamma + \gamma_0 + \zeta_{ht} + \varepsilon_{iht}. \tag{3}$$

Since patient morbidity index (y^*_{iht}) is unobserved, we estimate (3) using two observed outcome variables, mortality and unplanned readmission. Both are binary indicator variables; they show respectively whether the patient died within 30 days of discharge and whether the patient was readmitted (unplanned) to a hospital, also within 30 days of discharge. Let y_{iht} be the outcome of the patient in episode i and who were admitted to hospital h in year t such that

$$y_{iht} = \begin{cases} 1 & \text{if } y^*_{iht} > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where y_{iht} is either death or unplanned readmission. Equation (4) links the unobserved patient morbidity index to the observed binary outcomes. It states that an adverse outcome (death or unplanned readmission) is observed if the patient morbidity index exceeds some threshold, which we normalise to zero in this case.

To estimate (3), let $M_{iht} \equiv [X_{iht}, Z_{ht}]$ and assume that the error term $\varepsilon_{iht} \mid (M_{iht}, \zeta_{ht})$ is i.i.d. and follows a type-one extreme value distribution. We can write

$$\ln\left[\frac{\Pr(y_{iht} = 1 \mid (M_{iht}, \zeta_{ht}))}{1 - \Pr(y_{iht} = 1 \mid (M_{iht}, \zeta_{ht}))}\right] = M_{iht}\Gamma + \zeta_{ht}, \tag{5}$$

where $\Gamma = [\beta, \gamma]$ is the vector of parameters to be estimated.

The model is estimated using maximum likelihood. Recall that y_{iht} is conditionally independent given ζ_{ht} and M_{iht}. To obtain the unconditional joint probability of y_{iht}, we need to integrate out ζ_{ht}. However, the integral does not have a closed form and has to be approximated using numerical integration.[8]

[8] We fit the model in (5) using the Stata command *xtmelogit*, which uses the numerical method known as adaptive Gaussian quadrature.

Table 3: Hospital competition measures by hospital types

Hospital type	Freq.	*HHI*		No. competing hospitals					
				All types		Private		Public	
	N	Mean	S.d.	Mean	S. d.	Mean	S. d.	Mean	S. d.
Teaching Hospitals	105	3,932	1,778	17.8	10.2	9.7	6.5	8.1	4.7
Large Regional Hospitals	107	5,906	2,311	7.4	6.0	3.2	4.1	4.2	2.4
Regional General Hospitals	69	6,886	2,349	3.6	2.3	1.0	1.4	2.6	1.3
Area Hospitals	115	6,671	2,380	3.5	2.1	0.9	1.2	2.6	1.3
Local Hospitals	102	6,058	2,543	3.3	2.8	0.6	1.7	2.7	1.5
Private Hospitals	318	3,670	2,351	16.6	13.1	9.9	8.3	6.7	5.4
Others	76	4,460	2,635	12.6	10.0	7.1	7.0	5.5	3.4

4 Estimation Results

Our empirical estimation make use of two measures of hospital competition: the number of competing hospitals and the degree of concentration, the latter is measured by $(1 - HHI)$.[9] In some specifications we further distinguish between competing private and public hospitals to allow the effect of competition to differ depending on the ownership of hospitals. We hypothesise that since most private hospitals are for-profit entities, they are likely to be more responsive than public hospitals when faced with greater competitive pressure. Table 4 presents the coefficient estimates and odds ratios of the competition variables.[10]

Table 4: Selected estimates—competition coefficients and odds ratios

	Dep var = Mortality				Dep var = Unplanned Readmission			
	Model A1		Model A2		Model B1		Model B2	
	Coef.	Odds ratio	Coef.	Odds ratio	Coef.	Odds ratio	Coef.	Odds ratio
No. competing hospitals	0.0156	1.02	–	–	0.0063	1.01	–	–
	(0.0108)				(0.0083)			
(No. competing hospitals)^2	-0.0002	1.00	–	–	-0.0001	1.00	–	–
	(0.0002)				(0.0002)			
No. competing private hospitals	–	–	0.0023	1.00	–	–	-0.0094†	0.99
			(0.0072)				(0.0050)	
No. competing public hospitals	–	–	0.0019	1.00	–	–	0.0184**	1.02
			(0.0103)				(0.0070)	
Competition $(1 - HHI)$	0.2683	1.31	0.3711†	1.45	-0.3170*	0.73	-0.3460**	0.71
	(0.2055)		(0.1925)		(0.1289)		(0.1229)	
$Var(\zeta_{ht})$	0.0867		0.0894		0.0509		0.0431	
	(0.0248)		(0.0258)		(0.0174)		(0.0155)	
intraclass correlation (ρ)	0.0257		0.0265		0.0152		0.0129	
log likelihood	-12,719		-12,720		-31,286		-31,282	
No. admission episodes	157,427							
No. hospitals	208							

Figures in parentheses are standard errors.
Included in the regressions are 18 other covariates denoting personal and hospital characteristics.
Significance levels: †: 10% *: 5% **: 1%

The results indicate that competition has important but mixed effect on quality—$(1-HHI)$ is positively related to mortality but negatively related to unplanned readmissions. The

[9] We use $(1 - HHI)$ in the estimation to facilitate the interpretation of the results. An increase in competition is represented by a rise in $(1 - HHI)$, meaning that a positive coefficient on $(1 - HHI)$ implies quality is adversely affected by competition.

[10] Full listings of coefficient estimates can be found in the Appendix.

coefficient estimates are statistically significant, except in Model A1, and large in magnitude. The number of competing hospitals, on the other hand, appear to have little effects on quality; the coefficient estimates are small in magnitude and statistically insignificant except in model B2, and the odds ratios are close to 1. The estimates of interclass correlation (ρ) given in Table 4 are small for both quality indicators, suggesting that the unexplained heterogeneity between hospitals is small relative to the variations across admission episodes within hospitals.

The importance of competition is also reflected in the estimated odds ratios. However, since the *HHI*-derived competition variable is bounded, the interpretation of the odds ratios is difficult. To obtain a clearer picture, we compute the average partial effects of *HHI* on quality, and obtain the corresponding standard errors via bootstrapping.[11] Table 5 presents the average partial effects by hospital type. The average effects are obtained by taking the unweighted mean of the individual partial effects over all observations under the respective hospital type.

Table 5: Average partial effects of *HHI* by hospital types under RI Logit-M

	Mortality				Unplanned readmission			
	Model A1		Model A2		Model B1		Model B2	
Hospital type	APE	Std. err	APE	Std. err	APE	Std. err	APE	Std. err
Teaching Hospitals	0.005	0.0037	0.007†	0.0037	-0.020†	0.0103	-0.022*	0.0100
Large Regional Hospitals	0.005	0.0038	0.007†	0.0037	-0.022†	0.0112	-0.024*	0.0108
Regional General Hospitals	0.005	0.0038	0.008*	0.0037	-0.021†	0.0110	-0.023*	0.0109
Area Hospitals	0.005	0.0041	0.007†	0.0041	-0.017†	0.0091	-0.018*	0.0089
Local Hospitals	0.007	0.0059	0.010†	0.0060	-0.015†	0.0079	-0.017*	0.0078
Private Hospitals	**0.005**	**0.0038**	**0.007**†	**0.0037**	**-0.008**†	**0.0044**	**-0.008**†	**0.0044**
Others	0.013	0.0123	0.017	0.0132	-0.013†	0.0070	-0.013†	0.0071
All hospitals	0.005	0.0038	0.007†	0.0038	-0.018†	0.0091	-0.019*	0.0089

Standard errors are obtained via bootstrapping with 100 replications.
Significance levels: †: 10% *: 5% **: 1%

The results in Table 5 indicate that the association between competition and mortality rates is not strong and are mostly not statistically significant. A slight increase in competition is linked with an in increase in mortality rate by about 0.005 to 0.008, a relatively

[11] Due to the random effects term in the logistic regression, it is not possible to obtain the standard errors via analytical methods such as the delta method.

small magnitude in terms of the unadjusted sample mortality rate of 0.043. It is worth noting that the size of the effects are comparable for private and public hospitals. In contrast, the average partial effects of competition on unplanned readmission are in the region of -0.018 to -0.021, which are substantial in the light of the sample mean of 0.048 for unplanned readmission. Moreover, these effects are statistically significant at 10 per cent or lower. Interestingly, here the effects on private hospitals differ substantially from those on public hospitals—a slight increase in competition would lower unplanned readmissions of all hospitals by about 1.8 to 1.9 percentage point, whereas the effect on private hospitals would only be about 0.8 percentage point.[12] Taken together, these results suggest that more intense competition, or a lowering in hospital concentration, could lead to fewer unplanned readmissions but greater patient mortality. The estimated average partial effects suggest that the lowering of unplanned readmissions is relatively large in relation to the increase in mortality.

4.1 Robustness

An important criticism of our approach is that some unobserved hospital and patient characteristics may affect both quality and level of competition. To address this endogeneity concern, we consider two alternative specifications below. In addition, we also estimate our model using a restricted sample that only contains episodes admitted via the emergency department, on the argument that patients admitted in an emergency situation were likely to go to the nearest hospital, thus reducing the possibility of any systematic selection bias. In all cases, while some quantitative variations are observed, the qualitative nature of our results remain unchanged.

The first alternative specification is an extension of the random intercept logistic model to include the Mundlak (1978) adjustment. In (3), an important consideration is some

[12]One possibility is that critically ill patients in private hospitals may be readmitted to public hospitals such that readmission rates of private hospitals might be understated ((Beggs et al., 1996; Sabourin and Funk, 1999) as cited in Fasken et al. (2001). However, as explained earlier, our readmission rates take into account both readmission to the same hospital as well as to other hospitals.

(or all) elements of X could be correlated with ζ due to unobserved heterogeneity at the admission episode level. For example, patients with more complex conditions may have a preference for high-quality hospitals which are likely to have better facilities. We address this endogeneity problem by including the cluster means of X as regressors, as discussed in Mundlak (1978) (see also Wooldridge, 2002). The estimating equation thus becomes:

$$y^*_{iht} = X_{iht}\beta + \bar{X}_{\cdot ht}\theta + Z_{ht}\gamma + \gamma_0 + \zeta_{ht} + \varepsilon_{iht}, \tag{6}$$

where $\bar{X}_{\cdot ht}$ contains yearly hospital mean values of all variables in X. Our primary focus, however, remains on estimating γ, particularly on the effects of competition on quality. Table 6 presents the coefficient estimates of interest.[13]

The Mundlak-adjusted estimates for the competition variables presented in Table 6 are very similar to the non-adjusted estimates given in Table 4. In most cases no material differences are observed, with the exception that the coefficient on (1-*HHI*) for Model MB1 is no longer significant at the 10 per cent level.

For further robustness checks, we also attempted a two-step estimation that involves first risk-adjusting the casemix differences of hospitals at the admission episode level and then estimating the effect of competition at the aggregate hospital level. The first step of this two-step estimation is similar in spirit to the usual fixed effects estimation.

Intuitively, this approach seeks to adjust for casemix differences of hospitals before estimating, at the aggregate hospital level, the effect of competition on quality. For continuous dependent variables we would use fixed effects estimates as the measure of risk-adjusted quality. However, because in our context the dependent variables, mortality and unplanned readmission, are binary, the first step estimation involves a logistic regression at the admission episode level:

$$\Pr(y_{iht} = 1 \mid X_{iht}) = g(X_{iht}\beta).$$

For each admission episode i we obtain predicted probability $\hat{p}_{iht} = g(X_{iht}\hat{\beta})$. The risk-

[13]Detailed coefficient estimates are available from the authors upon request.

Table 6: Selected coefficient estimates of Mundlak-adjusted random intercept logit estimation

	Mortality		Unplanned Readmission	
	Model A1	Model A2	Model B1	Model B2
No. competing hospitals	-0.0018	–	0.0010	–
	(0.0112)		(0.0078)	
(No. competing hospitals)^2	0.0000	–	0.0000	–
	(0.0002)		(0.0001)	
No. competing private hospitals	–	-0.0101	–	-0.0090†
		(0.0073)		(0.0049)
No. competing public hospitals	–	0.0109	–	0.0192**
		(0.0101)		(0.0069)
Competition $(1 - HHI)$	0.2625	0.2357	-0.3238**	-0.3819**
	(0.2017)	(0.1897)	(0.1216)	(0.1177)
log likelihood	-12,703	-12,702	-31,250	-31,246
No. admission episodes	157,427			
No. hospitals	208			

Figures in parentheses are standard errors.
Included in the regressions are 18 other covariates denoting personal and hospital characteristics, and seven mean values of the covariates.
Significance levels: †: 10% *: 5% **: 1%

adjusted measure is computed by taking the difference between observed hospital mortality or readmission rates and hospital average predicted probability, i.e.,

$$y_{ht}^{\mathrm{RA}} = \frac{1}{N_h}\left(\sum_{i\in h}(y_{iht} - \hat{p}_{iht})\right),$$

where y_{ht}^{RA} denotes the risk-adjusted measure of y and N_h is the total number of admission episodes in hospital h.

The second step of the two-step approach simply involves OLS regression of y_{ht}^{RA} on competition measures and other hospital characteristics. The relevant parameter estimates of the second step OLS regression are given in Table 7.[14]

The results in Table 7 suggest that competition $(1-HHI)$ has a positive effect on mortality but a negative effect on unplanned readmission. This mixed result is consistent with that of Table 4, although there are variations in the statistical significance of individual estimates. In particular, the statistical significance of most coefficients in Table 7 are lower than those

[14]A complete listing of coefficient estimates for both steps is available from the authors upon request.

Table 7: Selected coefficient estimates—Two-step estimation

	Mortality		Unplanned readmission	
	Model A1	Model A2	Model B1	Model B2
No. competing hospitals	0.0019†	–	-0.0004	
	(0.0010)		(0.0008)	
(No. competing hospitals)^2	0.00004†	–	0.00000	
	(0.00002)		(0.00001)	
No. competing private hospitals	–	0.0005	–	-0.0005
		(0.0008)		(0.0006)
No. competing public hospitals	–	-0.0007	–	0.0009
		(0.0012)		(0.0009)
Competition $(1 - \mathit{HHI})$	0.0297†	0.0463**	-0.0094	-0.0145
	(0.0171)	(0.0153)	(0.0135)	(0.0120)
No. observations	892	892	892	892
Adjusted R^2	0.116	0.113	0.014	0.015

Figures in parentheses are standard errors.
Significance levels: †: 10% *: 5% **: 1%

in Table 4. However, it should be noted that the dependent variable in the second step of the two-step approach is an estimated quantity, thus the use of OLS estimation is consistent but inefficient, since the information on the standard error of the estimated quantity is not used in the estimation.[15]

In addition to the two alternative specifications, we also follow Bloomm et al. (2010) by estimating the random intercept logistic model using a restricted sample that only contains episodes admitted via the emergency department. Since patients admitted in an emergency situation were likely to go to the nearest hospital, the possibility of any systematic selection bias is less of a concern. The estimation results show no material differences from results obtained using the full sample.[16]

5 Conclusions

This paper investigates the effect of competition on hospital quality using administrative data from hospitals in the State of Victoria, Australia. Two quality indicators are used: mortality and unplanned readmission, both within 30 days of discharge. We define hospital markets using the notion of catchment areas as per Melnick and Zwanziger (1988), and compute standard measures of competition including Herfindahl-Hirschman index and the number of competing public and private hospitals.

Consistent with previous findings on hospital competition in other countries (e.g., Mutter et al., 2008; Propper et al., 2008), we find that competition has a mixed effect on quality of care. Increasing competition is associated with higher mortality but lower readmission. Our evaluation of the average partial effects suggests that competition has a large effect on unplanned readmission but a moderate effect on mortality.

We conjecture that the results could be related to the availability of appropriate care and

[15]Unfortunately there is no analytical solution for the standard errors, a bootstrap approach will be computationally intensive and has not been attempted.

[16]A complete listing of all coefficient estimates are available from the authors upon request.

the desire of patients in seeking such care. Patients with severe conditions are more likely to end up in large hospitals where they could obtain appropriate care. Mortality among these patients is naturally higher than that of other patients, even though we control for patient conditions in the form of gender, age, and illness severity. Given that large hospitals are found mostly in urban areas where competition is more intense, the effect of competition on mortality thus captures to some extent the proximity of large hospitals to urban areas. However, the adverse effect of competition on mortality is relatively weak in both magnitude and statistical significance.

On the other hand, competition appears to have a positive effect on quality as measured by unplanned readmission. The effect of competition again could reflect the fact that patients are more likely to obtain appropriate care in urban areas than in rural areas where the choice of hospitals are usually limited. Naturally the likelihood of unplanned readmission is lower if appropriate care is given. This could possibly explain the seemingly contradictory results on unplanned readmission and mortality.

We also find that the effect on unplanned readmission differs substantially between private and public hospitals. The average partial effects show that the quality-improving effect on unplanned readmission for private hospitals is less than half of that on public hospitals. No such patterns, however, are observed on the effects on mortality—the quality-lowering effects are approximately the same for private and public hospitals. The conjecture of Mutter et al. (2008) could perhaps apply in this context—the quality-improving effects on unplanned readmission are related to quality dimensions that are not easily observed or understood by patients. Thus, when facing greater degree of competition, private hospitals may divert resources to areas in which patients could easily observe (e.g., 'hotel'-style amenities) rather than on improving aspects that are difficult to observe such as unplanned readmission.

For robustness, we also conduct two alternative model specifications addressing the possible endogeneity problem caused by unobserved heterogeneity. The first specification is a Mundlak-adjusted random intercept logistic model, the second is a two-step estimation approach which is similar in spirit in first estimating a hospital-level fixed effects and then regressing the estimated fixed effects on competition and other hospital characteristics. In addition, we also perform the estimation using a restricted sample that only contains admission episodes of patients admitted via the emergency department. In all cases the qualitative aspects of our results remain unchanged.

We emphasize that the results we present are preliminary and the interpretation we offer is far from definitive. In addition, our measure of competition is not perfect; like all empirical-based approaches, our approach could not capture potential competition, i.e., the number of potential rival firms that could enter an industry. Finally, there is some recent evidence suggesting that mortality and unplanned readmissions may be endogenous to each other (Gorodeski et al., 2010); thus there is a case for future research modelling the explicitly relationship between the two quality dimensions.

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Appendix A: Main Estimation Results

Table A1: Random intercept logistic regression—Mortality

Dependent variable	30-day mortality			
	Coeff. estimate	Std. err.	Coeff. estimate	Std. err.
No. competing hospitals	0.0156	0.0108	–	
(No. competing hospitals)^2	-0.0002	0.0002	–	
No. competing private hospitals	–		0.0023	0.0072
No. competing public hospitals	–		0.0019	0.0103
Competition $(1 - \mathit{HHI})$	0.2683	0.2055	0.3711†	0.1925
Charlson comorbidity index	0.3092**	0.0102	0.3091**	0.0102
First-time heart disease diagnosis	-0.2142**	0.0525	-0.2147**	0.0525
Emergency admission (dummy, 1=yes)	0.3016**	0.0569	0.2973**	0.0568
Same-day separation (dummy, 1=yes)	-0.3356**	0.0590	-0.3355**	0.0590
Transfer between hospitals (dummy, 1=yes)	0.4160**	0.1033	0.4224**	0.1033
Catastrophic or severe CC (dummy, 1=yes)	1.2102**	0.0443	1.2119**	0.0443
Age	-0.0230	0.0144	-0.0232	0.0144
(Age)^2	0.0006**	0.0001	0.0006**	0.0001
Male (dummy, 1=male)	0.3355**	0.0387	0.3350**	0.0387
Australian born (dummy, 1=yes)	0.0664	0.0420	0.0646	0.0420
Private hospital insurance (dummy, 1=yes)	0.1118*	0.0492	0.1110*	0.0492
Total hospital volume	-0.3050	0.3292	-0.2464	0.3310
Total hospital prop. zero Charlson episodes	-0.8324**	0.2357	-0.8302**	0.2379
Total hospital prop. non-ICU episodes	-0.0209	0.0889	-0.0263	0.0894
Total hospital prop. private-patient episodes	-0.6241**	0.1393	-0.6013**	0.1399
Teaching hospital status (dummy: 1=teaching)	-0.1884	0.1384	-0.1557	0.1375
Principal diag. I20 Angina Pectoris	-1.4147**	0.1802	-1.4112**	0.1801
Principal diag. I25 Chronic Isch. Heart Disease	0.2454	0.1948	0.2506	0.1948
Principal diag. I47 Paroxysmal Tachycardia	-0.7670**	0.2033	-0.7657**	0.2034
Principal diag. I48 Atrial Fibri. & Flutter	-0.7901**	0.1640	-0.7890**	0.1641
Principal diag. I49 Other Cardiac Arrhythmias	-1.0113**	0.2114	-1.0114**	0.2115
Principal diag. I70 Atherosclerosis	0.6541**	0.0788	0.6538**	0.0788
Principal diag. R00 Abnormalities of Heart Beat	-0.9684**	0.1697	-0.9675**	0.1698
Principal diag. R55 Syncope and Collapse	0.0119	0.1297	0.0117	0.1297
ARDRG F66 Coronary Atherosclerosis	0.1682	0.1818	0.1654	0.1817
ARDRG F71 Non-maj Arrhythmia & Conduction Dis.	0.0398	0.1606	0.0405	0.1607
ARDRG F72 Unstable Angina	0.5187**	0.1852	0.5169**	0.1851
ARDRG F73 Syncope and Collapse	-0.9701**	0.1248	-0.9679**	0.1248
Year	-0.1176†	0.0687	-0.1266†	0.0685
(Year)^2	0.0124	0.0112	0.0139	0.0111
Constant	-5.6126**	0.5831	-5.5711**	0.5827
Random intercept variance ($\hat{\psi}$)	0.0867	0.0248	0.0894	0.0258
Residual intraclass correlation ($\hat{\rho}$)	0.0257	–	0.0265	–
Log likelihood	-12,718.9		-12,719.9	
Number of obs.	157,427			

Significance levels: †: 10% *: 5% **: 1%

Table A2: Random intercept logistic regression—Unplanned Readmission

Dependent variable	30-day Unplaneed Readmission			
	Coeff. estimate	Std. err.	Coeff. estimate	Std. err.
No. competing hospitals	0.0063	0.0083	–	
(No. competing hospitals)^2	-0.0001	0.0002	–	
No. competing private hospitals	–		-0.0094†	0.0050
No. competing public hospitals	–		0.0184**	0.0070
Competition $(1 - HHI)$	-0.3170*	0.1289	-0.3460**	0.1229
Charlson comorbidity index	0.1132**	0.0095	0.1133**	0.0095
First-time heart disease diagnosis	-3.0572**	0.0673	-3.0572**	0.0673
Emergency admission (dummy, 1=yes)	2.5282**	0.0699	2.5242**	0.0692
Same-day separation (dummy, 1=yes)	-0.1892**	0.0283	-0.1897**	0.0283
Transfer between hospitals (dummy, 1=yes)	0.9008**	0.0768	0.9064**	0.0767
Catastrophic or severe CC (dummy, 1=yes)	0.1829**	0.0291	0.1831**	0.0291
Age	-0.0152**	0.0049	-0.0154**	0.0049
(Age)^2	0.0001	0.0000	0.0001	0.0000
Male (dummy, 1=male)	0.0154	0.0223	0.0154	0.0223
Australian born (dummy, 1=yes)	0.0366	0.0243	0.0362	0.0243
Private hospital insurance (dummy, 1=yes)	-0.2063**	0.0301	-0.2060**	0.0301
Total hospital volume	0.0101	0.2501	0.1147	0.2428
Total hospital prop. zero Charlson episodes	0.0271	0.1897	0.1037	0.1869
Total hospital prop. non-ICU episodes	-0.0290	0.0644	-0.0274	0.0620
Total hospital prop. private-patient episodes	0.2191†	0.1189	0.2566*	0.1149
Teaching hospital status (dummy: 1=teaching)	-0.0035	0.1066	0.0027	0.0994
Principal diag. I20 Angina Pectoris	0.5537*	0.2186	0.5558*	0.2185
Principal diag. I25 Chronic Isch. Heart Disease	0.4740*	0.2410	0.4728*	0.2409
Principal diag. I47 Paroxysmal Tachycardia	0.4201*	0.1668	0.4215*	0.1668
Principal diag. I48 Atrial Fibri. & Flutter	0.4621**	0.1595	0.4640**	0.1595
Principal diag. I49 Other Cardiac Arrhythmias	-0.3180†	0.1847	-0.3171†	0.1847
Principal diag. I70 Atherosclerosis	0.7643**	0.1194	0.7635**	0.1193
Principal diag. R00 Abnormalities of Heart Beat	-1.5098**	0.1794	-1.5082**	0.1794
Principal diag. R55 Syncope and Collapse	-0.2967**	0.0918	-0.2968**	0.0918
ARDRG F66 Coronary Atherosclerosis	0.5375*	0.2272	0.5373*	0.2272
ARDRG F71 Non-maj Arrhythmia & Conduction Dis.	1.0002**	0.1635	1.0000**	0.1635
ARDRG F72 Unstable Angina	0.9432**	0.2269	0.9417**	0.2269
ARDRG F73 Syncope and Collapse	0.7277**	0.1037	0.7295**	0.1037
Year	-0.0271	0.0409	-0.0320	0.0404
(Year)^2	-0.0039	0.0066	-0.0048	0.0066
Constant	-4.8019**	0.2497	-4.8369**	0.2455
Random intercept variance ($\hat{\psi}$)	0.0509	0.0174	0.0431	0.01552
Residual intraclass correlation ($\hat{\rho}$)	0.0257	–	0.0265	–
Log likelihood	-31,285.7		-31,282.2	
Number of obs.	157,427			

Significance levels: †: 10% *: 5% **: 1%