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Abstract

This paper investigates the effects of competition on hospital quality. It proposes to extend the Elzinga-Hogarty quantity flow approach of defining markets by first determining the trading cluster to which each hospital belongs and then delineating markets using patient flow information. After defining hospital markets and computing measures of competition, this paper examines the effect of competition on hospital quality using hospital administration data from the state of Victoria, Australia. We approximate quality using two indicators, namely mortality within 30 days of discharge and unplanned readmission within 28 days of discharge. For each quality indicator, a random intercept logit model is estimated. Two main findings are reported. First, the boundaries of markets and hence the degree of competition depend on the nature of the medical services provided. Second, competition is found to have a mixed effect on quality of hospital care–increasing the number of private hospitals appears to lower quality, while increasing the number of public hospitals has the opposite effect. The intensity of competition, on the other hand, does not appear to have a statistically significant effect on quality.

Keyword(s): Hospital markets; Elzinga-Hogarty; Hospital competition; Hospital Quality.

JEL Code(s): I11, D24

1. Introduction

This paper investigates the effects of competition on hospital quality. It proposes an extension of the quantity flow approach (Elizinga and Hogarty, 1973) of defining hospital markets, on the basis of which measures of competition between hospitals are computed. Using hospital administration data of heart disease patients, it then examines the effect of competition on hospital quality, in terms of mortality and unplanned readmission, in the state of Victoria, Australia.

The relationship between competition and hospital quality is an important issue for health policymaking, since in many cases government policies have a direct impact on the degree of competition between hospitals. For examples, the use of casemix funding and the way privately-insured patients are funded in public hospitals have a direct impact on how hospitals compete against each other. A longstanding question in the literature is whether competition between hospitals affects the quality or costs of hospital care.[1] In a textbook competition environment, hospitals compete against each other by offering either lower costs or higher quality of care. However, if consumers do not bear the full costs of care, hospitals will tend to compete by offering higher quality services.[2]

Quality of hospital care encompasses many different dimensions, some of which are more easily understood or observable than others. Competition may lead hospitals to improve quality along dimensions that are easily understood or observable. For example, suppose consumers do not observe or understand unplanned readmission as easily as hospital amenities, competition may well result in hospitals improving amenities in lieu of efforts to reduce the rate of unplanned readmission.

However, to understand the effects of competition, we must first measure competition. To do so, we need to define the markets in which the hospitals compete. A common approach in the literature is to construct hospital markets based on geographical areas delineated by geopolitical boundaries (e.g., county) or fixed distances (e.g., all hospitals within a 15-mile radius of some point). In some studies, patient flow information is used in conjunction with geographical boundaries (e.g., Dalmau-Matarrodona and Puig-Junoy, 1998).

This paper proposes an extension of the quantity flow approach of Elzinga and Hogarty (1973) in defining hospital markets. Our approach seeks to first determine the trading cluster to which each hospital belongs, then uses the quantity flow information to delineate the market

[1] See the review by Gaynor (2006) and the references cited therein.
[2] We make no welfare judgement here as to whether better quality of care is socially beneficial. It may well be that competition results in 'over-servicing' (e.g., unnecessary tests) and a form of 'medical arms race' in which hospitals over-invest in equipment and technologies from the social welfare perspective.

for a given cluster. This way, it not only avoids the arbitrariness of using geographical boundaries (a criticism of Dranove and Shanley, 1989). but also has two further advantages. First, it relies entirely on quantity or patient flow information to delineate markets, an approach that is theoretically more compelling than the ad hoc approach of relying on geographical boundaries or fixed distances. Second, it is possible to account for different disease types, levels of severity and complexity, and hospital specialties. It can, for example, allow for the fact that minor hospital services are mainly provided for local population, while major services such as cardiac surgeries tend to draw from a much wider area.

We implement the procedure using administrative data of heart disease patients from all hospitals in the State of Victoria, Australia. We first divide heart disease admission episodes into three classes based on Diagnostic-Related Groups (DRGs) and depending on the severity of patient conditions. We label these classes as Major Medical (MAME), Minor Medical (MIME) and Surgical (SURG) episodes. Although MAME and MIME episodes were broadly similar in terms of aggregate statistics, we find that the market characteristics were rather different—the markets for MIME episodes were substantially less competitive than those for MAME episodes. In terms of the number of markets for Victoria, there were also fewer markets under MAME than under MIME. For SURG episodes, we find that all hospitals were competing in a single, competitive, market. Our approach shows that the boundaries of markets and hence the degree of competition depend critically on the nature of the medical services provided. For example, services provided for MIME episodes tend to be relatively uncomplicated, whereas services required for MAME and SURG episodes tend to be more complex or severe, and the patients are more willing to travel farther, hence widening the boundary of the markets.

Once markets are defined, we can measure the degree of competition by counting the number of public and private hospitals in each market and by using the Herfindahl-Hirschman Index (HHI). Using these competition measures we then examine the effect of competition on hospital quality, where the latter is approximated using two quality indicators, namely mortality within 30 days of discharge and unplanned readmission within 28 days of discharge. For each quality indicator, a two-level random intercept logit model is estimated. We find that competition has a mixed effect on quality—increasing the number of private hospitals tends to lower quality, but increasing the number of public hospitals has the opposite effect. However, the intensity of competition, as captured by the HHI, does not appear to have any statistically significant effect on quality.

The plan of this paper is as follows. Section 2 briefly discusses the empirical framework under which we define markets and measure hospital competition. Section 3 presents an empirical model that links hospital quality to competition. Section 4 discusses the data used; while the main results are presented in Section 5. Finally, some concluding remarks are given in Section 6.

2. Defining hospital markets

In microeconomics, firms are said to operate in the same market if their pricing and production decisions affect each other. Thus in the competition law literature, markets are defined to include products or services that have a high degree of substitutability. In practice, it is common to determine market areas by using cross-elasticity of demand with respect to price or non-price variables of interest.

However, the usual way of defining markets is not practicable for hospitals since the presence of health insurance means that consumers often do not pay the full price of hospital services. The unavailability of price information leads researchers to turn to other ad hoc measures of delineating market boundaries, among the popular ones are geopolitical boundaries (Noether, 1988; Dranove et al., 1992, 1993), fixed and variable radius (Luft et al., 1990; Gresenz et al., 2004; Propper, 1996), and by patient flows or catchments areas (Zwanziger and Melnick, 1988; Zwanziger, 1989). A review of these measures can be found in Gaynor and Vogt (2000) and Wong et al. (2005), among others.[3]

Among these ad hoc measures, a theoretically more compelling measure that makes use of quantity flow information is the approach first proposed by Elzinga and Hogarty (1973). Under this approach, hospital markets are determined by patient flows to and from some geographic areas.[4] A market is defined as the smallest geographic area with no more than *x* per cent of the hospital services consumed within the area coming from hospitals outside of the area and no more than x per cent of the hospital services produced within the area consumed by patients outside the area, where *x* has been set arbitrarily at 10, 20 or 30 per cent.

There are several practical problems in implementing the Elzinga-Hogarty method.[5] First, the method requires location information of both hospitals and patients. If, as in our data,

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[3] More recently, there is also a body of literature on structural demand modeling that sidesteps the issue of delineating market boundaries; see, for examples, Town and Vistnes (2001), Gaynor and Vogt (2003), Tay (2003), Geweke et al. (2003) and Kessler and Geppert (2005). While this approach has its appeal, it demands data on prices or their proxies and can be computationally intensive.
[4] For example, see Dalmau-Matarrodona and Puig-Junoy (1998); see also Gaynor and Vogt (2000) for a review.
[5] Other problems associated with the Elzinga-Hogarty method were discussed in Gaynor and Vogt (2000), Dranove and White (1994) and Zwanziger et al. (1994).

the location information of some hospitals is unavailable, searching over all possible combinations of hospitals and regions imposes an unrealistic computational burden.[6] For this reason the method is often implemented by restricting the search pattern using geographical information, e.g., searching over adjacent regions (Dalmau-Matarrodona and Puig-Junoy, 1998).

However, restricting the search patterns creates a second problem—the non-uniqueness problem—the number and composition of markets can be different depending on the direction of search, and also whether one begins with the largest possible market and narrows it down using the above-mentioned criteria, or with the smallest possible market and expands it up. by adding more hospitals or areas.

A third practical problem arises in relation to the extent to which markets are permitted to overlap. It seems reasonable to expect markets to overlap in their geographical boundaries, such that some hospitals may operate in two or more markets. However, if markets are allowed to overlap, the extent of overlaps needs to be determined a priori and this decision is entirely arbitrary.[7]

In this paper, we propose an extension of the Elzinga-Hogarty method. Our approach makes use of quantity flow information between hospitals and regions but require no location information of hospitals. It can therefore be used for data sets in which the identity of hospitals has been masked. Our approach imposes two requirements on any given hospital market. First, hospitals and patients in the market must be in 'connected' in the sense of a trading cluster. Second, we impose the usual Elzinga-Hogarty requirements that the cluster must be a relatively 'self-contained' group of hospitals and patients; that is, there are few patients who seek treatment in hospitals outside the group (outflow) and there are few outside patients treated in the hospitals in the group (inflow).

Given that the trading clusters are determined entirely from the quantity flow information, we avoid the arbitrariness of restricting the search pattern and the non-uniqueness problem mentioned earlier. More importantly, our approach allows the extent of the markets to vary according to hospital specialties and nature of care as reflected in patient flows. As will be shown below, we delineate markets for three different types of hospital services that are classified by DRGs.

[6] There are 21 possible combinations if there are two hospitals and three regions; the number of possible combinations increases to 49 if there are three hospitals and three regions.

[7] Some practical considerations include whether two markets can overlap by more than 50 per cent, and if so whether a market can exist within a larger market.

We illustrate the idea of a trading cluster by way of an example. Consider an example of five hospitals and five regions (identified by postcodes) given in Table 1. Hospital and postcode identifiers are given in respectively the first and second columns. The patient flow information shows that certain number of patients from postcodes 101 and 102 seek treatment in hospital A, some number of patients from postcode 102 also seek treatment in hospital B, and patients in these two postcodes do not seek treatment in any other hospitals. Likewise, hospital B draws its patients entirely from postcodes 102 and 103. We say that postcodes 101 and 102 are connected, because patients from these two postcodes seek treatment in hospital A. Further, and hospitals A and B are also connected, because they both draw patients from postcode 102. Our objective is to identify clusters of connected trading partners, where connectedness can be either direct (such as Hospitals A and B) or indirect via another member in the cluster (such as Hospital A and postcode 103–postcode 103 is connected to postcode 102 via Hospital B, which in turns is connected to Hospital A via postcode 102). Using the quantity flow information in Table 1, we can distinguish two clusters, the first consists of Hospitals A and B and patients in postcodes 101, 102 and 103; the second cluster consists of Hospitals C, D and E and patients in postcodes 105 and 106.[8] This way of identifying trading clusters can be implemented using any standard clustering algorithm.[9]

Table 1: Illustration of a trading cluster

Hospital id.	Postcode	No. of patients	Market id.
A	101	*nnn*	1
A	102	*nnn*	1
B	102	...	1
B	103		1
C	105		2
C	106		2
D	105		2
E	106		2

Having established the trading clusters, we next identify clusters that are hospital markets by examining the inflow of and outflow of patients from each cluster as per the Elzinga-Hogarty approach. In simple terms, the rate of outflow from a cluster refers to the proportion of

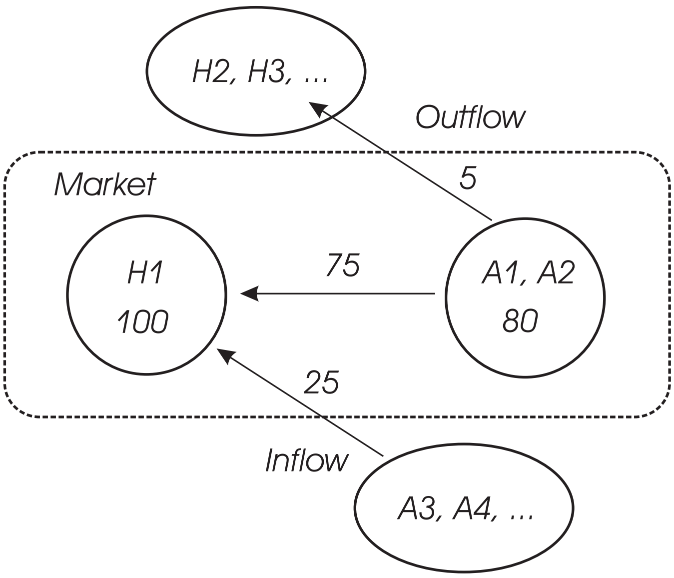
[8] The idea of connectedness here is similar to the notion of multi-market contacts, where firms are thought to be connected because of production decisions, production costs, or one is perceived as a potential entrant by another; see Chen and Ross (2007) for a review of the multi-market contact literature. Here, however, we only restrict the connectedness to quantity flows. Thus, in the example, hospitals D and E do not draw patients from any common areas but are potentially in the same market because of hospital C. They are thought to be connected because an action (e.g., a public relation strategy) by hospital C may affect patient flows to both hospitals D and E, and whose responses to hospital C may in turn affect each other.

[9] We implement the algorithm using the Stata command ‘superclust’ which was developed by Jann (2005).

patients who reside in the cluster but who seek treatment in hospitals outside the cluster. Similarly, the rate of inflow refers to the proportion of patients who seek treatment in hospitals in the cluster but who reside outside the cluster.

Figure 1 provides an illustration of a hypothetical cluster consisting of one hospital, H1, and two regions, A1 and A2. Hospital H1 has 100 patients, 75 of which are from inside and 25 are from outside the cluster. The inflow is therefore 25 per cent. Regions A1 and A2 have 80 patients in total, 75 of which seek treatment inside at hospital H1 and 5 seek treatment outside the cluster at other hospitals. Thus the outflow is approximately 6 per cent. The cluster constitutes a market if the rates of outflow and inflow are within a predetermined bound of, say, 25 per cent. Thus in this case we would regard the cluster consisting of H1, A1 and A2 as a market.

Figure 1: Inflows and Outflows of a Market



For clusters that do not satisfy the bound of inflow and outflow, we do not expand the cluster as in other applications of the Elzinga-Hogarty approach. Rather, the cluster is discarded from the analysis. This way, the cluster identification in the first step can be thought of as a data driven approach that eliminates the arbitrariness and non-uniqueness of the resulting market definition in the conventional Elzinga-Hogarty approach.

Besides avoiding the arbitrariness and non-uniqueness of the conventional approach, our data driven approach also allows for markets to be defined for different hospital specialties and nature of care. It can, for example, allow for the fact that minor hospital services are mainly provided for local population, while major care such as cardiac surgeries tends to draw from a much wider area. More importantly, a further advantage of this approach is it does not require location information of the hospitals, only geographical information of patients is required. This feature is critical for the present study since our data do not contain location information of private hospitals.

After defining the hospital markets, we can measure the intensity of competition for each market using standard measures of competition. As pointed out by Wong et al. (2005), the two most frequently used methods of capturing competition intensity are the number of hospitals in each market and the Herfindahl-Hirschman Index (HHI). To derive the latter, we let x_h be the total number of patients served by hospital $h \in H_j$ given market j. Define S_h as the market share of hospital $h \in H_j$, i.e., $S_h = x_h \big/ \sum_{k \in H_j} x_k$. The HHI for market j can be computed as

$$HHI_j = \sum_{h \in H_j} S_h^2 \, ,$$

which ranges from 0 to 1, where the former corresponds to a perfectly competitive market and the latter to a monopoly. In practice the index is often re-scaled by multiplying the number with 10,000 so that it ranges from 0 to 10,000. Under the Horizontal Merger Guidelines issued by the U.S. Department of Justice and the Federal Trade Commission, three types of markets are distinguished: (i) non-concentrated markets are those with HHI lower than 1,000; (ii) moderately concentrated markets are those with HHI between 1,000 and 1,800; and (iii) highly concentrated markets are those with HHI greater than 1,800.

3 Model of hospital quality and competition

This section outlines an empirical model that relates competition to quality, where hospital quality is treated as an endogenous variable. We exploit the nested structure of the data—admission episodes are nested within hospitals—by specifying a two-level random intercept model using a latent-response formulation. The basic idea is that for each patient (i.e., admission-episode) there is an (unobserved) health measure, or more precisely, morbidity index which values depend on the characteristics of the patient as well as the quality of the hospital treating the patient.

Let there be H hospitals indexed by $h = 1, \ldots, K$ and for each hospital there are N_h episodes indexed by $i = 1, \ldots N_h$. Let y_{ih}^* denotes the (unobserved) morbidity of a patient-episode i and admitted to hospital h. How y_{ih}^{*} depends on hospital quality is specified in equation 1 below:

$$y_{ih}^{*} = X_{ih}\beta + \eta_{h}^{*} + \varepsilon_{ih} \qquad (1)$$

where X_{ih} represents the patient demographic and morbidity characteristics such as principal diagnoses, age, gender, comorbidity and so on, η_{h}^{*} represents an (unobserved) hospital quality index, and explanatory variables, and ε_{ih} is an independently and identically distributed error term.

We next specify the latent hospital quality index to depend on market competition and hospital characteristics:

$$\eta_{h}^{*} = \gamma_{0} + Z_{h}\gamma + \zeta_{h} \qquad (2)$$

where Z_{h} is a vector of competition variables and variables denoting hospital characteristics such as the proportion of private patients admitted to the hospital, proportion of non-complex episodes and so on. The random term ζ_{h} captures the effect of unobserved hospital-specific characteristics that cause some hospitals to have higher or lower average patient morbidity levels than others. We assume ζ_{h} to be normally distributed with mean zero and constant variance (ψ) and uncorrelated with ε_{ih}.

Substituting (2) into (1) yields

$$y_{ih}^{*} = X_{ih}\beta + Z_{h}\gamma + \gamma_{0} + \zeta_{h} + \varepsilon_{ih} \qquad (3).$$

Equation (3) is our estimating equation and our primary interest is in estimating γ, particularly in the element that relates to the effects of competition on quality (η_{h}^{*}).

Since patient morbidity index (y_{ih}^{*}) is unobserved, we estimate (3) using two observede outcomes, namely indicator variables of whether or not the patient died within 30 days of separation and whether the patient was readmitted (unplanned) to hospital within 28 days. That is, let y_{ih} be the outcome of the patient in episode i and who were admitted to hospital h such that

$$y_{ih} = \begin{cases} 1 & \text{if } y_{ih}^{*} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad (4),$$

where y_{ih} is either death within 30 days or unplanned readmission within 28 days.

To estimate (3), let $M_{ih} \equiv [X_{ih}, Z_{h}]$. The error term $\varepsilon_{ih} | (M_{ih}, \zeta_{h})$ is assumed to be i.i.d. and follows a logistic distribution. Thus we can write

$$\ln\left[\frac{\Pr(y_{ih}=1|(M_{ih},\mu_h))}{1-\Pr(y_{ih}=1|(M_{ih},\mu_h))}\right]=M_{ih}\Gamma+\zeta_h+\varepsilon_{ih} \qquad (5)$$

where $\Gamma=[\beta,\gamma]$ is a vector of parameters.

The model is estimated using maximum likelihood. Recall that y_{ih} is conditionally independent given ζ_h and M_{ih}. To obtain the unconditional joint probability of y_{ih}, we need to integrate out ζ_h. However, this integral does not have a closed form and has to be approximated using numerical integration. Thus, we fit the model in (5) using the Stata command *xtmelogit*, which uses the numerical method known as the adaptive Gaussian quadrature.

We can measure the correlation of the latent morbidity variable between episodes in the same hospital using the residual intraclass correlation, ρ, defined as

$$\rho\equiv Corr\left(y_{ih}^{*},y_{i'h}^{*}\middle|(M_{ih},M_{i'h})\right)=\frac{\psi}{\psi+\pi^2/3} \qquad (6)$$

where $\pi^2/3$ is the variance of ε_{ih}. In essence, ρ gives the proportion of total variation that is due to between-hospital heterogeneity.

We also consider the linear model as an alternative specification. We use the same notation as before and write

$$\Pr[y_{ih}=1|(M_{ih},\mu_h)]=g(M_{ih}\Gamma+\zeta_h+\varepsilon_{ih}) \qquad (7)$$

The linear model is obtained by setting $g(\bullet)$ to be the identity link function and making the following distributional assumptions:

$$\zeta_h|M_{ih}\sim N(0,\psi) \text{ and } \varepsilon_{ih}|(M_{ih},\zeta_h)\sim N(0,\theta).$$

Note that logistic model (5) can also be obtained using the same approach by setting $g(\bullet)$ as the inverse logit link function. We discuss the estimation results of both the logistic and linear probability models in Section 5 below.

4. Data

The data are extracted from the Victorian Admitted Episode Dataset (VAED), which contains detailed information on admitted patient episodes reported by all public and private acute hospitals in the state of Victoria, Australia. The data set comprises demographic, clinical and administrative details for all admitted episodes of care occurring in Victorian acute hospitals. The hospital admission data were linked to the death registry via a statistical linking process developed by the Victorian Department of Human Services. Note that the data we use are de-identified, both patient and hospital identifiers have been randomly assigned.

In defining hospital markets, we make use of a sample of 386,837 heart disease related episodes over a five-year period, from 2000/01 to 2004/05. These episodes were classified in 45 DRGs,[10] and are grouped into three classes according to patient conditions and treatment types. For ease of reference we label these classes as Minor Medical (MIME), Major Medical (MAME) and Surgical (SURG) episodes. The data contain location information of patients, available in the form of postcodes.

Table 2 provides a brief summary of the sample. It shows that MIME and MAME episodes were similar in terms of aggregate statistics such as the number of episodes, the number of hospitals and postcodes involved. In contrast, there were far fewer episodes under SURG, since DRGs under SURG cover heart-related surgical procedures such as coronary bypass and major reconstructive vascular procedures. Naturally, there are also fewer hospitals and postcodes under SURG.

Table 2: Descriptive statistics of full sample

	MIME	MAME	SURG
Total number of episodes	162,480	179,451	44,906
Number of DRGs	14	16	15
Total number of hospitals	208	202	112
Total number of postcodes	1,211	1,270	928

Note: MIME = Minor Medical; MAME = Major Medical; SURG = Surgical

While there are over 200 hospitals in the sample, a large number of these hospitals were involved in only a small number of the sample episodes. Similarly, there are more than 1,200 postcodes in the sample, most however have few number of patients in the sample. The distributions of hospitals and postcodes by volume (i.e., number of episodes) are presented in Table 3. For MIME, MAME and SURG, averaging across the sample period, there were on average respectively 81, 86 and 47 hospitals which had 30 or fewer number of patients per year. The volume distribution of postcodes is similarly skewed, with majority of the postcodes accounting for fewer than 10 episodes each year.

5. Results

We report two sets of results, the first pertaining to the hospital markets we defined using the approach outlined in Section 2. The second set of results is obtained from fitting the regression model in equation (5). We discuss each in turn below.

Table 3: Number of hospitals and postcodes by volume

	Yearly average		
	MIME	MAME	SURG
Hospital volume			
High volume ($N_h > 500$)	19.0 (0.8)	24.0 (0.9)	8.0 (0.7)
Medium volume ($100 < N_h \leq 500$)	41.3 (1.7)	52.6 (1.9)	10.6 (0.8)
Low volume ($30 < N_h \leq 100$)	36.6 (3.0)	40.1 (2.3)	9.6 (2.0)
Very low volume ($30 \leq N_h$)	81.4 (1.3)	85.7 (4.1)	46.6 (3.1)
Postcode volume			
High volume ($N_k > 100$)	108.4 (3.4)	133.6 (7.7)	4.0 (0.8)
Medium volume ($50 < N_k \leq 100$)	107.3 (2.8)	90.0 (5.6)	30.0 (5.0)
Low volume ($10 < N_k \leq 50$)	186.1 (3.0)	193.1 (7.8)	204.8 (1.7)
Very low volume ($10 \leq N_k$)	417.0 (3.8)	443.4 (6.7)	394.3 (10.2)

(): Standard deviation

5.1 Characteristics of hospital markets

We treat each DRG class as a distinct hospital service and obtain all trading clusters under each DRG class and for each financial year using the Stata package 'supclust'. In order to obtain meaningful number of trading clusters, we remove any hospital-postcode pairs that had fewer than 5 episodes from the sample. After obtaining the trading clusters, we next restrict the inflow and outflow of patients to below 35 per cent to arrive at a collection of hospitals and postcodes that we identify as markets. It is important to note that using our procedure, a hospital cannot belong to two or more markets, neither can a postcode.

Table 4 provides a descriptive summary of the hospital markets we defined. Since we defined the markets on a year-by-year basis, the number of markets could vary across years. Table 4 shows that the number of markets under MIME and MAME vary between 11 and 15 under the former and between one and six markets under the latter, while there was only a single market under SURG throughout the five-year period. Note that the markets we defined did not cover all admission episodes, since not all trading clusters we identified could satisfy the inflow and outflow requirements. Moreover, in identifying trading clusters, we also dropped all hospital-postcode pairs that registered fewer than five admission episodes.

The market coverage under MIME and MAME in terms of admission episodes was at about 94 per cent, while the coverage for SURG is at 82 per cent. The market coverage in

[10] The list of DRGs and the number of episodes under each are reported in Appendix A.

terms of the number of hospitals and postcodes were however considerably lower, due to the fact that a significant proportion of hospitals and postcodes registered few episodes, as we have shown earlier in Table 3.

Table 4: Hospital markets and market coverage for cardiac disease in Victoria

	MIME	MAME	SURG
No. of markets [min, max]	[11,15]	[2, 6]	[1, 1]
Total no. of episodes covered by markets	153,260	168,736	36,831
Proportion of episodes covered by markets (%)	94.3	94.0	82.0
No. of hospitals covered by markets	149	161	36
Proportion of hospitals covered (%)	71.6	79.7	32.1
No. of postcodes covered by markets	542	516	302
Proportion of postcodes covered (%)	44.8	40.6	32.5

Note: standard deviations are given in parentheses.

After defining the hospital markets, we proceed to measure the intensity of competition. Tables 5 presents statistics related to the competition of markets under the three DRG classes. It is evident from the HHI statistics that the markets in MIME are the least competitive among the three DRG classes. By the U.S. DOJ and FTC horizontal merger guideline, the markets in MIME are moderately concentrated. In contrast, markets in MAME and SURG are not concentrated. It should, however, be noted that hospitals in SURG compete in a single competitive market, whereas there are a number of monopoly markets (i.e., markets served by a single hospital) under MAME.

Table 6 presents a detailed breakdown of markets in terms of concentration measures. From the table, it can be seen that MIME and MAME each has a single non-concentrated market that includes the majority of admission episodes, hospitals, and postcodes under the DRG class. Interestingly, even though MIME and MAME have similar characteristics as summarised in Table 2, they turn out to have rather different levels of market competition. There were more markets under MIME than MAME–there were between 11 and 15 markets under MIME, compared to between two and six markets under MAME. Moreover, markets under MIME had an average HHI that ranged from 1,204 to 1,732, which were considerably higher than the average HHI of between 428 and 636 under MAME. More importantly, under MIME not only the number of markets was increasing over time, but the market were also becoming more concentrated as indicated by the higher average HHI values. In contrast, the number of markets was decreasing over time under MAME and, judging from the decreasing average HHI values, these markets were becoming more competitive over time.

Comparing the market competition levels across the three DRG classes, we see that, moving from MIME to MAME and SURG, competition increased significantly as hospital

Table 5: Market power of Victorian hospitals for heart disease

	2000/01	2001/02	2002/03	2003/04	2004/05
Minor Medical episodes					
Number of markets	11	15	12	15	15
Number of episodes	29,431	31,150	31,977	30,710	29,992
Number of hospitals	128	126	121	118	121
Number of postcodes	429	448	454	435	442
Mean HHI of hospitals	1,204.4	1,452.3	1,357.0	1,534.5	1,731.5
Major Medical episodes					
Number of markets	6	5	2	3	3
Number of episodes	31,017	35,507	33,817	34,893	35,502
Number of hospitals	137	125	123	124	127
Number of postcodes	403	410	404	418	424
Mean HHI of hospitals	635.7	587.2	368.9	438.7	428.1
Surgical episodes					
Number of markets	1	1	1	1	1
Number of episodes	7,610	8,230	7,408	6,960	6,623
Number of hospitals	30	30	33	29	27
Number of postcodes	230	231	238	223	225
Mean HHI of hospitals	682	627	647	664	664

services move from the care of relatively minor to major conditions and conditions requiring surgical interventions. This increase in competition as patient conditions become more complex and severe is as expected, since patients with complex and severe conditions are more likely to travel farther for treatment, thereby expanding the boundary of the market and hence reducing the market power of hospitals.

Using HHI, we further break down the markets under MIME and MAME into non-concentrated ($0 \leq HHI < 1000$), moderately concentrated ($1{,}000 \leq HHI < 1{,}800$), highly concentrated ($1{,}800 \leq HHI < 10{,}000$) and monopoly markets ($HHI = 10{,}000$). The results are presented in Table 6, which again show that the level of competition in MAME and MIME was diametrically different. For both MIME and MAME, the majority of admission episodes were handled by hospitals in the single non-concentrated market. However, the number of hospitals belonging to this market were increasing over time for MIME but declining for MAME, and to a lesser extent this pattern also holds in terms of the number of postcodes in this market. Likewise, by counting the number of hospitals that were in a monopoly market, we see that the number were increasing under MIME but decreasing under MAME.

Table 6: Market power of Victorian hospitals (Minor and Major Medical)

	2000/01	2001/02	2002/03	2003/04	2004/05
Minor Medical episodes					
Non-concentrated market (HHI < 1, 000)					
Number of markets	1	1	1	1	1
Number of episodes	27,756	30,041	30,867	29,664	27,755
Number of hospitals	106	109	104	102	96
Number of postcodes	385	407	420	401	385
Moderately concentrated market (1, 000 ≤ HHI < 1,800)					
Number of markets	0	0	0	0	0
Number of episodes	-	-	-	-	-
Number of hospitals	-	-	-	-	-
Number of postcodes	-	-	-	-	-
Highly concentrated market (1, 800 ≤ HHI < 10, 000)					
Number of markets	3	2	4	1	4
Number of episodes	1,473	663	713	402	1,764
Number of hospitals	15	5	10	3	15
Number of postcodes	31	19	21	12	40
Monopoly market (HHI = 10, 000)					
Number of markets	7	12	7	13	10
Number of episodes	202	446	397	643	473
Number of hospitals	7	12	7	13	10
Number of postcodes	13	22	13	22	17
Major Medical episodes					
Non-concentrated market (HHI < 1, 000)					
Number of markets	1	1	1	1	1
Number of episodes	31,922	32,415	33,790	34,868	35,469
Number of hospitals	132	121	122	122	125
Number of postcodes	397	405	403	416	422
Moderately concentrated market (1, 000 ≤ HHI < 1,800)					
Number of markets	0	0	0	0	0
Number of episodes	-	-	-	-	-
Number of hospitals	-	-	-	-	-
Number of postcodes	-	-	-	-	-
Highly concentrated market (1, 800 ≤ HHI < 10, 000)					
Number of markets	0	0	0	0	0
Number of episodes	-	-	-	-	-
Number of hospitals	-	-	-	-	-
Number of postcodes	-	-	-	-	-
Monopoly market (HHI = 10, 000)					
Number of markets	5	4	1	2	2
Number of episodes	95	92	27	25	33
Number of hospitals	5	4	1	2	2
Number of postcodes	6	5	1	2	2

Taken together, results in Tables 5 and 6 show that markets for MIME and MAME differed markedly in terms of competition. Given that a hospital may compete in both MIME and MAME, these results also suggest that the same hospital could face different levels of competition depending on the types of services offered. Thus it would be incorrect to classify a hospital as a whole as either competitive or non-competitive, which a radius-based approach of defining markets would tend to do. Having computed the competition measures for each hospital, we next turn to investigate the effect of competition on hospital quality by implementing two random intercept regression models for MIME. Since MAME and SURG episodes had little variation in their competition measures, it is not feasible to estimate the effect of competition for these two DRG classes.

5.2 Effects of competition on quality

We make use of two indicators to proxy hospital quality, namely death within 30 days of discharge and unplanned readmission within 28 days of discharge, and estimate each quality indicator independently. Before estimating the model, we have to deal with a difficult problem of assigning mortality outcomes to episodes that involving transfers between hospitals.[11] Of the 146,133 episodes in MIME, approximately 8 per cent involved transfers between two or more hospitals. Given that there is no natural way of assigning the mortality outcome for these episodes, we have arbitrarily assigned the outcome to the hospital in which the patient stayed for the longest time. After assigning outcomes for episodes that involve transfers, we end up with a sample of 139,887 episodes. Table 7 gives an overview of the MAME sample by market concentration. We see that episodes in the sample are mostly in non-concentrated markets. Concentrated markets cover only a small proportion of the sample. This is hardly surprising given the small geographic size of Victoria and that the significantly higher population density in urban than rural areas.

Table 8 presents some summary statistics, by markets concentration, of the dependent and explanatory variables used in the estimation. The dependent variables, 30-day mortality and 28-day unplanned readmission rates, are similar in magnitude for concentrated and non-concentrated markets. Included in the explanatory variables are episode- and hospital-level explanatory variables. The former include clinical-type variables that are designed to capture the severity and/or complexity of the episode as well as personal characteristics such as age,

[11] A typical situation goes as follows. A patient is admitted to Hospital A for some days, transferred to Hospital B for some additional days, discharged from Hospital B and dies in less than 30 days after discharge. It is impossible to attribute this patient's mortality outcome to either Hospitals A or B unless one has detailed clinical information about the care the patient receives from both hospitals.

gender, and whether the patient had private hospital insurance cover. Variables of a clinical nature include the Charlson comorbidity index,[12] the length of stay (in days), 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 are clinical complications as identified by the DRG.

Table 7: MIME Sample by market concentration

	Market concentration		
	Not concentrated	Concentrated	All
Number of episodes	132,039	7,848	139,887
	(94.4%)	(5.6%)	(100%)
Number of hospitals	119	26	145
	(82.1%)	(17.9%)	(100%)
Number of postcodes	475	61	536
	(88.6%)	(11.4%)	(100%)

In addition to episode-level variables, we also construct hospital-level characteristics using all episodes that the hospital handled in each year (i.e., the entire annual caseload volume, not just restricted to the 45 heart-disease related DRGs). These hospital-level variables include total annual caseload volume, the proportion of episodes with no comorbidity, and teaching hospital status. These variables are intended to capture, respectively, the scale effect, complexity of cases handled and teaching hospital effect.

Besides the variables summarised in Table 8, we also include in our estimation three measures of competition at the hospital-level: the number of competing private hospitals and the degree of competition measured by (1 − HHI).[13] We distinguish the number of competing private hospitals from public hospitals because we believe competition in a market depends on the mix of public and private hospitals in the market, rather than the total number of competing hospitals.

The estimation results are presented in Table 9.14[14] The results for both models suggest that competition has a mixed effect on quality–the number of competing private hospitals were positively associated with the risks of mortality and unplanned readmission while the number

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

[13] We use (1 − HHI) in the estimation, where HHI has been rescaled to between 0 and 1, to facilitate interpretation of the results. An increase in competition is reflected by a rise in (1−HHI), implying that a positive coefficient on (1 − HHI) means quality is adversely affected by an increase in competition.

[14] The estimation is performed using the Stata command 'xtmelogit'.

of public hospitals had the opposite effect. The effects were more pronounced for unplanned readmission than mortality, the coefficients on both variables were statistically significant at the one per cent level for the former, while for the latter only the coefficient on the number of competing private hospitals was statistically significant, and only at the ten per cent level. However, the measure of competition intensity, (1 − HHI), is not statistically significant for both quality indicators. Taken together, these results suggest that the presence of more private hospitals could hurt hospital quality, and more intense competition between hospitals have no statistically significant effect on quality.

Table 8: Mean and standard deviation of variables by market concentration

Variable	Market concentration			
	Not concentrated		Concentrated	
	Mean	Std. dev.	Mean	Std. dev.
Dependent variables				
30-day mortality	0.021	0.143	0.022	0.147
28-day unplanned readmission	0.084	0.278	0.090	0.286
Episode characteristics				
Charlson comorbidity index	0.483	1.047	0.441	0.971
First-time heart diagnosis	0.264	0.441	0.270	0.444
Emergency admission	0.740	0.438	0.786	0.410
Same-day separation	0.314	0.464	0.154	0.361
Length of stay (days)	3.131	5.033	3.766	15.799
Transfers between hospitals	0.039	0.194	0.012	0.110
With clinical complications	0.198	0.398	0.197	0.398
Age (years)	69.7	14.6	70.6	14.0
Male	0.523	0.499	0.492	0.500
Australian born	0.639	0.480	0.852	0.355
With private hospital insurance	0.312	0.463	0.191	0.393
*Hospital characteristics**				
Caseload volume (100,000 separations)	0.107	0.141	0.025	0.034
Episode with no comorbidity (Charlson=0)	0.690	0.133	0.675	0.095

*Hospital characteristics are based on annual total caseload volume of hospitals.

The other coefficient estimates given in Table 9 are broadly in line with expectations. Higher Charlson comorbidity and the presence of clinical complications are all associated with greater risks of mortality and unplanned readmission. Admission via the emergency department tends to increases the risk of mortality but is associated with a lower risk of unplanned readmission. Age has a nonlinear and broadly similar effect on mortality and unplanned readmission, the risk of both is declining for younger patients and then increasing for older patients.

Table 9: Random intercept logistic regression estimation results

	Dependent variable					
	30-day mortality			28-day unplanned readmission		
Explanatory variables	Coefficient		Std. error	Coefficient		Std. error
Charlson comorbidity index	0.3108	***	0.0106	0.1095	***	0.0087
First-time heart disease diagnosis	-0.1558	***	0.0543	-3.0958	***	0.0642
Emergency admission (1=yes)	0.3133	***	0.0569	-0.1336	***	0.0288
Same-day separation (1=yes)	-0.2979	***	0.0597	-0.1105	***	0.0246
Transfer between hospitals (1=yes)	0.3255	***	0.0923	-0.1424	***	0.0504
Catastrophic or severe clinical complication (1=yes)	1.2646	***	0.0460	0.1658	***	0.0268
Age	-0.0340	**	0.0145	-0.0227	***	0.0043
Age^2	0.0007	***	0.0001	0.0001	***	0.00003
Sex (1=male)	0.3382	***	0.0400	0.0530	***	0.0201
Australian born (1=yes)	0.0647		0.0433	0.0112		0.0219
Private hospital insurance (1=yes)	0.0634		0.0498	-0.0612	**	0.0252
Number competing private hospitals	0.0109	*	0.0058	0.0106	***	0.0030
Number competing public hospitals	-0.0049		0.0043	-0.0070	**	0.0021
Competition (1 − HHI)	-0.0634		0.3418	0.1409		0.1693
Hospital volume	-0.4019		0.2657	-0.0430		0.1641
Hospital prop. of zero Charlson episodes	-0.7955	***	0.2786	-0.0227		0.1601
Teaching hospital status (1=teaching)	0.1197		0.1219	0.0167		0.0755
Constant	-5.6601	***	0.5959	-2.4433	***	0.2066
Random intercept variance ($\hat{\psi}$)	0.0708		0.0215	0.0309		0.0075
Residual intraclass correlation ($\hat{\rho}$)	0.0211			0.0093		
Log likelihood	-11,913.3			-37,822.3		
Number of observations	146,796			146,796		

Note: Regressions include four 2-digit DRG dummy variables and six groups of principal diagnosis dummy variables, the estimates of which are not shown. Statistical significance levels are shown as: * (10%), ** (5%), and ***(1%).

Among the hospital-level characteristics, hospital volume and teaching status do not appear to have any statistically significant effect on quality. The proportion of low complexity episodes seems to have a positive effect on quality, but the coefficient is only statistically significant for the mortality regression.

A useful statistic for measuring the degree of heterogeneity between hospitals is the residual intraclass correlation, defined as

$$\rho = \frac{\psi}{\psi + \pi^2/3}$$

where $\pi^2/3$ is the residual variance of the logistic model. In essence, ρ gives the proportion of total variation that is due to between-hospital heterogeneity. The estimates of ρ given in Table

9 are small for both quality indicators, suggesting that the unexplained heterogeneity between hospitals is small relative to the variations across episodes within hospitals.

Table 10 presents the estimated odds ratios and the corresponding 95 per cent confidence intervals. We note that the effects of all three competition measures are small in terms of raising or lowering the odds of mortality or unplanned readmission. The estimated odds ratios for the number of competing private hospitals and public hospitals are only slightly above unity for both quality indicators, suggesting that having an additional private (or public) hospital in the market would only increase (or decrease) the odds of mortality and unplanned readmission by about one per cent in both cases. These effects are comparatively small in comparison to other variables such as age and gender.

Table 10: Logistic odds ratio estimates

	Dependent variable					
	30-day mortality			28-day unplanned readmission		
Explanatory variables	Odds ratio	95% Conf. Interval		Odds ratio	95% Conf. Interval	
		Lower	Upper		Lower	Upper
Charlson comorbidity index	1.365	1.337	1.393	1.116	1.097	1.135
First-time heart disease diagnosis	0.856	0.769	0.952	0.045	0.040	0.051
Emergency admission (1=yes)	1.368	1.224	1.529	0.875	0.827	0.926
Same-day separation (1=yes)	0.742	0.660	0.835	0.895	0.853	0.940
Transfer between hospitals (1=yes)	1.385	1.156	1.659	0.867	0.786	0.957
Catastrophic or severe clinical compl. (1=yes)	3.542	3.237	3.876	1.180	1.120	1.244
Age group (50–60 years)	0.967	0.939	0.994	0.978	0.969	0.986
Age group (60–70 years)	1.001	1.001	1.001	1.000	1.000	1.000
Sex (1=male)	1.402	1.297	1.517	1.054	1.014	1.097
Australian born (1=yes)	1.067	0.980	1.161	1.011	0.969	1.056
Private hospital insurance (1=yes)	1.065	0.966	1.175	0.941	0.895	0.988
Number competing private hospitals	1.011	1.000	1.022	1.011	1.005	1.017
Number competing public hospitals	0.995	0.987	1.004	0.993	0.989	0.997
Competition (1 − HHI)	0.939	0.480	1.834	1.151	0.826	1.604
Hospital volume	0.669	0.397	1.126	0.958	0.695	1.321
Hospital prop. of zero Charlson episodes	0.451	0.261	0.779	0.978	0.714	1.338
Teaching hospital status (1=teaching)	1.127	0.888	1.431	1.017	0.877	1.179

6. Conclusion

This paper proposed an extension of the quantity-flow (Elzinga and Hogarty, 1973) approach of defining hospital markets. The proposed approach imposes two requirements. First, hospitals and residential postcodes must be connected in a trading cluster. Second, the inflow and outflow of patients should not exceed 35 per cent of all patients in the trading cluster. We applied this extension to investigate the effect of competition on hospital quality using hospital administration data of heart disease admission episodes of all hospitals in the State of Victoria, Australia. We divided heart disease admission episodes into three classes based on DRG groupings; these classes are labelled Major Medical, Minor Medical and Surgical DRG episodes. We found that, although Minor Medical and Major Medical episodes were broadly similar in terms of aggregate descriptive statistics, the hospital markets we defined were diametrically different in terms of the degree of competition. We concluded that the boundaries of markets and hence the degree of competition depended on the nature of the medical services provided. For complicated medical services, patients were willing to travel farther, hence widening the boundaries of markets. Thus it is inappropriate to define hospital markets based on distance, without taking into account the nature of hospital services.

Once markets were defined, we examined the effect of competition on quality of hospital care using two quality indicators, namely mortality within 30 days of discharge and unplanned readmission within 28 days of discharge. We restricted this part of the investigation to Minor Medical episodes only, since there was little variation in competition for Major Medical and Surgical episodes. We found that competition had a mixed effect on quality of services provided for Minor Medical episodes—increasing the number of private hospitals had a positive effect on quality, while increasing the number of public hospitals had the opposite effect. However, increasing the intensity of hospital competition does not appear to have any statistically significant effect.

Although our approach of defining markets has several advantages over existing approaches, there remain some unresolved issues. Firstly, our approach does not allow markets to overlap, thus a hospital that is identified as serving market A is by construction not serving market B. Secondly, in defining the `self-contained' property of the market, we arbitrarily limited patient inflow and outflow to 35 per cent. Changing the limits obviously has an immediate and in some cases large effect on the number of markets defined. Tightening this requirement by lowering the limits towards zero would decrease the number of markets and in the limit all hospitals will be competing in a single market. Lastly, it should be emphasized that, like all empirical-based approaches, our approach could not capture potential competition, i.e., the number of potential rival hospitals that could enter an industry. One can argue that potential competition, rather than the actual number of competitors, is a more accurate measure of competition.

Appendix A Sample Statistics

Table A1: Number of episodes by DRGs—Minor medical

DRG	Description	No. episodes
F65A	Peripheral Vascular Disorders W Catastrophic or Severe CC	3,209
F65B	Peripheral Vascular Disorders W/O Catastrophic or Severe CC	10,319
F66A	Coronary Atherosclerosis W CC	6,240
F66B	Coronary Atherosclerosis W/O CC	15,675
F67A	Hypertension W CC	1,830
F67B	Hypertension W/O CC	5,050
F69A	Valvular Disorders W Catastrophic or Severe CC	899
F69B	Valvular Disorders W/O Catastrophic or Severe CC	5,698
F71A	Non-Major Arrhythmia and Conduction Disorders W Catastrophic or Severe CC	8,658
F71B	Non-Major Arrhythmia and Conduction Disorders W/O Catastrophic or Severe CC	43,197
F72A	Unstable Angina W Catastrophic or Severe CC	6,451
F72B	Unstable Angina W/O Catastrophic or Severe CC	35,508
F73A	Syncope and Collapse W Catastrophic or Severe CC	4,960
F73B	Syncope and Collapse W/O Catastrophic or Severe CC	14,966
Total		

Table A2: Number of episodes by DRGs—Major medical

DRG	Description	No. episodes
F41A	Circ. Disorders W AMI W Invasive Cardiac Inves Proc W Cat or Sev CC	3,565
F41B	Circ. Disorders W AMI W Invasive Cardiac Inves Proc W/O Cat or Sev CC	5,563
F42A	Circ. Disorders W/O AMI W Invasive Cardiac Inves Proc W Complex DX/Pr	19,004
F42B	Circ. Disorders W/O AMI W Invasive Cardiac Inves Proc W/O Complex DX/Pr	41,594
F60A	Circ. Disorders W AMI W/O Invasive Cardiac Inves Proc W Cat or Sev CC	10,034
F60B	Circ. Disorders W AMI W/O Invasive Cardiac Inves Proc W/O Cat or Sev CC	18,359
F60C	Circ. Disorders W AMI W/O Invasive Cardiac Inves Proc, Died	2,319
F62A	Heart Failure and Shock W Catastrophic CC	12,633
F62B	Heart Failure and Shock W/O Catastrophic CC	41,604
F63A	Venous Thrombosis W Catastrophic or Severe CC	1,440
F63B	Venous Thrombosis W/O Catastrophic or Severe CC	4,079
F70A	Major Arrhythmia and Cardiac Arrest W Catastrophic or Severe CC	1,508
F70B	Major Arrhythmia and Cardiac Arrest W/O Catastrophic or Severe CC	4,493
F75A	Other Circulatory System Diagnoses W Catastrophic CC	1,495
F75B	Other Circulatory System Diagnoses W Severe CC	2,593
F75C	Other Circulatory System Diagnoses W/O Catastrophic or Severe CC	9,168
Total		179,451

Table A3: Number of episodes by DRGs—Surgical

DRG	Description	No. episodes
F04A	Cardiac Valve Proc W CPB Pump W/O Invasive Cardiac Inves W Cat CC	4,229
F04B	Cardiac Valve Proc W CPB Pump W/O Invasive Cardiac Inves W/O Cat CC	1,297
F05A	Coronary Bypass W Invasive Cardiac Inves W Catastrophic CC	2,599
F05B	Coronary Bypass W Invasive Cardiac Inves W/O Catastrophic CC	2,198
F06A	Coronary Bypass W/O Invasive Cardiac Inves W Catastrophic or Severe CC	9,428
F06B	Coronary Bypass W/O Invasive Cardiac Inves W/O Catastrophic or Severe CC	2,797
F08A	Major Reconstruct Vascular Procedures W/O CPB Pump W Catastrophic CC	2,898
F08B	Major Reconstruct Vascular Procedures W/O CPB Pump W/O Catastrophic CC	4,725
F11A	Amputation for Circ System Except Upper Limb and Toe W Catastrophic CC	511
F11B	Amputation for Circ System Except Upper Limb and Toe W/O Catastrophic CC	357
F14A	Vascular Procs Except Major Reconstruction W/O CPB Pump W Cat CC	1,613
F14B	Vascular Procs Except Major Reconstruction W/O CPB Pump W Sev CC	2,225
F14C	Vascular Procs Except Major Reconstruction W/O CPB Pump W/O Cat or Sev CC	8,639
F21A	Other Circulatory System O.R. Procedures W Catastrophic CC	972
F21B	Other Circulatory System O.R. Procedures W/O Catastrophic CC	688
Total		44,906

Table A4: Number of episodes by principal diagnosis—MIME sample

ICD-10	Description	Freq.
I20, I24, I25	Ischemic heart diseases	57,342
I44, I45, I47–I49	electrical conduction system of the heart	45,201
I70–I74, I77, I78	Diseases of arteries, arterioles and capillaries	8,136
I95, I97, I99	Other and unspecified disorders of the circulatory system	3,521
R00-R02	Symptoms and signs—circulatory and respiratory systems	4,180
R55	General symptoms and signs—Syncope and collapse	15,360
Others		13,056
Total		146,796

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