

# Bringing Responsibility for Small Area Variations in Hospitalization Rates Back to the Hospital

## *The Propensity to Hospitalize Index and a Test of the Roemer's Law*

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**Objective:** To assign responsibility for variations in small area hospitalization rates to specific hospitals and to evaluate the Roemer's Law in a way that does not artificially induce correlation between bed supply and utilization.

**Data Sources/Study Setting:** We used data on hospitalizations and outpatient treatment for 15 medical conditions of nonmanaged care Part B eligible Medicare enrollees of 65 years and older in Massachusetts in 2000.

**Study Design:** We used a Bayesian model to estimate each hospital's pool of potential patients and the fraction of the pool hospitalized (its propensity to hospitalize, PTH). To evaluate the Roemer's Law, we calculated the correlation between hospitals' PTH and beds per potential patient. Patient severity was measured using All Patient Refined Diagnosis Related Groups.

**Results:** We show that our approach does not artificially induce a correlation between beds and utilization whereas the traditional approach does. Nevertheless, our approach indicates a strong relationship between PTH and beds ( $r=0.56$ ). Eighteen (of 66) hospitals had a high PTH that differed significantly from 16 hospitals with a low PTH. Average patient severity in the high PTH hospitals was lower than in the low PTH hospitals. Although the difference was not statistically significant ( $P=0.12$ ), there was a medium effect size (0.58).

**Discussion:** Variation across hospitals in the PTH index, the strong relationship between beds and the PTH, and the lack of relationship between severity and the PTH suggest the importance of policies that limit bed growth of high PTH hospitals and create incentives for high PTH hospitals to reduce hospitalizations.

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Following Wennberg and Gittelsohn's<sup>1</sup> seminal study, a number of studies have reported variations in hospitalization rates and procedures across small geographic areas.<sup>2–15</sup> Over the last decade, however, small area variation work has largely disappeared from the literature. The Dartmouth Atlas of Health Care has played a prominent role in shifting the focus to larger geographic areas in which variations in systems of care can be more clearly distinguished. These variations are part of current debates about healthcare reform.<sup>16,17</sup>

A major problem with studies of geographic variations is the difficulty in assigning responsibility for variations, particularly in densely populated areas where different hospitals provide substantial care. There are hospital and health system managers, but there are not geographic area managers, which makes it difficult to translate observations about variations into managerial and policy recommendations. In this study, we describe an approach for relating variations in small area hospitalization rates to specific hospitals. We use a Bayesian model to estimate the size of the pool of "potential" patients from each area that would go to a particular hospital if they were hospitalized and the hospital's tendency to admit patients from its pool of potential patients, something we call the "propensity to hospitalize" (PTH) index.

Our motivation for this study was not to develop the PTH index but to look more deeply into an important conclusion drawn from studies of geographic variations: the role of supply-induced demand as a cause of variations. One form of this hypothesis, popularly known as the Roemer's Law,<sup>18,19</sup> suggests that the availability of hospital beds is an important factor determining hospitalization rates. Wennberg et al<sup>20</sup> have been strong advocates of this position.

There are 2 serious problems that arise when studying the relationship between bed supply and hospital utilization. The first is the method used to determine the number of hospital beds in an area. The traditional approach is to allocate beds to areas based on utilization, an approach used in the Dartmouth Atlas.<sup>20</sup> For example, if 20% of inpatient days at a particular hospital were used by residents of an area, then 20% of the hospital's beds would be assigned to

that area. The problem is that if beds are allocated to areas based on utilization, a correlation between bed availability and utilization results even if there is no supply-induced demand.<sup>5</sup> The analytical approach induces the correlation, something we illustrate in our analysis. The second is attributing causation based on a correlation between beds and utilization: it may well be that anticipated demand is the reason that more beds are available in certain areas rather than that more beds in an area generate demand.

In this study, we consider an approach that avoids the bias induced by the traditional approach used to allocate beds to areas. Specifically, we develop a Bayesian model to estimate each hospital's PTH index; test the Roemer's Law by examining the correlation between the PTH index and the number of beds a hospital has relative to the size of its pool of potential patients; show that this correlation is not induced by our method of analysis; and finally, to further illustrate the usefulness of the PTH index, examine the relationship between a hospital's PTH index and the severity of illness of its inpatients. This study was approved by the Boston University Institutional Review Board.

## METHODS

### Database

We used a previously developed database described in more detail elsewhere.<sup>14</sup> To summarize, the data include hospitalizations and outpatient treatment for nonmanaged care Part B eligible Medicare enrollees of 65 years and older in Massachusetts in 2000. The database includes both admissions and outpatient treatment for 1 of 15 medical conditions defined initially by Diagnosis-Related group (DRG; Table 1) and then reduced by requiring a principal diagnosis from selected ICD-9-CM codes. In Massachusetts in 2000, there were 52,746 people admitted to the state's 66 acute care hospitals and 302,905 people treated on an outpatient-only basis with one of these 15 conditions.

Small geographic areas were created using the Ward clustering algorithm. We used areas formed after over 700 initial zip codes had been grouped into 70 clusters. The  $R^2$  associated with the 70 clusters was 0.88, suggesting a high degree of similarity in the pattern of hospital use by the residents of the zip codes comprising the clusters.  $R^2$  started to noticeably decline as the number of clusters was decreased below 70.

We estimated the number of licensed beds at each hospital using the Massachusetts Department of Health FY 2000 403 Cost Reports.

### Determining Severity of Illness

We used All Patient Refined Diagnosis Related Groups (APR-DRGs)<sup>21</sup> to measure patient severity. The APR-DRG software adds 4 subclasses to each DRG based on mortality risk. Using a reference population of 4.5 million Medicare patients from approximately 1000 hospitals from a previous study,<sup>22</sup> we calculated the risk of in-hospital mortality for each subclass in each of our 15 DRGs. To develop a relative risk score, we divided the mortality risk for each DRG/APR-DRG subclass (60 total) by the overall risk of mortality for

**TABLE 1. Medical Conditions Considered\***

DRG 15:	Transient ischemic attack
DRG 88:	Chronic bronchitis and emphysema
DRG 89:	Bacterial pneumonia
DRG 127:	Heart failure
DRG 130:	Peripheral vascular disease
DRG 132:	Ischemic heart disease
DRG 138:	Cardiac arrhythmia and conduction disorder
DRG 140:	Angina pectoris
DRG 141:	Syncope and collapse
DRG 143:	Chest pain
DRG 243:	Medical back problems
DRG 277:	Cellulitis and abscess
DRG 294:	Diabetes
DRG 296:	Fluid and electrolyte disorder
DRG 320:	Kidney and urinary tract infections

\*Within most DRGs, clinical homogeneity was increased by considering only discharges with a principal diagnosis from selected ICD-9-CM codes.<sup>14</sup>  
DRG indicates diagnosis-related group.

the entire population. We then assigned each hospitalized patient in our sample a relative risk score based on their DRG/APR-DRG subclass and calculated the average score for the hospital.

### Bayesian Model to Estimate the PTH Index and Test the Roemer's Law

In the traditional approach to evaluating the Roemer's Law, beds are allocated to areas and then allocated beds compared with area hospitalization rates. We used an alternative approach that considers potential hospital patients in each area: those diagnosed and treated on an outpatient-only basis and those admitted to the hospital. Potential hospital patients in each area are allocated to each hospital and then the beds per potential patient are compared with the hospital's tendency to hospitalize potential patients (its PTH index). Our hypothesis is that hospitals with more beds per potential patient have a higher PTH. The challenge is to estimate potential patients from each area that would go to each hospital as we only observe some of them (those actually hospitalized). In what follows, we describe our model to do this.

We observe the following data:

$I_{ij}$  = observed number of patients in area  $i$  that were admitted to hospital  $j$

$O_i$  = observed number of patients in area  $i$  that were treated as outpatients-only

$beds_j$  = number of beds available at hospital  $j$

The unknown parameters in the models are

$p_j$  = hospital  $j$ 's propensity to hospitalize patients (its PTH index)

$n_{ij}$  = number of patients in area  $i$  that would go to hospital  $j$  if they were hospitalized (ie, hospital  $j$ 's potential patients from area  $i$ )

The statistical model is

$(I_{ij}|n_{ij}, p_j) \sim \text{Poisson}(n_{ij} p_j)$

$(O_i|n_{i1} \dots n_{i66}, p_1 \dots p_{66}) \sim \text{Poisson}[\sum_j n_{ij} (1-p_j)]$

To estimate  $p_j$  and  $n_{ij}$ , we placed vague priors on the parameters [specifically,  $n_{ij} \sim \text{uniform}(0.25000)$  and  $p_j \sim \text{uniform}(0.1)$ ] and used Gibbs sampling as implemented in

WinBUGs 1.4.<sup>23</sup> We report posterior means from Gibbs sampling and the 95% credible intervals (the interval within which we are 95% certain the random variable lies). To evaluate the Roemer's Law, we computed within WinBUGs the correlation between  $p_j$  and  $bed_j/\sum_i n_{ij}$  (beds per potential patient at hospital  $j$ ). [In the Appendix, A.1 (Supplemental Digital Content 1 <http://links.lww.com/MLR/A243>) we show the BUGs program used to estimate parameters and discuss an alternative to the above model.]

We compared our evaluation of the Roemer's Law to the traditional approach, which we implemented by (1) calculating beds allocated from hospital  $j$  to area  $i$  as  $(I_{ij}/\sum_i I_{ij}) \times beds_j = Abeds_{ij}$ ; and (2) examining the correlation of  $(\sum_j Abeds_{ij})/\text{pop}_i$  and  $\sum_j I_{ij}/\text{pop}_i$ , where  $\text{pop}_i$  = population 65 and older in area  $i$ . We also calculated the correlation between the PTH index and the average severity of patients admitted to each hospital.

To provide some insight into our approach, we considered 2 non-Bayesian approaches. First, we estimated each hospital's potential patients in each area under the assumption that patients currently treated as outpatients-only would use hospitals in the same proportion as patients who were hospitalized from the area. Specifically, we calculated outpatients from area  $i$  that are allocated to hospital  $j$  as  $O_i \times (I_{ij}/\sum_j I_{ij}) = A_{ij}$ . Potential patients at hospital  $j$  equals  $\sum_i (I_{ij} + A_{ij})$ . To test the Roemer's Law, we examined the correlation of  $beds_j/\sum_i (I_{ij} + A_{ij})$  and  $I_{ij}/\sum_i (I_{ij} + A_{ij})$ . Second, we used the traditional approach to allocate beds to areas but then examined the correlation between beds per observed potential patient in the area, that is,  $\sum_j Abeds_{ij}/(\sum_j I_{ij} + O_i)$ , and the percentage of observed potential patients hospitalized, that is,  $\sum_j I_{ij}/(\sum_j I_{ij} + O_i)$ . We call these approaches, respectively, the non-Bayesian outpatient allocation method and the non-Bayesian bed-allocation method.

To demonstrate that the Bayesian model does not induce a correlation between  $p_j$  and the beds per potential patient, we randomly generated 200 datasets. Each dataset was generated by selecting values of  $n_{ij}$  from a uniform distribution between 100 and 1000 and  $p_j$  from a uniform distribution between 0 and 1. Given the  $n_{ij}$ 's and  $p_j$ 's, we then generated  $I_{ij}$  and  $O_i$  according to a Poisson distribution. In each dataset, we calculated the correlation between beds and utilization using (1) the Bayesian model; (2) the traditional approach; and (3) the non-Bayesian bed allocation method described above. (In the Appendix A.2, Supplemental Content, we show the BUGs program used for the simulation.)

To examine the validity of the Bayesian model, we computed how close observed inpatients and outpatient-only patients were to expecteds, specifically,

$$(I_{ij} - n_{ij}p_j) / \sqrt{n_{ij}p_j} \text{ and}$$

$$(O_i - \sum_j n_{ij}(1 - p_j)) / \sqrt{(\sum_j n_{ij}(1 - p_j))}.$$

### RESULTS

Figure 1 is a histogram of the ratio of observed to expected discharges (calculated using indirect standardization to adjust for the age/sex distribution in an area). The ratios ranged from 0.52 to 1.33, indicating the large variation in hospitalization rates relative to expected across areas.

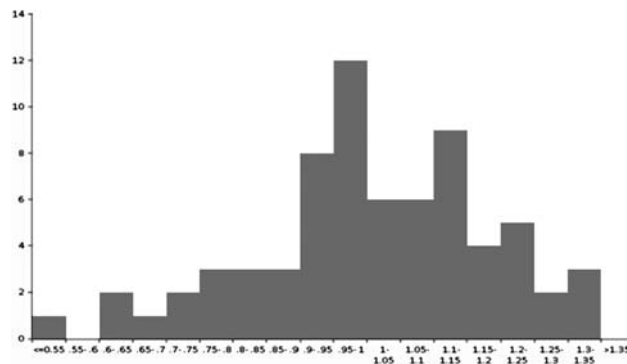


FIGURE 1. Histogram of ratio of observed to expected hospital discharges in a geographic areas.

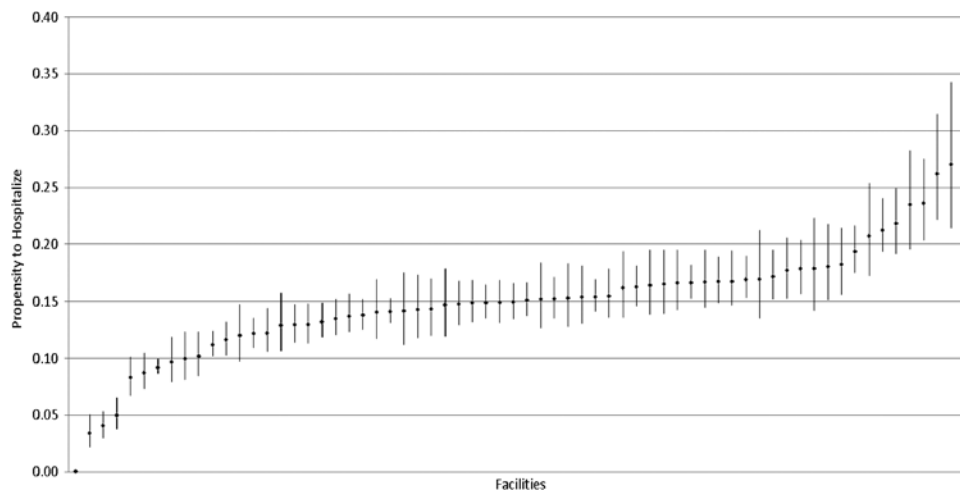
Figure 2 shows the point estimates and 95% credible intervals for the PTH indices. The indices ranged from 0.001 to 0.278 and average 0.163 (median, 0.154). The 4 hospitals with the lowest PTH indices included 2 largely specialty hospitals and 4 very small hospitals on the Cape Cod islands, all with under 30 beds allocated to the 15 medical conditions. As indicated by the triangles in the figure, of the 10 hospitals with the highest PTH indices, 5 were members of the Council of Teaching Hospitals and Health Systems, indicating they were major teaching hospitals. However, not all of the major teaching hospitals had high PTH indices.

As shown in Figure 2, for many of the hospitals, 95% credible intervals overlapped, indicating the difficulty in distinguishing their PTH. However, there were 18 hospitals whose PTH was significantly below the median propensity of 0.15 and another 16 whose propensity to hospitalize was significantly above the median. Clearly, these 2 sets of hospitals differed from each other in their PTH.

There was a high correlation ( $r=0.56$ , 95% credible interval 0.51 to 0.62) between the PTH index and the number of beds per potential patient, providing strong support for the Roemer's Law. The traditional approach also provided support for the Roemer's Law ( $r=0.46$ , 95% confidence interval 0.24 to 0.68). When the Roemer's Law was evaluated using the non-Bayesian outpatient allocation method, there was almost no correlation between beds per allocated patients and the proportion of allocated patients that were hospitalized ( $r=0.09$ ). However, when the Roemer's Law was evaluated using the non-Bayesian bed allocation method, the correlation was the same as that estimated using the Bayesian model ( $r=0.56$ ).

Simulated datasets were generated with no correlation between beds and utilization. Both the Bayesian approach and the non-Bayesian bed allocation method found no correlation ( $r$ ,  $-0.01$  and  $-0.00$ , respectively). The traditional approach found a strong correlation ( $r=0.63$ ).

For only 32 of the 4620 area/hospital cells was the observed number of hospitalizations more than 2 standard errors from expected; for 5 of the 70 areas, observed outpatients were more than 2 standard errors from expected. The areas with large outpatient deviations tended to have a low number of outpatient visits (the 5 areas were among the 7 smallest areas in terms of outpatient counts). The model overestimated expecteds for these areas.



**FIGURE 2.** Propensity to hospitalize indices and associated 95% credible intervals.

With the exception of 1 specialty hospital with a particularly low severity score (0.27), severity scores for the other hospitals ranged from 0.62 to 1.19 (average, 0.81; median, 0.82). Over all hospitals, there was no relationship between the PTH indices and severity ( $r=0.01$ , 95% credibility interval  $-0.04$  to  $0.06$ ). However, when we eliminated the 2 specialty hospitals and the 2 Cape Cod island hospitals, there was weak indication that hospitals with a high PTH (lower end of the credible interval  $>0.15$ ,  $n=16$ ) had lower severity than hospitals with a low PTH (upper end of the credible interval  $<0.15$ ,  $n=14$ ). Average severity in the high propensity group was 0.79 vs. 0.86 in the lower group. Although the difference was not statistically significant ( $P=0.12$ ), there was a moderate effect size (0.58).

## DISCUSSION

We found strong support for the Roemer's Law. Examining hospitalizations for a set of 15 medical conditions, which as Wennberg et al<sup>20</sup> noted should be sensitive to the supply of hospital beds, we found a correlation of 0.56 between a hospital's PTH index and beds per potential patient. Furthermore, we showed that our approach does not artificially induce a correlation between beds and utilization, in contrast to the traditional approach which does.

Evaluation of the Roemer's Law by allocating outpatients to hospitals based on inpatient utilization patterns does not work well (in the sense that the results are very different than those from the Bayesian analysis). Estimated patterns of utilization from the Bayesian model are more complex than suggested by simple extrapolation from inpatient utilization. However, the correlation between beds allocated to an area per observed potential patient in the area (ie, people treated as inpatients or on an outpatient-only basis) and the proportion of observed potential patients hospitalized was similar to that from the Bayesian model and seems to provide a reasonable basis for testing the Roemer's Law. Contrasting the traditional approach to our non-Bayesian approach provides some insight into its advantages.

The traditional approach examines the correlation of beds per population and inpatients per population. As a result of the way beds are allocated to areas, if 2 areas have the same population, the area with a higher number of inpatients will have a higher number of beds allocated to it. An analysis that compares the 2 areas will find support for the Roemer's Law—the area with more beds per population has more inpatients per population. However, this reflects nothing other than the way in which beds are allocated to areas. Our approach examines the correlation of beds per potential patient [ $\text{beds}/(I+O)$ ] and inpatients per potential patient [ $I/(I+O)$ ]. It is still the case that when the number of inpatients in an area is higher, the number of beds allocated to the area is higher. However, it is not necessarily the case that the area with more inpatients will have higher ratios of  $I/(I+O)$  and  $\text{beds}/(I+O)$ . It depends on the mix of inpatient and outpatients in the two areas, something we illustrate with a simple example in Appendix A.3 (Supplemental Digital Content 1, <http://links.lww.com/MLR/A243>). It is for this reason that our approach does not suffer from the bias inherent in the traditional approach.

Most studies examining the relationship between capacity and utilization measure utilization by raw hospitalization rates or by age/sex adjusted rates. There are, no doubt, other individual-level factors that account for differences in disease prevalence across geographic areas. The strength of our study is that by using both inpatient and outpatient data, we start with those in each area who have been diagnosed with the conditions of interest and then look at hospital utilization among this group. However, this approach gives rise to a concern, namely, that the likelihood of diagnosis may be related to the likelihood of hospitalization, that is, high (or low) "intensity of practice" in an area may be manifest both in high (or low) rates of people diagnosed and treated on an outpatient-only basis and in high (or low) rates of hospitalization.<sup>24</sup> To examine this possibility, we calculated the correlation between the observed-to-expected ratio of outpatient-only treatment and the observed-to-expected ratio of inpatient treatment. The correlation was

–0.14 ( $P=0.23$ ). At least in our data, there was no indication that areas with higher hospitalization rates were also more likely to have higher rates of outpatient-only treatment.

It was noteworthy that a single hospital-level variable, the PTH index, could explain observed patterns of inpatient utilization and outpatient-only treatment. This finding suggests the following question: if outpatient data were not available and one wanted to examine hospitalization rates in the population, could a single PTH variable explain utilization patterns? To examine this question, we used a simple model that included only the population in area  $i$  ( $pop_i$ ) and assumed  $(I_{ij}|pop_i, p_j) \sim \text{Poisson}(pop_i p_j)$ . This model did not fit the data. Sixty-five percent of the residuals (ie,  $I_{ij}-pop_i p_j$ ) were more than 2 standard errors from expected. More complex models are obviously needed if the base from which hospitalizations are considered is the population in the area rather than those with the condition.

The PTH index has value other than for examining the Roemer's Law. It is a way to assign responsibility for variations in area hospitalization rates to specific hospitals. In a set of 66 hospitals, we were able to clearly distinguish a group of 16 hospitals with a high PTH from a group of 14 with a low PTH (well more than the 3 to 4 hospitals with a high or low PTH expected due to chance variation). From various characteristics that could be analyzed to identify differences between the 2 groups, we examined the severity of their hospitalized patients. Our hypothesis, supported by some literature,<sup>25,26</sup> was that high PTH hospitals are "digging deeper" into their pool of potential cases and, at the margin, admitting less severe cases. Although we had poor power to detect a statistically significant difference in severity between the 2 groups, there was a moderate effect size, with severity being lower in the high propensity group. This finding is consistent with our hypothesis.

There has been a large literature examining hospital markets and competition. Some of the more recent analyses, initiated by Kessler and McClellan,<sup>27</sup> are based on individual level models of hospital choice. The predicted probabilities from these models can be aggregated to the small areas and then used to allocate hospital resources to areas. For example, in allocating beds to areas, Kessler and McClellan<sup>27</sup> calculate beds "per probabilistic patient faced by each hospital," (p 591), similar to our measure of beds per potential patient. Rather than explicitly incorporating other variables in the model, our approach assumes that the main driver of hospital choice is location, a reasonable assumption,<sup>28</sup> and that the effect of factors other than distance (eg, insurance status) is reflected in area-specific hospital use patterns. Nevertheless, our analysis shares the key feature of Kessler and McClellan's work: "... it uses expected patient shares [the  $n_{ij}$ s] based upon exogenous determinants of patient flows, rather than potentially endogenous measures such as bed capacity or actual patient flows ..."<sup>27</sup> (p 589). It is for exactly this reason that our approach does not artificially induce a correlation between beds and utilization when none exists, whereas traditional approaches based on actual utilization do.

Since 2000, there have been a number of hospital closures and mergers, and changes in hospital utilization patterns. Hence, conclusions regarding individual hospitals may have little current policy relevance. However, our

approach may be useful in studying current geographic-based variations in hospitalization rates and in stimulating analyses to better understand reasons for differences in hospitals' PTH index. It is particularly important to distinguish legitimate reasons associated with patient needs from supply-based, system-based, and market-based factors. For example, are higher PTH indices related to higher hospitalization rates for ambulatory-sensitive conditions, which may reflect access problems? Are higher PTH indices related to the competitive structure of markets and the existence of dominant market players that may be driving up costs? Once these factors are better understood, it will be possible to better determine the need for hospital beds in an area and to assess the value of policies to limit the expansion of beds by hospitals with a high propensity to hospitalize patients.

In an era of accountable care organizations and possible shifts from fee-for-service reimbursement to episode-based and population-based payment, the PTH index could become a useful performance measure for senior hospital managers. Hospitals with a high PTH will be particularly motivated to evaluate and modify hospital-wide or department-based policies and procedures that might encourage unnecessary or inappropriate hospitalizations; to consider ways in which incentives for physicians or senior managers might be changed to reduce hospitalizations; to ask questions about their hospital's strategic priorities, organizational alignment and culture that might implicitly encourage hospitalizations; and to identify new programs or methods of supporting patients in ambulatory care settings that might forestall or eliminate hospitalizations. These types of activities would benefit our healthcare delivery system.

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