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Geospatial analysis of HCAHPS pain management experience scores in U.S. hospitals

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Abstract

Although prior work has investigated the interplay between demographic and intra-survey correlations of Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) scores, these prior studies have not included geospatial analyses, or analyses which take into account location effects. Here, we report the results of a geospatial analysis (not equivalent to simple geographical analysis) of patient experience scores pertaining to pain.

HCAHPS data collected in 2011 were examined to test the hypothesis that HCAHPS patient experience with pain management (PEPM) scores were geospatially distributed throughout the United States using Moran's I, which measures the association between PEPM scores and hospital location.

After limiting the dataset to hospitals in the continental U.S. with nonzero HCAHPS response rates, 3645 hospitals were included in the analyses. 'Always' responses were geospatially clustered amongst the analyzed hospitals. Clustering was significant in all distances tested from 10 to 5000 km ($P < 0.0001$). We identified six demarcated groups of hospitals.

Taken together, these results strongly suggest a regional geographic effect on PEPM scores. These results may carry policy implications for U.S. hospitals with regard to acute pain outcomes.

Further analyses will be necessary to evaluate policy explanations and implications of the regional geographic differences in PEPM results.

Keywords

Geospatial analysis; Patient experience; Pain management; Acute pain

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Introduction

Data regarding the quality of healthcare in the United States has itself been of variable quality [27]. A consortium of public and private organizations formed the Hospital Quality Alliance (HQA) overseen by The Joint Commission and the Centers for Medicare and Medicaid Services in response to this deficit. The HQA began releasing data from the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey in March of 2008 [15]. Although prior work examining these data investigated the interplay between demographic and intra-survey correlations of HCAHPS scores, these prior studies have not included geospatial details [17,22]. Yet geospatial effects, or the effects of geographic location itself, play a critical role in a host of public health concerns, including substance abuse, crime, trauma, infectious disease, and heart disease [3–6,8,24,28,31,32]. Further, while geographic variation in both patient-reported and clinical quality of care measures have been well documented, similar descriptions do not yet exist for patient experience with pain [19,20]. The HCAHPS survey assesses multiple domains of patient experience, including doctor and nurse communication, discharge instructions, hospital cleanliness, overall satisfaction, and pain control. With continuing questions concerning the association between patient experience with pain management (PEPM) and the quality of delivered pain care, there is a need to identify potential sources of variance in patient experiences with pain management. It stands to reason that patient experiences with pain management may vary based on hospital location, given regional differences in demographics and socioeconomic drivers of hospital-based healthcare. Such findings could provide opportunity to more closely examine factors leading to “high success” geographical regions and therefore provide actionable information regarding regions in which educational and/or healthcare system interventions may be most needed to improve pain care.

Here, we report the results of a geospatial analysis of patient experience scores pertaining to pain management. Patient experience scores were collected from the 2011 HCAHPS survey system. The geospatial analyses were designed to answer two questions pertaining to geographic differences in PEPM scores. First, are PEPM scores clustered, randomly distributed, or dispersed across U.S. hospitals? And second, are there regional differences in PEPM profiles for U.S. hospitals? Taken together, the results can provide valuable information regarding patient access to satisfactory inpatient pain care in U.S. hospitals.

Methods

This study was approved by IRB-01 at the University of Florida. This was a cross-sectional study performed on HCAHPS data collected in 2011. The study was designed to test the hypothesis that HCAHPS PEPM scores were geospatially or regionally distributed throughout the United States. Two analytical approaches were used to test this hypothesis. In the first, we tested whether PEPM scores were distributed across U.S. hospitals in a clustered, dispersed, or random geospatial distribution. In the second approach, we combined PEPM hospital profiles with geospatial data to examine regional differences in PEPM scores.

Geospatial analyses refer to those statistical analyses that incorporate the effects of the relative location of an object. Mathematically, It is worth noting that this is a subtly more generalized approach compared with geographic analyses, which may also incorporate information on the natural features (e.g., rivers, mountains, forests) found on the Earth's surface. Geospatial analyses may be used to independently describe certain features of an object, or as an extension of other inferential statistical approaches to incorporate the effects of spatial location amongst other variables. For example, a geospatial analysis of body mass index would consider the effects of living in a given location, taking into account the distances and direction between different locations. Compare this with a typical statistical approach, whereby location would be considered as a nominal variable, and the effects on BMI from the relative relationship between locations as measured by distance and direction are not considered.

HCAHPS data for 2011 were obtained from the medicare.data.gov website. The dataset included hospital name, street address, zip code, county, state, and responses to HCAHPS questions. The relevant PEPM data were formatted as, "Percent of patients who reported that their pain was "always" well controlled, where "usually," and "never" were substituted for "always" to create three separate variables. Those hospitals not within the continental U.S., and those hospitals with a zero percent HCAHPS survey response rate, were excluded from further analysis. The street address for each hospital was converted to a geo-coordinate system using the ArcGIS geocoding schema. The coordinates were then converted to a Mercator projection to ensure stable distance measurements across different types of analyses. Classes of responses were defined using the Jenks Natural Breaks algorithm, which reduces variance within classes and maximizes variance between classes [21].

In our first analytic approach, we determined how HCAHPS PEPM scores were spatially organized within the United States. Organizational patterns were determined separately for "always" and "never" PEPM ratings for those hospitals with a response rate of over 5% on the HCAHPS survey. When HCAHPS is used as a hospital performance measure, U.S. hospitals are typically graded via a binary schema: either a patient rates their experience for a typical measure as "always," or not. Any grade other than "always" is considered a failing grade. We elected to include "always" and "never" PEPM ratings to demonstrate the polarized proportion of patients who were presumably strongly satisfied or strongly dissatisfied with the pain management aspect of their hospitalization. To provide additional insights into the relationship of "always" and "never" responses within hospitals, we included the ratio of "always" to "never" responses as an additional metric of comparison. Of the included hospitals, 22 had a positive value for "always" yet a zero value for "never"; the ratio here was considered to be 100%.

The geospatial distribution of U.S. hospital performance measures reflects how these measures are distributed by location. One of the more common methods of measuring this geospatial distribution is via measures of spatial organization. The three main categories of spatial organization include clustering (whereby closer hospitals would exhibit similar PEPM characteristics than would more distant hospitals), random (no association between hospital location and PEPM characteristics), and dispersed (more distant hospitals have more PEPM characteristics in common than do those hospitals in proximity to one another).

Spatial organization was assessed at three different scales. The first simply examined the general spatial arrangement of PEPM scores across the U.S. by testing for Global Moran's I, which is a measure of the spatial autocorrelation between attributes (PEPM scores) and feature location (where the hospitals were located) [29]. Positive scores for Moran's index suggest a tendency toward clustering, and negative scores a tendency toward dispersion. For instance, given the example of a black and white checkerboard, the perfectly dispersed arrangement of alternating black and white squares would yield a Moran's I of -1 , whereas a board arranged such that all black squares were clustered on one side and white squares clustered on the other would have a Moran's I of $+1$. If the black and white squares were randomly distributed throughout the board, the Moran's I would be zero. Spatial relationships were assessed using the inverse distance method based upon Euclidean, or "airplane", distances as opposed to "Manhattan", or roadway, distances.

To further assess how autocorrelation between PEPM scores and hospital location changed across different inter-hospital differences, we also conducted an incremental spatial autocorrelation test. This test replicates the Global Moran's I at different distance thresholds to determine whether clustering and/or dispersion differ with increasing inter-hospital distance. Here again, higher positive Index scores (and z-scores when statistically significant) for incremental spatial autocorrelation suggest higher degrees of clustering for a given distance, and negative scores suggest greater degrees of dispersion. Ten distances were tested ranging from 10 km to 5000 km between hospitals.

To repeat the above tests at the hospital-level, we conducted an Anselin Local Moran's I to identify "hot spots", "cold spots", and spatial outliers [1]. Here, Moran's I is again calculated, this time reflecting the contribution of each hospital to the Global Moran's I. Each hospital is assigned a code distinguishing it as part of a cluster, thus sharing PEPM characteristics with neighboring hospitals based on the Moran's index, or as an outlier, with a negative Moran's index and different PEPM characteristics compared with neighboring hospitals. Thus hospitals are assigned to one of five separate categories: no statistically significant difference between hospitals; a high-scoring hospital surrounded by other high-scoring hospitals; high-scoring hospitals surrounded by low-scoring hospitals; low-scoring hospital surrounded by high-scoring hospitals; or low scoring hospitals surrounded by other low-scoring hospitals. These assignments are then plotted on a map of the U.S. for visual comparison. This approach was included given the relatively small range of values given for "always," thus permitting the detection of statistical outliers within a geospatial context.

In our second analytic approach, we combined PEPM hospital profiles with geospatial data using graph analytic approaches to examine regional differences in PEPM scores. This approach simultaneously considered the proportions of "always," "usually," and "never" ratings, the ratio of "always:never," and the geospatial location of each hospital. Briefly, this approach creates a multimodal graph, whereby each hospital's PEPM score and location are considered nodes, and the edges connecting the nodes are weighted according to the similarity between nodes across both PEPM scores and geospatial location [2,10,18]. The resulting minimum spanning tree is then "pruned" by cutting the weakest edges, or those indicating low similarity between the connected nodes. This is repeated until a pre-specified number of groups remain. The dual but offsetting goals of regionalization are thus

maintained: identified subgroups maintain homogeneity within the group, including proximity in location, while groups with different characteristics are separated. Because the location of the hospital is considered a critical feature in the creation of the nodes within the minimum spanning tree, effects of geographic density are considered within the context of the likeness of two adjacent nodes. Practically, a large number of groups are first tested, the pseudo F-statistics of the resulting groups are plotted, and a cutoff identifying the peak pseudo F-statistic is selected. Spatial constraints were entered using the K-nearest neighbors method with number of neighbors set to 10. The first run specified 10 groups, following which a peak pseudo F-statistic suggested that a group size of four would offer the optimal differentiation amongst groups. Groups were then compared for each response level to examine for differences between each assigned group. Ultimately, this produced a map of hospital clusters, whereby those hospitals that were similar in their geospatial and PEPM scores were clustered together via different colors. The boundaries separating each cluster represent the edges of the pruned branches of the spanning tree, metaphorically pruning a mess of bush branches into visually separable plants.

All geospatial analyses were conducted using ArcGIS 10.1. Investigations into group assignments were compared using the Kruskal-Wallis test for each response, and post hoc comparisons were corrected using the Steel-Dwass method. Kruskal-Wallis tests and the Steel-Dwass method were implemented using JMP 10.0.02 (SAS Institute, Cary, NC) [9]. Response data were generally reported as mean $\pm$ standard deviation. Nonparametric methods were employed in the group assignment analysis due to variance in sample sizes between groups. Statistical significance was set at $P=0.05$.

Results

The 2011 HCAHPS dataset included data from 4648 hospitals. After limiting the dataset to hospitals in the continental U.S. with nonzero response rates, 3645 hospitals were ultimately included in the analyses. All states and the District of Columbia were represented. Louisiana hospitals had the largest proportion of patients with PEPM “always” responses at $75\% \pm 7\%$, while the District of Columbia had the lowest proportion at $64\% \pm 5\%$. Likewise, the District of Columbia had the highest proportion of “never” responses at $12\% \pm 5\%$, and Nebraska had the lowest proportion of “never” responses at $4\% \pm 1\%$ (Table 1). The ratio of “always” to “never” events similarly ranged from 5.4 in the District of Columbia to 16.3 in Nebraska. Appendix A shows the relationships between “always,” “never,” and the ratio of “always:never.”

Hospital locations were clustered throughout the United States, with fewer hospitals noted in the Midwest and Northwest compared with the Northeast corridor. Figure 1 shows the PEPM scores for each hospital separately for the responses “always” (Fig. 1A), “never” (Fig. 1B), and the ratio of “always” to “never” responses (Fig. 1C).

Global Moran’s I were analyzed separately for “always” and “never” responses, as well as for the ratio of “always:never.” For “always” responses, Moran’s I was positive (0.91) and statistically significant (z-score 3.3, $P = 0.0009$), indicating that “always” responses were geospatially clustered among the analyzed hospitals. For “never” responses, there was a

non19 statistically significant trend (index 0.42, z-score 1.6, $P = 0.12$) toward clustering. For the ratio of “always:never” responses, the results suggested that the ratios exhibited complete spatial randomness (index 0.078, z-score 0.3, $P = 0.78$).

Tests of incremental spatial autocorrelation were also analyzed separately for “always” and “never” responses, as well as for the “always:never” ratio. For “always” responses, Moran’s index was statistically significant in all distances tested from 10 to 5000 km (Appendix B). However, between 2510 and 3010 km, the index changed from 0.006 to -0.001 , suggesting a change from a clustering spatial motif to a dispersed spatial motif (Fig. 2A). This suggests that PEPM scores are clustered amongst nearby hospitals at distances of less than 3000 km, and that PEPM scores are dispersed amongst hospitals at distances of greater than 3000 km. Similar results were observed for “never” responses, with a conversion from clustering (Moran’s Index, 0.0005) to dispersion (Moran’s Index, -0.003) between 3010 and 3510 km (Fig. 2B), as well as for the “always:never” ratio, with a conversion from clustering (Moran’s Index, 0.007) to dispersion (Moran’s Index, -0.003) between 2510 and 3510 km (Fig. 2C).

At the hospital level, geographic differences were found for both “always” and “never” responses using Anselin Local Moran’s I. Clusters of hospitals with high proportions of “always” responses were found throughout the Midwest, and clusters of hospitals with low proportions of “always” responses were found in the mid-Atlantic states, Florida and coastal California (Fig. 3A). Inverse findings were observed for “never” responses, with the exception of higher clustering in the southeast for high proportions of “never” responses and less clustering of “never” responses in coastal California (Fig. 3B). The findings for the ratio of “always:never” were generally aligned with the findings for “always” responses, albeit with more clusters of high ratios of always:never found in the northern as opposed to southern Midwest, and fewer clusters of hospitals with low ratios of always:never in the mid-Atlantic states, Florida and coastal California (Fig. 3C).

The spatial cluster analysis by minimum spanning tree edge removal showed four distinct groups of hospitals with relatively distinct geographic boundaries (Figure 4). There were statistically significant differences between groups ($P < 0.0001$) for “always” responses, “usually” responses, “never” responses, and the ratio of “always:never” (Figure 5). Post hoc comparisons between groups for “always” showed statistically significant differences between all pairs ($P < 0.0001$). Post hoc comparisons between groups for “usually” showed statistically significant differences between all pairs ($P < 0.0001$) with the exception of groups 4 and 3 ($P = 0.1$). Post hoc comparisons between groups for “never” showed statistically significant differences between all pairs ($P < 0.0001$) with the exception of groups 1 and 3 ($P = 0.2$). Post hoc comparisons for comparisons between groups for the ratio of always:never showed statistically significant differences between all pairs ($P < 0.0001$) with the exception of groups 1 and 3 ($P = 0.03$) (Appendix C).

Discussion

Our results suggest that there are geographic disparities in PEPM during hospitalization as measured by the HCAHPS reporting system. The data suggest that hospitals are clustered,

rather than dispersed, in their geospatial distribution with regards to patients stating that they were “always” satisfied with their pain management during hospitalization. Additionally, spatial cluster analysis by minimum spanning tree edge removal identified distinct geographic boundaries, which separated hospitals into groups according to their results of “always,” “usually,” and “never” PEPM responses.

A cursory review of Figure 1 suggests loco-regional differences in PEPM scores for U.S. hospitals. However, given the heterogeneity of hospital results, and the substantial overlap induced by the map scale, one cannot definitively ascertain geospatial differences in PEPM scores. This was the impetus to employ more advanced methods of geospatial analyses, beginning with the Global Moran’s I statistic.

The Moran’s I statistic was designed to determine whether a feature, when distributed over a geographic space, exhibited clustering, random placement, or dispersion. One might intuit that hospitals that are closer together may be more similar than those hospitals that are further apart [33,36]. We might alternatively hypothesize that socioeconomic pressures result in dispersion of hospitals of similar characteristics, such as for Level One trauma centers and hospitals involved in high-risk procedures throughout the U.S. [7,25,26,30]. Our results suggest that at national, regional, and local levels, U.S. hospitals exhibit clustering of PEPM scores rather than dispersion. This effect was more pronounced with “always” respondents versus “never” respondents, suggesting that hospitals performing very poorly with regards to PEPM scores may be a somewhat more random occurrence. These results might also suggest that for hospital clusters with high PEPM scores, competitive pressures could theoretically explain the increases in clustering observed especially in areas with higher population densities throughout the eastern U.S.

Our analysis of spatial autocorrelation variance by distance noted a relative peak in clustering between 500 km and 2,000 km for both “always” and “never” responses. Beyond 3,000 km, the trend shifted towards a dispersion of effects. For reference, the United States is approximately 4,000 km wide. Our results suggest then that the peaks in clustering are not necessarily at the metropolitan level, but rather differentiating the Southeast, Northeast, Midwest, and West Coast. These results are in general agreement with those obtained via clustering analysis of a minimum spanning tree, despite the substantially different methods used in these two analyses. The cluster analysis of the minimum spanning tree highlighted differences at the regional level where cluster sizes were measured in thousands of kilometers.

Despite the general trend towards clustering of features that was also shown by the Anselin Local Moran’s I maps in Figure 2, these maps also highlighted exceptions within clusters of high and low-performing hospitals with regards to PEPM scores. The exceptions are best demonstrated by examining those hospitals labeled HL or LH. Our data suggest that although geographic location may be associated with hospital PEPM performance, the location certainly does not present insurmountable barriers toward high or low PEPM performance.

Social demographics, economic status, and other cultural factors may play critical roles in explaining the observed geographic variance [11,16,34]. More specifically, the urban versus rural status of a hospital, hospital size, case and payor mix, proportion of medical versus surgical volume, and prevalence of “extreme” procedures (e.g., hemipelvectomy, forequarter amputation, extensive burns, etc.) may all influence PEPM partially or fully independent of the quality of pain care delivered by a given hospital. Determination of such effects on PEPM scores will require the simultaneous consideration of hospital characteristics as well as sociodemographic data analyzed using geographic regression approaches in an attempt to isolate the effects of hospital characteristics and sociodemographic variables from pure location-based effects.

The separation of hospital clusters into distinct geosociopolitical regions, such as the Southeast, Northeast, Midwest, and Pacific coast, is nevertheless notable for their congruency with traditional regions of the U.S. One possible explanation for these results may be that deeper sociological characteristics of these regions underlie the observed PEPM scores, potentially minimizing the hospital effects of such outcomes. Indeed, the deduced counterargument, that U.S. hospitals drive not only PEPM scores but also broader, traditional definitions of U.S. geosociopolitical boundaries, would appear to be invalid on its face. While the spanning tree method takes into account the likeness of neighboring hospitals into its calculation of PEPM regions, the methods based upon Moran’s I are not driven on boundary effects. This further suggests that the observed results are not simply products of a given modeling method, but may reflect a national pattern of PEPM score distribution. Within the United States, cultural factors are not necessarily beholden to regional separation, but rather can also be embedded within individual metropolitan areas. This embedding of cultural microcommunities could explain some of the exceptions identified in Figure 2.

Importantly, the methods employed by this paper are insufficient to fully explain this confluence of regional patterns. Notably, some of the possible factors which may drive regional differences include some sociodemographic factors such as age, education and language that have already been adjusted out of HCAHPS data, and so which could not explain the observed variation in adjusted scores [12]. The geographic variation in hospital-level patient-reported pain control may reflect geographically-varying hospital practices. Ideally, the most direct empirical means of testing the contributions of hospitals versus unmeasured geographical effects would be to use a multi-level model of individual data which also includes the effects from both geography and individual hospitals. Indeed, using a similar approach for Medicare plans, prior work has found that what would have appeared to be purely geographic variations in HCAHPS measures given s restricted plan-level data was actually a mixture of both plan-level of geographic variation, with plan-level data dominating geography for some measures while geography dominated plans for other measures [38]. Further work will be necessary to associate the regional PEPM patterns with geosociodemographic factors throughout the U.S.

The fact that hospital PEPM scores differ by geographic setting within the United States may carry important policy implications. Currently, HCAHPS scores are used to vary hospital reimbursement by CMS through the Value Based Purchasing program. (<http://>

www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/hospital13value-based-purchasing/Downloads/FY-2013-Program-Frequently-Asked-Questions-about-Hospital-VBP-3-9-12.pdf) (<http://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/index.html?redirect=/hospitalqualityinits>) The above results suggest that geographic context may affect such scores, and so further analyses are necessary to evaluate the relative impact of PEPM scores on HCAHPS results within different geographic areas. Coupled with previously published concerns over the negative correlations observed between a hospital's HCAHPS scores and patient outcomes, the role of PEPM scores as a factor in setting reimbursement guidelines may need to be further examined to ensure that such incentives can be equitably applied across the U.S. [13]. Another policy implication is the distance patients must travel for access to hospitals with "satisfactory" PEPM scores, given the heterogeneous distribution of such facilities. Additionally, depending upon the socioeconomic underpinnings of these observed geographic differences, these results also carry important implications for targeting pain improvement educational interventions to different areas of the country.

Further, the relative importance of HCAHPS scores pertaining to pain, in comparison to other measures such as influenza vaccination, in evaluating hospital performance remains unclear. Many clinical quality indicators rely on assessments of quantitative outcomes, while assessments of patient experience with pain management rely reflect attempts to quantify an admittedly qualitative experience. Further, given the evidence that hospital-wide efforts to improve acute pain management can actually lead to significant increases in patient morbidity and adverse drug events, the results of surveys of patient experience surveys must be placed into a broader context of the safety and efficacy of delivered care [37].

Given that hospitals maintain address data for most patients, hospitals may wish to consider geospatial and geographic characteristics of their patients in forecasting patient outcomes regarding pain management and HCAHPS-related experience metrics. Furthermore, hospitals may wish to use similar geospatial approaches to assist with transitioning pain care from the inpatient to the outpatient setting, or even by providing pre-procedural patient education targeted to regions clustered according to patient-level pain outcomes.

This study was not designed to examine the associations between geographic differences, socioeconomic differences, and PEPM scores, but rather simply the measured HCAHPS PEPM outcomes by hospital location. Although our results showed geographic differences in PEPM scores, the study was not designed to discern if, or how, these geographic differences were separate from socioeconomic and cultural differences. To answer such a question, future work applying geospatially weighted regression techniques to HCAHPS data will be necessary. However, it remains unclear the extent to which the effects of location can be practically separated from the characteristics of people inhabiting a given location. It is also unclear to what extent patient experience with pain control is synonymous with "good" pain control as measured using structured pain reporting measures, or with "safe" pain control [35,37]. Furthermore, it is unclear as to whether increased attention to pain control, via HCAHPS metrics, can lead to effective improvements in pain control [14,23]. Regardless, patient experience scores remain a de facto metric for hospital comparison in the United States.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Appendix A. State-level correlations between pain-related HCAHPS responses

The correlations for “always”, “usually”, “never”, and the ratio of “always to never” are graphically depicted. While “usually” responses were not well correlated with “never” responses or the ratio of “always to never”, there was a considerable negative correlation between “always” and “usually” responses.

Summary

The results of a geospatial analysis of patient experience with pain management during hospitalization suggest a regional geographic effect on PEPM scores.

Fig. 1. U.S. map of hospital results for patient responses to pain-related HCAHPS questions
 Each hospital in the continental U.S. with a non-zero HCAHPS response rate is indicated by a colored dot. Responses indicate the percentage of patients who reported that their pain was "always" (A) or "never" (B) well controlled during their hospitalization, as well as a ratio of "always" to "never" responses (C). Classes of responses were defined using the Jenks Natural Breaks algorithm, which reduces variance within classes while maximizing variance between classes.

Fig. 2. Incremental spatial autocorrelation by distance

Global Moran's I statistics were computed separately for "always" responses (A), "never" responses (B), and the ratio of "always" to "never" responses (C). The z-score of the Global Moran's I statistics are plotted against interhospital distances ranging from zero to 5000 km. This broad range of distances was chosen to account for the effects of clustering and/or dispersion across the entire country. Positive z-scores represent geographic clustering of responses for hospital separated by the given distance, whereas negative z-scores represent geographic dispersion of responses across hospitals separated by the given distance.

Fig. 3. Cluster and outlier analysis of U.S. hospitals by Anselin Local Moran's I statistic
 Separate maps were created for "always" (A) and "never" (B) plots, as well as the ratio of "always" to "never" (C). Each hospital is assigned a code distinguishing it as part of a cluster, thus sharing PEPM characteristics with neighboring hospitals based on the Moran's index, or as an outlier, with a negative Moran's index and different PEPM characteristics compared with neighboring hospitals. Hospitals are then assigned to one of five separate categories: no statistically significant difference between hospitals (Not Significant); a high-scoring hospital surrounded by other high-scoring hospitals (HH); high-scoring hospitals

surrounded by low6 scoring hospitals (HL); low-scoring hospital surrounded by high-scoring hospitals (LH); or low7 scoring hospitals surrounded by other low-scoring hospitals (LL). In each case, a “high”- performing hospital is a hospital with a large proportion of “always” responses (A), or conversely, a large proportion of “never” responses (B).

Fig. 4. Spatial cluster analysis by minimum spanning tree edge removal

Hospitals were characterized by a multimodal minimum spanning tree network containing the following characteristics: geographic location, proportion of PEPm responses that were “always,” proportion of PEPm responses that were “usually,” and proportion of PEPm responses that were “never.” Edges within the spanning tree were algorithmically pruned until four separate groups were identified. Hospitals were then labeled by group assignment, highlighting the geographic separation of PEPm profiles.

Fig. 5. Comparison of response proportions across minimum spanning tree group assignments
 There were statistically significant differences between groups for “always” responses ($P < 0.0001$), “usually” responses ($P < 0.0001$), “never” responses ($P < 0.0001$), and the ratio of “always” to “never” ($P < 0.0001$).

Table 1

Percentage of patients reporting that their pain was well controlled: Mean $\pm$ SD

State	Number of hospitals	"Always"	"Usually"	"Never"	Ratio of "always" to "never"
AL	87	71% $\pm$ 5%	20% $\pm$ 4%	9% $\pm$ 4%	8.25
AR	44	71% $\pm$ 5%	22% $\pm$ 3%	7% $\pm$ 3%	9.83
AZ	60	70% $\pm$ 3%	23% $\pm$ 2%	7% $\pm$ 2%	9.93
CA	304	68% $\pm$ 6%	24% $\pm$ 4%	8% $\pm$ 3%	8.41
CO	58	70% $\pm$ 10%	23% $\pm$ 5%	6% $\pm$ 2%	12.42
CT	30	69% $\pm$ 7%	25% $\pm$ 7%	7% $\pm$ 2%	10.07
DC	7	64% $\pm$ 5%	24% $\pm$ 2%	12% $\pm$ 5%	5.40
DE	5	70% $\pm$ 1%	23% $\pm$ 2%	7% $\pm$ 1%	10.06
FL	164	67% $\pm$ 6%	24% $\pm$ 4%	9% $\pm$ 3%	7.22
GA	105	71% $\pm$ 5%	21% $\pm$ 3%	8% $\pm$ 3%	9.30
IA	67	71% $\pm$ 5%	24% $\pm$ 4%	5% $\pm$ 2%	15.25
ID	20	71% $\pm$ 5%	24% $\pm$ 4%	6% $\pm$ 2%	12.78
IL	141	70% $\pm$ 5%	23% $\pm$ 3%	7% $\pm$ 4%	9.48
IN	105	72% $\pm$ 4%	22% $\pm$ 3%	5% $\pm$ 2%	13.33
KS	64	71% $\pm$ 5%	23% $\pm$ 4%	5% $\pm$ 2%	14.08
KY	72	72% $\pm$ 5%	21% $\pm$ 4%	7% $\pm$ 2%	10.43
LA	97	75% $\pm$ 7%	18% $\pm$ 5%	7% $\pm$ 3%	10.71
MA	59	70% $\pm$ 10%	22% $\pm$ 4%	7% $\pm$ 2%	10.65
MD	44	68% $\pm$ 4%	24% $\pm$ 3%	9% $\pm$ 3%	7.81
ME	32	73% $\pm$ 4%	22% $\pm$ 3%	5% $\pm$ 2%	14.65
MI	108	72% $\pm$ 5%	22% $\pm$ 4%	6% $\pm$ 2%	11.65
MN	102	71% $\pm$ 5%	24% $\pm$ 4%	5% $\pm$ 2%	13.99
MO	78	69% $\pm$ 5%	24% $\pm$ 3%	7% $\pm$ 3%	9.95
MS	58	72% $\pm$ 5%	20% $\pm$ 4%	8% $\pm$ 3%	9.35
MT	24	70% $\pm$ 6%	24% $\pm$ 6%	6% $\pm$ 3%	11.44
NC	88	71% $\pm$ 4%	22% $\pm$ 3%	7% $\pm$ 2%	10.72
ND	9	69% $\pm$ 4%	25% $\pm$ 3%	7% $\pm$ 2%	10.46

State	Number of hospitals	“Always”	“Usually”	“Never”	Ratio of “always” to “never”
NE	35	72% ± 4%	24% ± 3%	4% ± 1%	16.30
NH	19	72% ± 3%	22% ± 2%	6% ± 2%	12.64
NJ	56	67% ± 5%	24% ± 3%	9% ± 4%	7.38
NM	32	70% ± 5%	22% ± 4%	8% ± 3%	9.26
NV	23	66% ± 6%	24% ± 3%	9% ± 3%	7.21
NY	160	66% ± 7%	25% ± 4%	9% ± 4%	7.49
OH	153	71% ± 5%	23% ± 4%	6% ± 2%	11.49
OK	91	72% ± 7%	22% ± 5%	6% ± 3%	11.66
OR	48	70% ± 4%	24% ± 3%	6% ± 2%	11.88
PA	140	69% ± 5%	24% ± 3%	7% ± 3%	9.92
RI	10	71% ± 4%	22% ± 3%	7% ± 2%	10.17
SC	53	72% ± 3%	21% ± 3%	7% ± 2%	10.40
SD	38	72% ± 7%	23% ± 6%	4% ± 3%	16.16
TN	98	71% ± 6%	21% ± 5%	7% ± 2%	9.61
TX	309	72% ± 5%	21% ± 4%	7% ± 3%	10.81
UT	37	72% ± 5%	23% ± 4%	5% ± 2%	14.98
VA	70	69% ± 3%	23% ± 3%	8% ± 2%	9.10
VT	10	71% ± 3%	23% ± 3%	6% ± 2%	11.48
WA	64	70% ± 4%	24% ± 3%	6% ± 2%	10.86
WI	113	72% ± 5%	23% ± 4%	5% ± 2%	14.33
WV	35	68% ± 5%	23% ± 3%	9% ± 3%	7.81
WY	19	69% ± 5%	24% ± 3%	7% ± 2%	10.13

Table 2

Anselin Local Moran's I Results for "Always" and "Never" Responses

	Distance(km)	Morans I	Expected I	Variance	Z-score	p-value
"Always"	10	0.6461888	-2.74E-04	4.44E-04	30.69	<0.0001
	510	0.0837435	-2.74E-04	1.71E-06	64.19	<0.0001
	1010	0.0412476	-2.74E-04	4.51E-07	61.86	<0.0001
	1510	0.0209255	-2.74E-04	1.69E-07	51.63	<0.0001
	2010	0.0157415	-2.74E-04	7.67E-08	57.82	<0.0001
	2510	0.0062583	-2.74E-04	4.20E-08	31.87	<0.0001
	3010	-0.0012616	-2.74E-04	2.62E-08	-6.10	<0.0001
	3510	-0.0045088	-2.74E-04	1.75E-08	-32.00	<0.0001
	4010	-0.0056935	-2.74E-04	1.17E-08	-50.20	<0.0001
	4510	-0.0048104	-2.74E-04	6.97E-09	-54.32	<0.0001
Never	10	1.0081334	-2.74E-04	4.45E-04	47.81	<0.0001
	510	0.1028062	-2.74E-04	1.72E-06	78.64	<0.0001
	1010	0.0587678	-2.74E-04	4.52E-07	87.86	<0.0001
	1510	0.0381231	-2.74E-04	1.69E-07	93.42	<0.0001
	2010	0.0244883	-2.74E-04	7.68E-08	89.33	<0.0001
	2510	0.0101514	-2.74E-04	4.21E-08	50.84	<0.0001
	3010	0.0005187	-2.74E-04	2.62E-08	4.90	<0.0001
	3510	-0.0029432	-2.74E-04	1.75E-08	-20.16	<0.0001
	4010	-0.0030622	-2.74E-04	1.17E-08	-25.81	<0.0001
	4510	-0.0018384	-2.74E-04	6.98E-09	-18.71	<0.0001

Table 3

Post-hoc Comparisons Between Spanning Tree Group Assignments

Response Level	Group	Group	Score	Mean Difference	Std Err Diff	Z-score	p-value	Hodges-Lehman	Lower CL	Upper CL
Always	2	1	514.463	97.85643	5.2573	<.0001		15	9	21
	6	1	272.877	24.8884	10.964	<.0001		3	2	3
	3	1	248.187	25.51825	9.7258	<.0001		2	1	3
	6	4	221.974	20.77145	10.6865	<.0001		4	3	5
	6	5	130.54	21.59005	6.0463	<.0001		2	1	2
	5	4	121.499	18.97345	6.4036	<.0001		2	1	3
	5	1	105.55	24.50343	4.3075	0.0002		1	0	2
	6	3	47.673	23.4223	2.0354	0.3221		0	0	1
	4	1	-93.239	25.70891	-3.6267	0.0039		-1	-2	0
	5	3	-102.998	22.82475	-4.5126	<.0001		-1	-2	0
	4	2	-147.519	28.10716	-5.2484	<.0001		-16	-22	-10
	4	3	-227.79	22.92244	-9.9374	<.0001		-3	-4	-2
	5	2	-302.903	59.77569	-5.0673	<.0001		-14	-20	-8
	6	2	-333.718	70.09276	-4.7611	<.0001		-13	-18	-6
	3	2	-409.864	82.26476	-4.9823	<.0001		-13	-19	-7
Usually	3	2	393.684	82.07934	4.7964	<.0001		11	5	16
	6	2	311.781	69.99267	4.4545	0.0001		10	4	15
	5	2	301.735	59.64415	5.0589	<.0001		13	6	18
	5	3	236.507	22.78064	10.3819	<.0001		2	1	2
	4	3	170.498	22.86332	7.4572	<.0001		2	1	2
	4	2	145.295	28.01953	5.1855	<.0001		13	6	18
	5	1	143.855	24.44715	5.8843	<.0001		1	1	1
	4	1	94.385	25.63721	3.6816	0.0032		1	0	1
	5	4	19.198	18.92378	1.0145	0.9133		0	0	1
	6	3	-99.884	23.37896	-4.2724	0.0003		-1	-1	0
	3	1	-145.351	25.45196	-5.7108	<.0001		-1	-1	0
	6	4	-203.107	20.73528	-9.7952	<.0001		-2	-3	-2
	6	1	-236.732	24.83802	-9.531	<.0001		-2	-2	-1

Response Level	Group	Group	Score Mean Difference	Std Err Diff	Z-score	p-value	Hodges-Lehman	Lower CL	Upper CL
	6	5	-276.742	21.56319	-12.834	<.0001	-3	-3	-2
	2	1	-495.031	97.59279	-5.0724	<.0001	-12	-17	-6
Never	3	2	245.838	81.77677	3.0062	0.0317	3	0	5
	6	2	218.611	69.72095	3.1355	0.0212	3	0	5
	4	3	217.075	22.80001	9.5208	<.0001	2	1	2
	5	2	147.668	59.21421	2.4938	0.1258	2	0	4
	6	5	132.805	21.43989	6.1943	<.0001	1	0	1
	4	2	116.133	27.92954	4.1581	0.0005	4	2	7
	4	1	59.121	25.55058	2.3139	0.1883	0	0	1
	6	3	36.982	23.29028	1.5879	0.6066	0	0	1
	5	3	-109.427	22.65533	-4.8301	<.0001	-1	-1	0
	6	4	-167.648	20.66292	-8.1135	<.0001	-1	-2	-1
	6	1	-213.993	24.75453	-8.6446	<.0001	-1	-1	-1
	5	4	-245.372	18.84469	-13.0207	<.0001	-2	-3	-2
	3	1	-275.48	25.38574	-10.8518	<.0001	-1	-2	-1
	5	1	-373.038	24.35949	-15.3139	<.0001	-2	-2	-2
	2	1	-386.919	97.2711	-3.9777	0.001	-4	-6	-1