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Do Hospital Service Areas and Hospital Referral Regions Define Discrete Health Care Populations?

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Background: Effective measurement of health care quality, access, and cost for populations requires an accountable geographic unit. Although Hospital Service Areas (HSAs) and Hospital Referral Regions (HRRs) have been extensively used in health services research, it is unknown whether these units accurately describe patterns of hospital use for patients living within them.

Objectives: To evaluate the ability of HSAs, HRRs, and counties to define discrete health care populations.

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Research Design: Cross-sectional geographic analysis of hospital admissions.

Subjects: All hospital admissions during the year 2011 in Washington, Arizona, and Florida.

Measures: The main outcomes of interest were 3 metrics that describe patient movement across HSA, HRR, and county boundaries: localization index, market share index, and net patient flow. Regression models tested the association of these metrics with different HSA characteristics.

Results: For 45% of HSAs, fewer than half of the patients were admitted to hospitals located in their HSA of residence. For 16% of HSAs, more than half of the treated patients lived elsewhere. There was an equivalent degree of movement across county boundaries but less movement across HRR boundaries. Patients living in populous, urban HSAs with multiple, large, and teaching hospitals tended to remain for inpatient care. Patients admitted through the emergency department tended to receive care at local hospitals relative to other patients.

Conclusions: HSAs and HRRs are geographic units commonly used in health services research yet vary in their ability to describe where patients receive hospital care. Geographic models may need to account for differences between emergent and nonemergent care.

Key Words: geography of health, health services research, hospital markets, research methodology, population health

(*Med Care* 2015;53: 510–516)

Geographic variation in health care spending, access, and quality is an intractable feature of the United States healthcare system.^{1–3} The Dartmouth Atlas of Health Care has provided the geographic tools through which variation has primarily been investigated.⁴ Studies have used Dartmouth-defined Hospital Referral Regions (HRRs) and Hospital Service Areas (HSAs) to demonstrate geographic variation in topics as diverse as end-of-life spending, chronic disease management, and patient satisfaction after hospital admission.^{5–7}

The methods used to develop HSAs and HRRs have been widely accepted. The geographic units are derived from Medicare data.⁸ First, US hospitals are assigned to towns in which they are located. Then, Zone Improvement Plan (ZIP) codes are assigned to towns when a plurality of Medicare beneficiaries in a ZIP code are admitted to hospitals located in the town. The set of ZIP codes assigned to a town serve as a preliminary HSA, with revisions to ensure adequate size

and geographic contiguity. The larger HRR units are subsequently built from HSAs on the basis of neurosurgical and cardiovascular surgery referral patterns.

The Institute of Medicine has emphasized the importance of evaluating health care quality across geographic regions and endorsed the concept of total population health, or the health of all people living in a region.⁹ However, it is unclear how those geographic regions should be defined.^{10,11} Counties are commonly used in geographic analyses of health care outcomes. HRRs have also been used in geographic analyses, but recent work has shown that substantial variation in health care spending exists within HRRs, suggesting that they are too large to capture local heterogeneity.¹² Smaller units, such as HSAs, may better define local health care populations and markets. Overall, little attention has been paid to whether these units accurately describe geographic patterns of hospital use or can be used to measure health care outcomes.^{10,13}

To our knowledge, no studies have evaluated whether HSAs and HRRs predict where patients actually go to receive care. Are patients treated in the same HSA or HRR in which they reside? Do HSAs represent local health care markets? Answers to these questions may vary according to local characteristics and other factors such as whether patients seek care in the emergency department (ED). In this study, we evaluated the ability of counties, HSAs, and HRRs to define discrete boundaries around health care populations.

METHODS

Data

This study used data from the 2010 Statewide Inpatient Database (SID) from the Health Care Utilization Project compiled by the Agency for Healthcare Research and Quality. The SID contains data for all admissions to hospitals located in a single state. Each admission is recorded as a separate observation, including hospital transfers. For patients admitted to multiple hospitals, each admission is a separate observation. The SID database includes deidentified data on patient demographics including patient ZIP code, ICD-9 codes, transfer status, in-hospital mortality, and a variable indicating the provision of ED services. The database also includes encrypted hospital identifiers, which can be linked to the 2010 American Hospital Association (AHA) annual survey. The AHA survey includes data on hospital type, size, teaching status, ZIP code, and urban or rural designation.

The analysis was limited to 3 states: Washington, Arizona, and Florida. The SID databases only include admissions to hospitals located within the state. These 3 states were selected for reasons including geographic diversity, size, and data availability. Importantly, the major population centers of these states are located far from borders with other states. In this analysis, we only included residents of Washington, Arizona, and Florida that received care at hospitals in those states. The analysis was also limited to general medical and surgical hospitals as identified by the AHA survey. Admissions to other types of hospitals, including pediatric, psychiatric, long-term acute care, and specialty centers, were excluded.

The HSA and HRR geographic units are each assigned to a single town, but they can extend across state borders. This analysis was limited to HSAs and HRRs assigned to towns in the states of Washington, Arizona, and Florida. We excluded HSAs and HRRs that were assigned to towns in neighboring states but also included portions of the 3 study states.

We included counties as defined by the United States Census Bureau.¹⁴ To determine the county of residence for patients, we linked ZIP codes to counties using tables provided by the US Department of Housing and Development.¹⁵ When ZIP code boundaries overlapped county boundaries, we assigned ZIP codes to counties in which the majority of residents live.

Statistical Analysis

The main outcomes were 3 metrics that have been used to characterize health care service regions.^{8,16} These metrics are: (1) localization index, (2) market share index, and (3) net patient flow. Figure 1 demonstrates how these metrics are calculated.

The units of analysis were HSAs, HRRs, and counties. As originally defined by the Dartmouth Atlas of Health Care, localization index is the proportion of patients who reside in the same HSA as the hospital to which they were admitted.⁸ It represents the tendency of residents of an area to receive inpatient care within their own area. Values are represented as a percentage. Market share index is the proportion of patients treated in an HSA who do not live there.¹⁶ It represents the tendency of hospitals in an area to draw residents from other areas. Values are represented as a percentage. Net patient flow is the ratio of “imported” patients to “exported” patients.¹⁶ More precisely, it is the ratio of non-HSA residents treated in an HSA to HSA residents not treated in that HSA. Values >1 indicate that patients tend to travel to the HSA for inpatient care, and values <1 indicate that patients

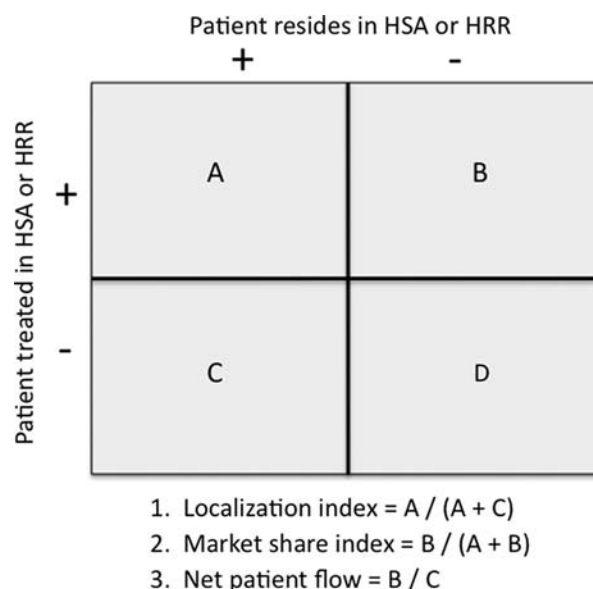


FIGURE 1. Calculation of metrics used to evaluate Hospital Service Areas (HSAs), Hospital Referral Regions (HRRs), and counties.

tend to leave the HSA for care. These metrics were also calculated at the HRR and county level.

Localization index and market share index were calculated separately for all admitted patients, patients admitted through the ED, and patients admitted without receiving ED services. We hypothesized that patients admitted through the ED would be more likely to be treated in the same HSA, HRR, or county in which they live, with relatively higher localization index and lower market share index. We compared values for each admission source using Student's *t* test.

Localization index and market share index were also calculated separately for 3 groups of patients with different insurance coverage: Medicare, Medicaid, and commercial insurance. We hypothesized that Medicare patients would have higher localization index and lower market share index for HSAs because these units were created with Medicare data. We compared values for the 3 groups with a 1-way analysis of variance test.

We investigated whether 2 HSA outcomes, localization index, and market share index, varied according to 5 HSA characteristics: the number of hospitals in an HSA, bed size of the largest hospital, presence of a teaching hospital, urban or rural location, and total number of hospital admissions. Each characteristic was analyzed in a separate, unadjusted regression model that aggregated HSAs from the 3 study states. For each outcome, we used ordinary least squares regression to investigate whether each HSA characteristic corresponded to the outcome in a linear manner. To account for potentially nonlinear relationships, we dichotomized each outcome by splitting localization index and market share index at the median value. We then used each as the outcome in a separate logistic regression model to assess each of the 5 HSA characteristics. Because the market share index outcome was not normally distributed, we generated a separate model using the log of that variable and assessed its relation to each of the 5 HSA characteristics with ordinary least squares regression.

The fit of each regression model was evaluated using conventional diagnostics. In addition, we performed a Moran's *I* test on the residual values generated from each model to test for the presence of spatial autocorrelation, which creates bias or imprecision in the effect estimates.¹⁷ No evidence of spatial autocorrelation was found. We performed separate regression analyses using random intercepts by state and robust estimates for SE to account for clustering of HSAs within HRRs. The results from all alternative models yielded results that were consistent with the results derived from the primary analysis, which is presented here.

Statistical analyses were performed in SAS Version 9.3. ArcGIS Version 10.1 were used to map spatial data. Shapefiles for mapping were provided by the Dartmouth Atlas of Health Care and the United States Census Bureau.¹³ All statistical tests were 2-tailed and *P*-values <0.05 were considered significant. The institutional review board at the University of Pennsylvania approved this study.

RESULTS

The study sample consisted of 3,775,304 hospital admissions for Washington, Arizona, and Florida. The characteristics

of excluded hospital admissions are shown in Supplemental Figure 1, Supplemental Digital Content 1, <http://links.lww.com/MLR/A909>. The 3 states contained 217 HSAs, 33 HRRs, and 121 counties. We excluded 11 HSAs and 5 HRRs that were assigned to neighboring states, such that 206 HSAs and 28 HRRs were analyzed (Supplemental Table, Supplemental Digital Content 2, <http://links.lww.com/MLR/A910>).

Localization index and market share index were calculated for each HSA, HRR, and county (Table 1). The mean HSA localization index for all states was 52% (range, 0%–98%; σ , 24%). The mean HRR localization index for all states was 88% (range, 65%–98%; σ , 8%). The mean HSA market share index for all states was 31% (range, 2%–96%; σ , 19%). The mean HRR market share index for all states was 10% (range, 2%–28%; σ , 7%). For counties, the mean localization index was 52% (range, 0%–99%; σ , 33%) and the mean market share index was 17% (range, 1%–62%; σ , 13%). A map of localization index for HSAs and counties is presented in Supplemental Figure 2, Supplemental Digital Content 3, <http://links.lww.com/MLR/A911>.

Net patient flow was calculated for each HSA and HRR. For all states, 31% (63) of HSAs had values >1. Values for HSA net patient flow ranged from 0 to 12.5. The proportions of HSAs with incoming patients as opposed to outgoing patients varied across the 3 states. In Washington, 61% (36) of HSAs had net patient flow >1 as compared with 18% (6) in Arizona. In Florida, 37% (42) of HSAs had net patient flow >1. For all states, 64% (18) of HRRs had values >1. Values for HRR net patient flow ranged from 0.2 to 3.6. The single HRR in Washington with more incoming patients than outgoing patients was Seattle. Arizona had 2 HRRs, Phoenix and Tucson, with more incoming patients than outgoing.

For HSAs in all 3 states combined, the distribution of localization index was roughly normal (Fig. 2). In total, 45% (92) of HSAs had a localization index of <50%, which means that fewer than half of the patients living in those HSAs remained for inpatient medical care. Localization index was 0% for 10 HSAs, signifying the absence of a hospital in the HSA. The distribution of market share index is skewed to the left. For 16% (33) of HSAs, more than half of the patients treated at their hospitals reside in another HSA. Few HSAs, therefore, received a majority of their patients from other areas.

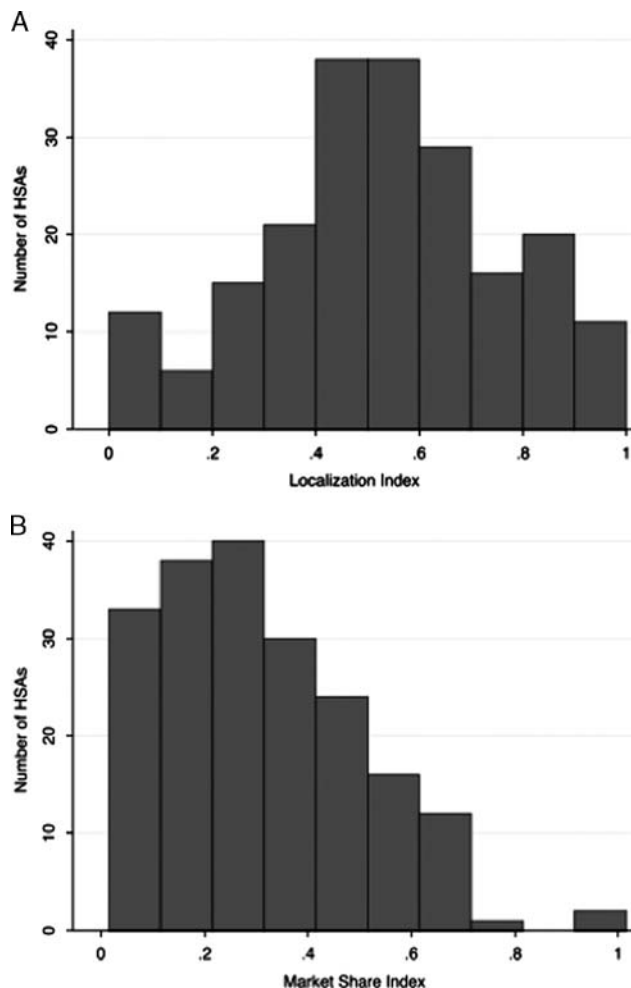
Although a significant proportion of HSAs had localization index of <50%, further analysis reveals that HSAs with low localization index contained fewer residents. To examine the relationship between localization index and population size, we ranked all HSAs by localization index and determined the cumulative percentage of patients from each HSA. Results are displayed in Supplemental Figure 3, Supplemental Digital Content 4, <http://links.lww.com/MLR/A925>. Fewer than 20% of all patients reside in HSAs with localization index of <50%. Similarly, 15% of patients reside in HSAs with market share index >50%.

We compared localization index and market share index for ED admissions and non-ED admissions. The mean of the HSA localization indices for ED admissions was 60% (0%–99%; σ , 25%) versus 43% (0%–98%; σ , 25%) for non-

TABLE 1. Calculated metrics for Hospital Service Areas (HSAs), Hospital Referral Regions (HRRs), and Counties in Washington, Arizona, and Florida

	Washington			Arizona			Florida		
	HSA (n = 59)	HRR (n = 6)	County (n = 39)	HSA (n = 33)	HRR (n = 4)	County (n = 15)	HSA (n = 114)	HRR (n = 18)	County (n = 67)
Localization Index (%)									
Mean	55	87	54	49	84	56	52	89	50
Range	14–98	75–96	0–99	0–97	65–98	0–99	0–94	72–98	0–97
SD	20	8	30	31	14	32	23	7	36
Market Share Index (%)									
Mean	27	9	16	19	15	11	36	10	20
Range	2–68	3–14	1–47	0–61	2–28	1–38	5–96	2–24	3–62
SD	18	5	12	16	11	10	19	7	13
Net Patient Flow* [n (%)]									
<1	23 (39)	5 (83)	7 (18)	27 (82)	2 (50)	12 (80)	72 (63)	10 (56)	51 (76)
>1	36 (61)	1 (17)	32 (82)	6 (18)	2 (50)	3 (20)	42 (37)	8 (44)	16 (24)

*Value >1 signifies that HSA, HRR, or county imports more admissions than it exports, and value <1 signifies that HSA, HRR, or county exports more admissions than it imports.

**FIGURE 2.** Distribution of metrics for Hospital Service Areas (HSAs), combined for all study states. A, Distribution of localization index. B, Distribution of market share index.

ED admissions (difference 17%, $P < 0.001$). The mean of the HSA market share index for ED admissions was 27% (2%–96%; σ , 18%) versus 37% (1%–99%; σ , 22%) for non-ED admissions (difference 10%, $P < 0.001$). These results suggest that patients admitted through the ED are more likely to remain in their own HSA for inpatient medical care. Analysis of counties and HRRs gave similar results.

We compared localization index and market share index between patients with different insurance coverage. Overall, 40% of all patients had Medicare, 22% had Medicaid, and 28% had commercial insurance. An additional 10% were self-paying or unknown. For HSAs, the mean localization index for Medicare patients was 58% (σ , 27%) versus 49% (σ , 28%) for those with Medicaid and 45% (σ , 25%) for those with commercial insurance. The difference between these groups was significant ($P = 0.011$, F -statistic = 4.60). Conversely, the mean market share index across HSAs was 27% (σ , 17%) for Medicare patients, 35% (σ , 22%) for Medicaid, and 35% (σ , 21%) for commercial insurance. This difference was not significant ($P = 0.053$, F -statistic = 2.99).

These metrics were correlated with HSA characteristics, as seen in Table 2. For all admissions regardless of type, localization index was positively correlated with populous, urban HSAs. Localization index was also positively correlated with the presence of multiple hospitals, teaching hospitals, and large hospitals. The effect size was reduced for ED admissions as compared with non-ED admissions for all of these characteristics except for urban designation, for which the effect size was paradoxically reduced for non-ED admissions. Market share index, however, was only positively correlated with urban HSAs. This regression analysis does not extend to HRRs and counties.

Finally, we examined the distribution of localization index for HSAs located within individual HRRs. These results are displayed in the box-and-whisker plot shown in Figure 3. HRRs are generally comprised of multiple HSAs. With few exceptions, any single HRR contained

TABLE 2. Localization Index and Market Share Index as a Function of HSA Characteristics for All Admissions, ED Admissions, and Non-ED Admissions*

	All Admissions (N = 3,775,304)				ED Admissions (N = 2,151,864)				Non-ED Admissions (N = 1,619,491)			
	LI		MSI		LI		MSI		LI		MSI	
	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P
Urban designation	0.216	<0.001	0.132	<0.001	0.241	<0.001	0.092	0.001	0.154	<0.001	0.191	<0.001
Presence of teaching hospital	0.294	<0.001	0.019	0.641	0.249	<0.001	−0.011	0.784	0.344	<0.001	0.041	0.400
No. patients living in HSA (in 10 thousands of patients)	0.031	<0.001	−0.002	0.661	0.044	<0.001	−0.007	0.240	0.085	<0.001	0.001	0.892
Size of largest hospital in HSA (in hundreds of beds)	0.048	<0.001	0.005	0.328	0.044	<0.001	0.000	0.925	0.049	<0.001	0.012	0.048
No. HSA hospitals												
≤ 1	Reference		Reference		Reference		Reference		Reference		Reference	
2	0.257	<0.001	−0.028	0.517	0.243	<0.001	−0.039	0.328	0.261	<0.001	−0.024	0.628
≥ 3	0.363	<0.001	−0.044	0.252	0.319	<0.001	−0.068	0.054	0.406	<0.001	−0.025	0.577

*Admission source could not be determined for 3949 admissions (0.10%).

ED indicates emergency department; HSA, hospital service area; LI, localization index; MSI, market share index.

HSAs with a wide range of values for localization index. For the state of Florida, the IQR of HSA localization index within HRRs ranged between 0.04 and 0.52 when excluding 2 HRRs consisting of a single HSA. In general, HSAs with either high or low localization indices were not clustered within HRRs.

DISCUSSION

The geographic units that constitute the Dartmouth Atlas of Health Care vary in their ability to predict where patients are admitted for hospital care. Patients who live in rural areas with 1 hospital are more likely to cross HSA boundaries to seek inpatient care. The converse is also true; hospitals located in urban HSAs treat higher proportions of patients who live elsewhere. The larger HRR units demonstrate a lesser degree of patient movement across boundaries. Although the units have been pivotal to the understanding of geographic variation in health care, these results suggest that the association between patient residence and assigned catchment area is variable. In particular, many HSAs do not represent discrete health care markets in which the population remains at local hospitals for inpatient care and may not be actionable for policy makers seeking to make population health interventions. Indeed, HSAs performed similar to counties with regard to the metrics examined in this study, although counties are not specifically oriented around health care markets. These results demonstrate that patient populations are dynamic regardless of the geographic model chosen.

Accurate geographic models for health care have become essential for many health services research and policy objectives, including measurement of population-level disease outcomes, implementation of accountable care organizations, adjustment of insurance reimbursement, disaster planning, and planning regionalized systems of care. The original intent of the Dartmouth Atlas of Health Care was to examine health system planning, but it has most commonly been used to examine variation in health care spending.^{4,18} The use of these geographic units has become widespread

and often regarded as superior to geopolitical boundaries such as counties. Adjustments for patient movement need to be incorporated into future evaluations of population health, particularly for small area analyses at levels comparable with HSAs.

The units that constitute the Dartmouth Atlas have additional potential limitations.⁸ First, HSAs and HRRs were created with Medicare data from 20 years ago. Revisions to these boundaries may reflect major changes in the health care system, ranging from hospital closures to increased utilization of EDs. Second, these units do not account for differences between disease conditions, such as elective surgeries versus emergent trauma. Third, the discrete boundaries of HSAs and HRRs do not describe shared areas where patients may be nearly as likely to visit one hospital as another. Fourth, these units do not capture important forces that influence the geography of health care, such as large HMOs, integrated delivery systems, and accountable care organizations. Novel geographic techniques, such as cluster analysis, may be able to describe shared or overlapping geographic areas, patterns for specific disease conditions, and scalable models that can vary in size. With geographic information system technology, new approaches can apply algorithms to any dataset, generate dynamic geographic units, and incorporate additional dimensions in the health care system.¹⁰

Our study demonstrates that patients are less likely to cross HRR boundaries to receive inpatient medical care, suggesting that these units better link patient residence to treatment area. In previous analyses of geographic variation, HRRs have often been the primary unit of analysis. It is important to note that the metrics used in this study partially depend on the size of the geographic area analyzed, by definition. For instance, the localization index for the entire United States would approach 100%, and market share index would approach 0%.

It has previously been shown that substantial variation in health care spending exists within HRRs, suggesting that these regions are too large for targeted, population-level payment reforms.¹² It is conceivable that the size of HRRs also obscures internal variation in quality and access to care. In this study, we found considerable variation in the local-

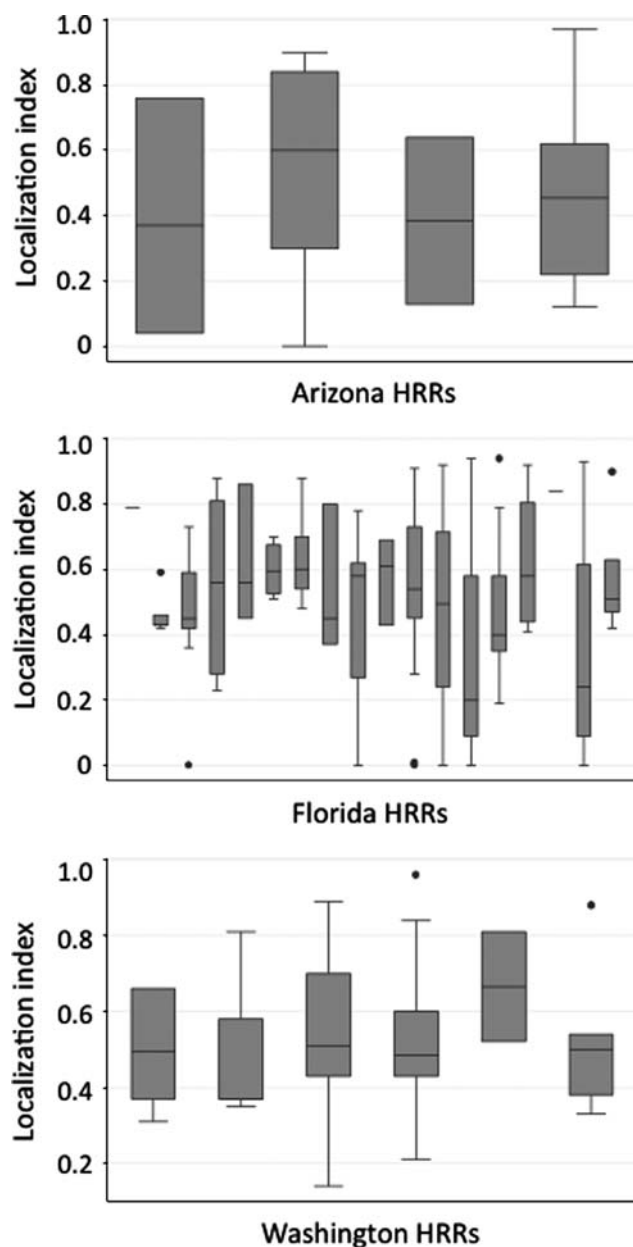


FIGURE 3. Distribution of Hospital Service Areas (HSA) localization index within Hospital Referral Regions (HRRs) for each state. This figure demonstrates the wide variation of localization indices for the HSAs located within any single HRRs in the 3 study states.

ization index of HSAs located within HRRs. These results do suggest that when patients leave their own HSA, they stay within their HRR for care.

In this study, patients admitted to EDs were more likely to use hospitals in the HSA, HRR, or county in which they live. This result is intuitive, as patients with life-threatening and urgent conditions are expected to be less likely to travel longer distances for care. As compared with elective care, patients may also be less capable of selecting hospitals and physicians based upon referrals or research.¹⁹

The phrase “geography is destiny” may be particularly relevant for patient utilization of EDs.²⁰ This analysis provides preliminary evidence that differences exist between geographic patterns for emergent hospital admissions and elective, direct, and other admissions. Geographic models need to account for these differences when applied for purposes of disaster planning or developing population-based systems of care for unplanned critical illness, such as trauma or stroke.

This study also demonstrated that patients with Medicare were more likely to remain in their own HSA for medical care, compared with patients with Medicaid or private insurance. There are multiple potential explanations for this result. As described above, the Dartmouth units were built using Medicare data and may better model hospital use for these patients. Alternatively, certain characteristics of Medicare patients such as age or severity of illness may predispose them to remain local. Conversely, patients with commercial insurance may better be able to seek care at greater distances. Ultimately, geographical models may need to adjust for differences in utilization patterns due to the constraints or opportunities afforded by different payers.

Finally, this study illustrates a methodological hurdle in geographic analysis. The outcomes of geographic studies may change depending on the geographic unit chosen. This methodological issue, termed the “modifiable areal unit problem,” arises from aggregating spatial data at different levels.^{21–23} For instance, counties may demonstrate significant variation with regard to certain health outcomes. However, an analysis of the same region aggregated at the HRR level may not demonstrate the same variation. Small units may have inadequate sample size, and large units can obscure potentially significant internal variation.^{21,22} This study emphasizes the need to analyze geographic data at multiple levels to examine the effects of patient movement as well as the modifiable areal unit problem.

This study has several limitations. First, patient residence does not perfectly correlate with the location at which patients become sick and require medical attention. Patients working or traveling to other areas may seek care at different hospitals than if they fell ill at home. Second, the data used in this study does not include admissions to hospitals located outside of the 3 study states. This may lead to overestimation of localization index, particularly for areas along state borders, as patients that cross state boundaries for care are not represented. A related limitation is that we only include residents of the 3 states in question; however, the percentage of out-of-state residents is <4%. Third, we excluded portions of the study states that fell under the domain of HSAs and HRRs assigned to nonstudy states due to the limitations of state-based databases and potential unreliability in the calculation of metrics for those regions.

Fourth, transfers between hospitals were included in the study. Approximately 4% of admissions were patients transferred to the hospital, and an unknown additional group of patients may have visited an ED before transfer. An alternative analysis excluding hospital transfers produced similar results to the primary analysis. Another limitation is that this analysis does not track patients with multiple admissions to different hospitals. Finally, this study only ex-

amined 3 states, and fewer than 10% of all HSAs and HRRs in the United States were examined. However, we intend for these results to prompt consideration of the effects of patient flow for other geographic areas. The methods in this study can be replicated with any database and provide tools for any geographic analysis of health care.

In conclusion, our study demonstrates that HSAs and HRRs, the geographic units that comprise the Dartmouth Atlas of Health Care, have variable ability to describe where patients receive inpatient hospital care. Patients living in urban, populous HSAs with large, multiple, and teaching hospitals are more likely to seek care in the same HSA in which they live. Patients admitted through the ED are also more likely to seek care at local hospitals than other admitted patients. Accurate geographic models of health care utilization are essential for health services research and policy objectives, and novel geographic models may need to account for patient movement across boundaries, overlapping catchment areas, health care delivery systems, and specific disease conditions.

REFERENCES

1. Zuckerman S, Waldmann T, Berenson R, et al. Clarifying sources of geographic differences in Medicare spending. *N Engl J Med*. 2010;363:54–62.
2. Radley DC, Schoen C. Geographic variation in access to care—the relationship with quality. *N Engl J Med*. 2012;367:3–6.
3. Baicker K, Chandra A. Medicare spending, the physician workforce, and beneficiaries' quality of care. *Health Aff*. 2004;W4:184–197.
4. Newhouse JP, Gardner AM. Geographic variation in Medicare services. *New Engl J Med*. 2013;368:1465–1468.
5. Barnato AE, Herndon MB, Anthony DL, et al. Are regional variations in end-of-life care intensity explained by patient preferences? *Med Care*. 2007;45:386–393.
6. Welch HG, Sharp SM, Gottlieb DJ, et al. Geographic variation in diagnosis frequency and risk of death among Medicare beneficiaries. *JAMA*. 2011;305:1113–1118.
7. Wennberg JE, Bronner K, Skinner JS, et al. Inpatient care intensity and patients' ratings of their hospital experiences. *Health Aff*. 2009;28:1103–1112.
8. Wennberg JE, Cooper MM. *The Dartmouth Atlas of Health Care*. Chicago, IL: American Hospital Publishing; 1996.
9. Institute of Medicine. *Toward Quality Measures for Population Health and the Leading Health Indicators*. Washington, DC: The National Academies Press; 2013.
10. Delamater PL, Shortridge AM, Messina JP. Regional health care planning: a methodology to cluster facilities using community utilization patterns. *BMC Health Serv Res*. 2013;13:333.
11. Jacobson DM, Teutsch S. An environmental scan of integrated approaches for defining and measuring total population health. National Quality Forum. 2012. Available at: <http://www.improvingpopulationhealth.org/PopHealthPhaseIICommissionedPaper.pdf>. Accessed January 10, 2014.
12. Zhang Y, Baik SH, Fendrick M, et al. Comparing local and regional variation in health care spending. *N Engl J Med*. 2012;367:1724–1731.
13. Shwartz M, Payne SM, Restuccia JD, et al. Does it matter how small geographic areas are constructed? Ward's algorithm versus the plurality rule. *Health Serv Outcomes Res Methodol*. 2001;2:5–18.
14. United States Census Bureau. Geography: Cartographic Boundary Shapefiles—Counties. Available at: https://www.census.gov/geo/maps-data/data/cbf/cbf_counties.html. Accessed November 15, 2014.
15. United States Department of Housing and Urban Development. Data Sets: HUD USPS ZIP Code Crosswalk Files. Available at: http://www.huduser.org/portal/datasets/usps_crosswalk.html. Accessed November 15, 2014.
16. Klauss G, Staub L, Widmer M, et al. Hospital service areas—a new tool for health care planning in Switzerland. *BMC Health Serv Res*. 2005;5:33.
17. Anselin L. Local indicators of spatial association. *Geogr Anal*. 1995;27:93–115.
18. Wennberg JE, Gittelsohn A. Small area variations in health care delivery. *Science*. 1973;182:1102–1108.
19. Carr BG, Conway PH, Meisel ZF. Defining the emergency care sensitive condition: a health policy research agenda in emergency medicine. *Ann Emerg Med*. 2010;56:49–51.
20. Carr BG, Addyson DK. Geographic Information Systems and Emergency Care Planning. *Acad Emerg Med*. 2010;17:1274–1278.
21. Wright DB, Ricketts TC. The road to efficiency? Re-examining the impact of the primary care physician on health care utilization rates. *Soc Sci Med*. 2010;70:2006–2010.
22. Gregorio DI, Dechello LM, Somociuk H, et al. Lumping or splitting: seeking the preferred areal unit for health geography studies. *Int J Health Geogr*. 2005;4:6.
23. Mobley LR, Kuo TM, Driscoll D, et al. Heterogeneity in mammography use across the nation: separating evidence of disparities from the disproportionate effects of geography. *Int J Health Geogr*. 2008;7:32.