RESEARCH ARTICLE

New evidence on geographic disparities in United States hospital capacity

Center for Financing, Access and Cost Trends, Agency for Healthcare Research and Quality, Rockville, Maryland, USA

Correspondence

Thomas A. Hegland, Agency for Healthcare Research and Quality, 5600 Fishers Lane, Rockville, MD 20857, USA. Email: thomas.hegland@ahrq.hhs.gov

Thomas A. Hegland PhD \bullet | Pamela L. Owens PhD \bullet | Thomas M. Selden PhD \bullet

Abstract

Objective: To characterize the quantity and quality of hospital capacity across the United States.

Data Sources: We combine a 2017 near-census of US hospital inpatient discharges from the Healthcare Cost and Utilization Project (HCUP) with American Hospital Association Survey, Hospital Compare, and American Community Survey data.

Study Design: This study produces local hospital capacity quantity and care quality measures by allocating capacity to zip codes using market shares and population totals. Disparities in these measures are examined by race and ethnicity, income, age, and urbanicity.

Data Collection/Extraction Methods: All data are derived from pre-existing sources. All hospitals and zip codes in states, including the District of Columbia, contributing complete data to HCUP in 2017 are included.

Principal Findings: Non-Hispanic Black individuals living in zip codes supplied, on average, 0.11 more beds per 1000 population (SE $=$ 0.01) than places where non-Hispanic White individuals live. However, the hospitals supplying this capacity have 0.36 fewer staff per bed (SE $=$ 0.03) and perform worse on many care quality measures. Zip codes in the most urban parts of America have the least hospital capacity (2.11 beds per 1000 persons; SEM $=$ 0.01) from across the rural-urban continuum. While more rural areas have markedly higher capacity levels, urban areas have advantages in staff and capital per bed. We do not find systematic differences in care quality between rural and urban areas.

Conclusions: This study highlights the importance of lower hospital care quality and resource intensity in driving racial and ethnic, as well as income, disparities in hospital care-related outcomes. This study also contributes an alternative approach for measuring local hospital capacity that accounts for cross-hospital service area flows. Adjusting for these flows is necessary to avoid underestimating the supply of capacity in rural areas and overestimating it in places where non-Hispanic Black individuals tend to live.

The findings and conclusions in this article are those of the authors and do not necessarily represent the views of the Department of Health and Human Services or the Agency for Health care Research and Quality (AHRQ).

Published 2022. This article is a U.S. Government work and is in the public domain in the USA.

KEYWORDS

capacity, disparities, geographic disparities, hospital bed capacity, hospital quality, quality indicators, quality of care

What is known on this topic

- Prior research characterizes variation in local hospital systems by assigning hospitals to particular geographic service regions.
- Hospital capacity measures imposing strict geographic markets do not account for geographic border crossings and hospital transfers, except when very broadly defined.
- Existing approaches to the identification of service areas do not adequately address access in rural areas and multihospital markets.

What this study adds

- We apply measures of hospital capacity based on hospital market shares that more flexibly account for hospital transfers, border crossings, and hospital usage patterns in multihospital markets.
- Non-Hispanic Black individuals and lower income individuals live in zip codes with a modestly greater hospital capacity locally, but with notably lower quality of care and resources per bed.
- Rural populations live further from their nearest hospital, but have access to greater quantities of hospital capacity without a systematic quality disadvantage.

1 | INTRODUCTION

Health services researchers have long been interested in the distribution of US hospital capacity. $1-3$ $1-3$ The COVID-19 pandemic has further highlighted the importance of understanding the geographic distribution of capacity since the pandemic has stretched hospital capacity to its limits in many areas while causing unprecedented disparities in hospitalizations and mortality across a range of socioeconomic dimensions. $4-6$ In this paper, we study the distribution of hospital capacity across the United States, focusing on geographically finegrained measures of both levels of hospital capacity and associated measures of hospital resources, care quality, and patient safety. Our method for measuring hospital capacity uses a near-census of hospital admissions to allocate hospital capacity to patient zip codes in proportion to hospitals' market shares in each zip code multiplied by the zip code population. This approach allows us to allocate hospital capacity across the United States in a manner that realistically reflects the structure of hospital markets and can be viewed as following in the tradition of patient-flow-based analyses used in other settings dating back to Zwanziger and Melnick.⁷

Many other approaches to hospital capacity allocation assign all of a given hospital's capacity to a fixed geographic area around the hospital. For example, a hospital's capacity might be assigned to the county in which it is located, as is done for the various county-level hospital capacity measures released as part of the Health Resources and Services Administration's Area Health Resources Files. Relatedly, the Dartmouth Atlas of Health Care produces hospital capacity measures at the hospital service area (HSA) level, where HSAs are fixed geographic areas around hospitals that approximately capture the region in which a given hospital is the most commonly used hospital (in terms of [1](#page-12-0)990s Medicare admissions). 1 HSAs have been used to study the geographic availability of intensive care unit capacity in the context of COVID-19, 8 the distribution of hospital capacity more generally,^{[9](#page-13-0)} and geographic variation in health care outcomes.^{[10](#page-13-0)} These approaches have advantages but carry two key drawbacks. First, they do not allow variation in capacity within the geographic areas used for capacity assignment. Second, they rule out the possibility of people accessing hospital capacity outside the specified region in which they live, shutting down the possibility of cross-border patient flows. Neither limitation affects our alternative, market share-based approach to allocation since it allows zip codes to access varying amounts of capacity from multiple hospitals, regardless of whether they share a zip code, county, or HSA.

The two drawbacks associated with traditional capacity allocation methods are significant. By ruling out variation in capacity within allocation regions, they implicitly assume equal access to hospital capacity within these areas. This assumption may not be reasonable when considering larger geographic areas, especially since even counties and HSAs contain substantial diversity in population characteristics across their subregions. Meanwhile, the limitation on cross-geographic border patient flows is problematic since these flows are actually quite common. Within our sample, 39.1% (SE = 1.0%) of hospitals' discharges flow to zip codes outside their own HSA, with the comparable county-level rate being 32.5% (SE = 1.4%). Border-crossing patient flows are common because hospital systems across the country tend to have a hub-and-spoke structure, where hub hospitals serve as large magnets for more specialized care while more numerous spoke hospitals focus on less complex and emergency care. Not accounting for

these patient flows risks missing that people in areas further from hub hospitals may nonetheless access the hospitals' capacity while also missing that people living near hub hospitals do not have an exclusive claim on their capacity. While this cross-border patient flow problem can be mitigated by expanding the size of capacity assignment regions, such as when researchers aggregate HSAs into the Dartmouth Atlas's larger Hospital Referral Regions, $11,12$ this comes at the cost of losing still further within-region variation of a sort likely to be important in a study of hospital capacity distribution such as ours. $3,13$

In addition to introducing our market share-based zip code-level hospital capacity estimates, in this paper, we provide comparisons of the quantity and quality of hospital capacity supplied to zip codes across a number of dimensions, including comparing across zip codes by poverty rate and urbanicity. We also compare the quantity of quality of hospital capacity in the average zip codes inhabited by people of different races and ethnicities, ages, and family income levels. We also compare our capacity allocations to those obtained using alternative allocation approaches and show that leading alternatives underestimate capacity levels in rural areas while overestimating the capacity available in the places where non-Hispanic Black Americans live.

2 | METHODS

2.1 | Capacity allocation

We allocate capacity from hospitals to the zip codes they serve using the 2017 State Inpatient Databases (SIDs) from the Healthcare Cost and Utilization Project (HCUP). Our sample includes a near census of domestic hospital discharges for all states and the District of Colum-bia, except for Alabama, Idaho, New Hampshire, and West Virginia.^{[14](#page-13-0)} Our allocation procedure begins by using nonelective discharges (i.e., discharges following hospitalizations beginning in the emergency department, excluding healthy newborns and obstetrics admissions) to calculate hospital market shares in each zip code. Next, we assign hospitals a share of each zip code's total population proportional to their market share in that zip code. We then divide each hospital's capacity evenly among the people assigned to it and obtain zip codelevel capacity measures by, for each zip code, summing the capacity assigned to all of its residents. This approach is designed to ensure that if a zip code's residents tend to use hospital A rather than hospital B for nonelective care, our capacity measure will more heavily reflect the characteristics of the former, even if the zip code is located closer to the latter. For a more detailed description of this methodology, including a mathematical characterization of our allocation method, please refer to the Technical Appendix in supporting information.

Our capacity allocation method is intended to yield a generalpurpose measure of the supply of hospital capacity available to each zip code. This is distinct from the amount of hospital capacity used by people in each zip code under typical conditions. While our capacity allocation mechanism does rely on market shares and so reflects typical hospital usage patterns at least to some degree, we mitigate this

by allocating capacity in proportion to market share multiplied by zip code population (as opposed to allocating in direct proportion to hospital usage or discharges). Whether a zip code has above- or belowaverage levels of hospital usage will thus not affect our measure of the amount of hospital capacity supplied to the zip code. Typical hospital usage patterns only affect our allocation by affecting the mix of hospitals we judge zip code residents to be likely to use when seeking nonelective care. We believe this strikes a useful balance by using real hospital usage patterns to assess the hospitals that are feasibly available to residents of a given zip code without reducing our capacity measure to a simple report of typical usage patterns.

2.2 | Capacity measures

Our hospital capacity measures derive primarily from the 2017 American Hospital Association survey. The most basic measure is the total number of staffed beds (hereafter referred to as "beds"), excluding bassinets and the neonatal intensive care unit. Categorizing beds according to function, we define Type 1 beds to include general medical-surgical beds, other general acute care beds, cardiac care unit beds, and intensive care unit beds (ICU/CICU). These beds reflect general-purpose hospital capacity that can be put to a wide array of purposes and likely represent hospitals' first choice of capacity for addressing patients facing pressing medical emergencies, including severe cases of COVID-19. Type 2 capacity consists of specialized adult acute care beds (beds in obstetrics units, burn care units, and all beds in other nonsubacute, nonlong-term care units). Type 3 capacity consists of long-term care (excluding swing beds) and other subacute care bed capacity. We supplement these bed capacity measures with measures of adult, nonspecialized intensive care unit beds (inclusive of cardiac intensive care units), as well as numbers of ventilators. Our measure of ventilator capacity was developed from HCUP data on observed ventilator use during the period of analysis (supplemented with American Hospital Association data).^{[15](#page-13-0)} In all of these cases, we normalize capacity by dividing by zip code population (in 1000s).

We also examine several hospital characteristics associated with capacity, most of which are measured in per bed terms. These include hospitals' number of full-time equivalent employees per bed and hospitals' total annual expenditure (in 2017 dollars) per bed, which we take as measures of hospitals' total annual variable input per bed and their labor inputs per bed (i.e., their staffing level). To assess the amount and vintage of hospital capital, we examined the total value of a hospital's capital (net of depreciation and measured in 2017 dollars) per bed and the percentage share of a hospital's initial purchased capital that has depreciated. We also calculate hospitals' annual average total bed occupancy rates.

Finally, to measure hospital quality across the hospitals contributing capacity to each zip code, we use the AHRQ Inpatient Quality Indicators (IQIs) and Patient Safety Indicators (PSIs) v2018,^{[16](#page-13-0)} which are derived from Healthcare Cost and Utilization Project State Inpatient Databases (HCUP, 2007–2018), 14 scaling all of these measures by 1000 for ease of interpretation. We also supplemented these measures with data from the Centers for Medicare & Medicaid Services' Hospital Compare project.¹⁷ These quality measures include rates for heart failure mortality (IQI 16), deaths in low mortality Medicare Severity-Diagnosis Related Groups (MS-DRGs) (PSI 02), perioperative pulmonary embolism and deep vein thrombosis (PSI 12), perioperative hemorrhage and hematoma (PSI 09), postoperative respiratory failure (PSI 11), type III and type IV pressure ulcers (PSI 03), and postoperative sepsis (PSI 13). In Appendix in supporting information, we also present additional results for rates of iatrogenic pneumothorax (PSI 06) and central venous catheter-related blood stream infections (PSI 07), and, from Hospital Compare, rates of catheterrelated urinary tract infections, hospital-acquired Methicillin-resistant Staphylococcus aureus (MRSA) infections, and hospital-acquired Clostridioides difficile infections. An important feature of these quality measures is that many report rates of rare but very severe adverse patient outcomes: small changes in many of these measures can have large implications for patient welfare.

2.3 | Socioeconomic data

Socioeconomic characteristics for our analysis come from the 2018 American Community Survey 5-year pooled data file provided by the IPUMS National Historical Geographic Information System.¹⁸ These zip code tabulation area characteristics include population totals, as well as population totals for various subpopulations. These subpopulations include persons under (or over) the age of 65, persons identifying as Hispanic, persons identifying as non-Hispanic and Black, persons identifying as non-Hispanic and White, and persons living in families with family incomes falling below (or above 200% of, or between 100% and 200% of) the federal poverty line. We also use these data to identify the top and bottom 10% of zip codes in terms of their poverty rate. Next, we supplement these data with the 2013 Rural-Urban Continuum Code urbanicity classifications (at the county level).^{[19](#page-13-0)} Finally, we use hospital location relative to zip code population-weighted centroids to compute the distance between hospitals and the average resident of each zip code, using this distance measure to compute the distance to the nearest hospital.

2.4 | Statistical analyses

The main results we report consist of varying types of populationweighted averages of zip code-level capacity and capacity quality measures. For any given capacity measure, the overall capacity estimate we present gives the total population-weighted average level of that zip code level capacity measure. This weighted average carries the interpretation of being the mean capacity level in the zip code inhabited by the average US resident. We favor this populationweighting approach because it centers our estimates around the capacity supply conditions that people actually face, rather than presenting an average across geographic areas without respect to their size or population level. In addition to these overall capacity estimates,

we produce capacity averages for the zip codes inhabited by the subpopulations of the full US population mentioned in the section above, calculating the same weighted averages as before but using subpopulation totals for each zip code rather than total zip code population. For example, we estimate the capacity level in the zip code inhabited by the mean non-Hispanic Black individual by taking the average of zip code capacity-weighted by the total number of persons in each zip code that identify as non-Hispanic and Black. We also produce estimates for zip codes by urbanicity and by their poverty rate.

In addition to providing the above capacity estimates, we also test whether the average zip code capacity levels encountered by different subpopulations are statistically significantly different from one another. Subpopulation capacity estimates that are statistically significantly different from their comparison subpopulation mean are marked with statistical significance indicators; we also accompany all subpopulation means (except subpopulations used as baseline comparison groups) with the standard error of the difference between the given mean and the comparison subpopulation mean. Our approach to testing for a difference in the mean capacity levels encountered by members of subpopulations X and Y is conceptually very similar to performing a two-sample t-test comparing each of the X and Y subpopulation's population-weighted mean capacity levels. However, we actually implement this test via regressions with standard errors clustered at the zip code level since this is the level at which capacity is allocated. For more details on how we implement these regressions, please refer to Technical Appendix in supporting information. Beyond these estimates, for the overall population-weighted mean and the subpopulations used as comparison groups, we accompany capacity means with the zip code cluster robust standard error of the mean (produced similarly to the standard errors for the difference in means).

3 | RESULTS

3.1 | Results by socioeconomic and demographic characteristics

The top portion of Table [1](#page-4-0) presents results by socioeconomic characteristics, while the bottom portion presents results by urbanicity (discussed below). We found that Americans, on average, lived in zip codes with a capacity of 2.31 total beds per 1000 persons. Only 1.52 and 0.18 of those beds, however, were Type 1 and ICU/CICU beds, respectively. The average number of unoccupied hospital beds available, meanwhile, was 0.68 per 1000 residents, as implied by the average annual occupancy rate having been 70.72%. The average person aged 65 or older lived in zip codes with more hospital-bed capacity (including Type 1 and ICU/CICU) than those under age 65. Individuals identifying as non-Hispanic and Black lived in zip codes with 0.11 more beds per 1000 persons (2.48 beds vs. 2.37; a 4.6% difference) than did persons identifying as non-Hispanic and White. However, non-Hispanic Black individuals' residential zip codes were served by hospitals with higher average occupancy rates (72.89% vs. 69.50%) and actually did not have an advantage in unoccupied bed terms.

TABLE 1 Hospital bed capacity and occupancy by individual and zip code characteristics (2017)

TABLE 1 (Continued)

Note: All estimates shown are population-weighted averages of zip code-level hospital capacity measures. All capacity measures are allocated from hospitals to zip codes in proportion to zip code population multiplied by zip code market share. The exact weighted average shown varies by row, with the row specifying either total population weights (all people), weights containing population counts for the specified subpopulation (e.g., persons aged 65 and over), or the total population-weighted average estimated among the specified subpopulation of zip codes (e.g., zip codes in the top ("high poverty") or bottom ("low poverty") 10% of the poverty rate distribution). The capacity measures used in this table include hospital bed counts per 1000 people for varying types of hospital beds and hospital bed annual average occupancy rates. Type 1 beds include general medical-surgical beds, other general acute care beds, cardiac care unit beds, and intensive care unit beds (ICU/CICU). Type 2 capacity consists of specialized adult acute care beds. Type 3 beds consist of long-term care and other subacute care beds, excluding swing beds. Capacity averages are paired with the standard error of the listed mean (calculated using zip code clustered standard errors) when averages are the first to appear in a group of measures. These capacity averages are used as the comparison group for the ensuing capacity averages, which have the zip code clustered standard error of the difference in means between them, and the comparison means listed.

Statistical significance markers flagging statistically significant differences in means at the 0.1 (*), 0.05 (**), and 0.01 (***) levels are also shown. Source: 2017 State Inpatient Databases from the Healthcare Cost and Utilization Project, 2017 American Hospital Association Survey, and 2018 American Community Survey 5-year pooled data.

These differences by age, race, and ethnicity, while statistically significant, so far are modest in size. One exception is that Hispanic individuals' residential zip codes had 0.25 fewer (10.5% less) total beds per capita, along with a 2.52 percentage point higher average bed occupancy rate, than the zip codes inhabited by non-Hispanic White people. Finally, differences in capacity by income level all modestly favored lower family income individuals' residential zip codes, with little associated differences in occupancy rates. However, we did find larger differences between zip codes with low versus high poverty rates, with capacity once again being negatively correlated with income.

Table [2](#page-6-0) shows that the average American lived in a zip code with 0.23 ventilators per 1000 persons, with this specialized type of hospital capital having been distributed in a fashion similar to bed capacity overall. In contrast to the bed capacity results, people age 65 and over lived in zip codes that were modestly disfavored in terms of employees per

hospital bed, expenditure per bed, capital per bed, and degree of capital depreciation. Compared to the zip codes where non-Hispanic White people live, non-Hispanic Black individuals lived in zip codes with 0.36 fewer staff per bed and \$73.11 less capital per bed, as well as lower expenditure per bed and higher rates of capital depreciation. Meanwhile, Hispanic individuals lived in zip codes with 0.47 fewer full-time employees per bed but \$11.51 more capital per bed and a lower share of depreciated capital. Compared to those with family incomes over 200 percent of the federal poverty line, those with family incomes below the federal poverty level on average lived in zip codes served by hospitals with lower levels of staff, expenditure, and capital per bed. These results are once again mirrored in the differences observed across zip codes varying in their poverty rates. The final column of Table [2](#page-6-0) explores differences in distance to the nearest hospital. We find mostly small differences in average distance to the nearest hospital across most groups, with no differences exceeding 2 miles.

TABLE 2 Hospital capacity characteristics by individual and zip code characteristics (2017)

TABLE 2 (Continued)

Note: All estimates shown are population-weighted averages of zip code-level hospital capacity measures. All capacity measures are allocated from hospitals to zip codes in proportion to zip code population multiplied by zip code market share. The exact weighted average shown varies by row, with the row specifying either total population weights (all people), weights containing population counts for the specified subpopulation (e.g., persons aged 65 and over), or the total population-weighted average estimated among the specified subpopulation of zip codes (e.g., zip codes in the top ("high poverty") or bottom ("low poverty") 10% of the poverty rate distribution). The capacity measures used in this table consist, for the most part, of measures of hospital resource availability. Capacity averages are paired with the standard error of the listed mean (calculated using zip code clustered standard errors) when averages are the first to appear in a group of measures. These capacity averages are used as the comparison group for the ensuing capacity averages, which have the zip code clustered standard error of the difference in means between them, and the comparison means listed. Statistical significance markers flagging statistically significant differences in means at the 0.1 (*), 0.05 (**), and 0.01 (***) levels are also shown. Source: 2017 State Inpatient Databases from the Healthcare Cost and Utilization Project, 2017 American Hospital Association Survey, and 2018 American Community Survey 5-year pooled data.

Table [3](#page-8-0) presents our results for selected measures of hospital quality of care and patient safety. Differences, even when statistically significant, were small across the zip codes inhabited by people of different ages. Relative to the zip codes inhabited by non-Hispanic White individuals, non-Hispanic Black individuals on averaged inhabited zip codes with substantively similar levels of care quality across a number of measures. However, the hospitals serving their zip codes did feature markedly worse quality in terms of perioperative embolism/deep vein thrombosis rates (18.0% higher), pressure ulcer rates (17.2% higher), and postoperative sepsis rates (10.1% higher). Meanwhile, relative to the zip codes inhabited by non-Hispanic White people, Hispanic individuals lived in zip codes that performed better in terms of a number of care quality and patient safety measures, but which performed worse in terms of perioperative pulmonary embolism and deep vein thrombosis rates, postoperative respiratory failure rates, and postoperative sepsis rates. Next, differences in quality measures across the residential zip codes of people with varying family incomes tended to be substantively rather small, though zip codes with concentrated high poverty rates did exhibit markedly lower quality and patient safety on a number of measures.

In addition to these primary quality and patient safety results, we present similar results in Table S1, examining the iatrogenic pneumothorax rate, central venous catheter-related bloodstream infections, catheter-related urinary tract infections, hospital-acquired MRSA infections and C. difficile infections. The associations found with these measures are qualitatively similar to those we found for other quality and patient safety measures in Table [3.](#page-8-0)

3.2 | Results by urbanicity

The bottom portion of Table [1](#page-4-0) presents differences in bed capacity and occupancy rates along the urban–rural continuum. Capacity levels are lowest (2.11 total beds per 1000 persons), and occupancy rates are highest (73.46%) in the average zip code inhabited by people living in metropolitan counties with urban populations exceeding 1 million people. Capacity levels tend to increase, while occupancy rates tend to decrease, as one examines increasing less populous and more rural areas, culminating in a residential zip code capacity level of 5.10 beds per 1000 persons for the people living in the most rural areas. This capacity gradient partly results from people in intermediary urbanicity places having the opportunity to avail themselves of both suburban hospital capacity and capacity at major urban magnet hospitals. It also likely results from the presence of rural hospitals that are large relative to the populations they serve due to having been situated to extend hospital access to a geographically large rural area.

Table [2](#page-6-0) shows that an opposite pattern tends to prevail by urbanicity when considering measures of hospital resource availability. Residents of more populous, more urban counties tend to live in zip codes with higher levels of expenditure and capital per bed, as well as lower rates of capital depreciation. However, staffing per bed does not follow this pattern, with the number of staff per bed actually peaking in intermediary urbanicity areas. Broadly, these differences suggest that more populous areas partially make up for their bed capacity supply disadvantage through higher use of other inputs.

TABLE 3 Hospital quality and patient safety measures by individual and zip code characteristics (2017)

TABLE 3 (Continued)

Metropolita pop. <50 k

SE for dift

urban pop

metro c

urban por

pop. $2.5-$

SE for dift

Metro non-a urban pop 2.5–20 k

> SE for diff metro o

> pop. <2.5 k

SE for dift

Metro non-adj, urban pop. <2.5 k

pop. 1 M+

SE for diff versus metro city, pop. 1 M+

52.31*** 0.847*** 2.57*** 2.22 4.52*** 0.588 3.82***

1.55 0.072 0.12 0.10 0.10 0.042 0.099

Note: All estimates shown are population-weighted averages of zip code-level hospital quality measures. All quality measures are averages across the total set of beds assigned from each hospital to the given zip code. The exact weighted average shown varies by row, with the row specifying either total population weights (all people), weights containing population counts for the specified subpopulation (e.g., persons aged 65 and over), or the total population-weighted average estimated among the specified subpopulation of zip codes (e.g., zip codes in the top ("high poverty") or bottom ("low poverty") 10% of the poverty rate distribution). The measures used in this table consist of care quality and patient safety measures giving rates of severe, adverse patient outcomes. Quality averages are paired with the standard error of the listed mean (calculated using zip code clustered standard errors) when averages are the first to appear in a group of measures. These quality averages are used as the comparison group for the ensuing capacity averages, which have the zip code clustered standard error of the difference in means between them, and the comparison means listed. Statistical significance markers flagging statistically significant differences in means at the 0.1 (*), 0.05 (**), and 0.01 (***) levels are also shown. Quality measures are all scaled by 1000 for easy examination.

Source: 2017 State Inpatient Databases from the Healthcare Cost and Utilization Project, 2017 American Hospital Association Survey, 2017 CMS Hospital Compare Data, and 2018 American Community Survey 5-year pooled data.

Finally, we find that the average minimum distance to the nearest hospital ranges from 3.93 miles in the most urban areas to 20.51 in the most rural areas. While small differences in travel distances may not be of practical concern, especially given travel times for set distances may vary across areas by urbanicity, some of these differences likely are important.

Table [3](#page-8-0) shows that there were large differences in hospital quality across the rural–urban continuum but that rural areas were not TABLE 4 Hospital bed capacity per 1000 people, allocated by hospital service area, county, and hybrid allocation methods (2017)

TABLE 4 (Continued)

Note: All estimates shown are population-weighted averages of zip code-level measures of total hospital bed capacity, allocating from hospitals to zip codes according to varying procedures. The main method allocates capacity from hospitals to zip codes in proportion to zip code population multiplied by zip code market share. The Hospital Service Area and County methods simply assign hospital capacity evenly across all people residing in the hospital service area or county in which the hospital is located. The hybrid approaches assign capacity in proportion to zip code population multiplied by zip code market shares within either hospital service areas or counties, with the restriction that hospitals cannot contribute any capacity to places outside their own hospital service area or county. The exact capacity-weighted average shown varies by row, with the row specifying either total population weights (all people), weights containing population counts for the specified subpopulation (e.g., persons aged 65 and over), or the total population-weighted average estimated among the specified subpopulation of zip codes (e.g., zip codes in the top ("high poverty") or bottom ("low poverty") 10% of the poverty rate distribution). Capacity averages, other than those produced using the paper's main allocation mechanism, are paired with the standard error of the difference between the listed mean and the corresponding capacity average produced using the main hospital allocation mechanism. This standard error is calculated using standard errors clustered at the level at which hospital capacity is assigned to zip codes.

Statistical significance markers flagging statistically significant differences in means relative to the allocations produced by the main assignment mechanism at the 0.1 (*), 0.05 (**), and 0.01 (***) levels are shown.

Source: 2017 State Inpatient Databases from the Healthcare Cost and Utilization Project, 2017 American Hospital Association Survey, and 2018 American Community Survey 5-year pooled data.

necessarily systematically disfavored by these differences. The heart failure mortality rate ranges from approximately one-half to twothirds greater at the hospitals serving people living in the most rural areas relative to the hospitals faced by people in metropolitan counties. People in more rural areas also generally lived in zip codes served by hospitals with higher death rates in low mortality MS-DRGs. In contrast, these same hospitals also exhibited perioperative pulmonary embolism and deep vein thrombosis rates that were up to a quarter lower than the rates in the most urban areas, alongside notably lower rates in terms of pressure ulcer prevalence and other measures. Overall, these results suggest that the hospitals serving people in more rural areas have serious quality deficiencies on some dimensions but perform better than the hospitals serving more urban areas on others. Notably, the hospitals serving rural areas tended to perform relatively well on quality measures less likely to be affected by patient travel distance (e.g., pressure ulcer rates). Poorer performance in terms of more time-sensitive quality measures like heart failure mortality rates may thus reflect the adverse consequences of increased travel time to hospitals rather than differences in the quality of care delivered at these hospitals per se.

3.3 | Comparison to other allocation methods

In this section, we explore differences between the hospital capacity allocations obtained using our allocation method and four alternative approaches: allocation of hospital capacity at the Dartmouth Atlas HSA level, allocation at the county level, and hybrid approaches that use our market share derived approach within each of either HSAs or counties but with the added restriction that capacity cannot be exchanged across HSA/county borders. Detail on the construction of

these alternative capacity measures is available in Technical Appendix in supporting information.

Table [4](#page-10-0) presents estimates of total bed capacity per 1000 persons across the same subpopulations used in Table [1](#page-4-0) but using the full slate of alternative allocation methods. To highlight the key findings, first, the level of total bed capacity allocated to the average zip code inhabited by non-Hispanic Black individuals is 3.6% lower (2.48 vs. 2.57) using our primary methodology relative to using HSAs and 10.1% lower (2.48 vs. 2.73) relative to using counties. These differences are statistically significant, as judged using the same style of approach to significance testing as the analyses in Table [1.](#page-4-0) In each case, the hybrid allocation measures actually increase the amount of capacity assigned to non-Hispanic Black individuals' residential zip codes. This suggests that alternative allocation methods may overestimate hospital capacity in these zip codes because they are near hub hospitals, which locals cannot take exclusive advantage of due to claims on hub hospital capacity by patients from outside the county or HSA. Second, and similarly, our allocation method assigns less hospital capacity to high poverty rate zip codes than all of the alternative methods. Finally, our allocation method assigns considerably more (often in excess of 20% more) total bed capacity to rural areas than the other allocation methods do, reflecting that people in relatively more rural areas tend to consume more care outside their home county and HSA.

In addition to results for overall hospital capacity, we have results comparing the distributions of hospital staff per bed, capital per bed, and assorted hospital quality measures obtained using the different allocation approaches in Tables S2–S9. We also provide in Table S10 a sensitivity analysis examining how the distribution of hospital bed capacity changes when we replicate our main allocation method but restrict hospitals from donating capacity to zip codes more than 25, 50, and 100 miles from their location.

4 | DISCUSSION

In this paper, we provide an alternative method for allocating the capacity of hospitals to the population bases they serve. The principal advantage of our approach is that it uses a near-census of hospital discharges to measure hospital use by patients in a flexible manner and thereby generates a more realistic assignment of hospital capacity to places. Unlike previous analyses, our approach accounts for the fact that often more than one hospital treats patients from a given zip code and that patients often cross geographic boundaries to seek care. Capacity analyses based on service areas with fixed borders have an intrinsic problem for a capacity distribution study such as ours: drawing borders narrowly enough to provide insights into social determinants leads to unacceptable numbers of border crossings, such that service areas no longer measure where services are actually obtained. In particular, we find that these issues bias leading alternative approaches that impose strict geographic boundaries to overestimate the supply of hospital capacity in the places where non-Hispanic Black Americans live and where Americans with low family incomes live while underestimating the supply of hospital capacity available in rural areas.

Allocating hospital resources using our more flexible capacity assignment mechanism leads to important new insights. Non-Hispanic Black individuals and low-income populations, on average, live in zip codes with greater hospital capacity. This capacity advantage, however, is largely erased by these zip codes being supplied capacity by hospitals with higher occupancy rates, lower resource levels in general, and poorer performance across many care quality and patient safety measures. Care quality disadvantages are particularly concerning since they likely have a greater day-to-day impact than total hospital capacity, at least outside the context of surges in demand for hospital care that cause capacity constraints to bind. Meanwhile, our approach shows that rural populations live in areas with significant total capacity advantages. The hospitals serving these areas also do not appear to offer systematically poorer quality care; in fact, they offer superior quality care in some respects. These hospitals, however, do tend to perform very poorly on quality dimensions that seem likely to be sensitive to patient travel time to the hospital, as it makes sense given that rural populations typically live further from their nearest hospital.

An important consideration is that our estimates only measure the supply of hospital capacity, not hospital usage or the demand for hospital care. Persons living in zip codes with ample supply of hospital capacity may nevertheless face financial constraints or other barriers preventing them from using the supplied capacity. Our objective was to focus on one factor that could play a role in generating disparities in hospital use and health outcomes, and we believe our results are best interpreted together with prior research on barriers to using hospital care,²⁰ factors driving differences in hospital usage across residents of the same zip code, 13 communities' histories with racial discrimination within the medical system, 21 and the role of provider discrimination.^{[22](#page-13-0)} We hope that our analysis and our approach to hospital capacity measurement will prove useful as inputs into further research on these and other topics.

ACKNOWLEDGMENTS

We wish to acknowledge the HCUP Partner organizations that contributed to the data used in this study: Alaska Department of Health and Social Services, Alaska State Hospital and Nursing Home Association, Arizona Department of Health Services, Arkansas Department of Health, California Office of Statewide Health Planning and Development, Colorado Hospital Association, Connecticut Hospital Association, Delaware Division of Public Health, District of Columbia Hospital Association, Florida Agency for Health Care Administration, Georgia Hospital Association, Hawaii Laulima Data Alliance, Hawaii University of Hawai'i at Hilo, Illinois Department of Public Health, Indiana Hospital Association, Iowa Hospital Association, Kansas Hospital Association, Kentucky Cabinet for Health and Family Services, Louisiana Department of Health, Maine Health Data Organization, Maryland Health Services Cost Review Commission, Massachusetts Center for Health Information and Analysis, Michigan Health & Hospital Association, Minnesota Hospital Association, Mississippi State Department of Health, Missouri Hospital Industry Data Institute, Montana Hospital Association, Nebraska Hospital Association, Nevada Department of Health and Human Services, New Hampshire Department of Health & Human Services, New Jersey Department of Health, New Mexico Department of Health, New York State Department of Health, North Carolina Department of Health and Human Services, North Dakota (data provided by the Minnesota Hospital Association), Ohio Hospital Association, Oklahoma State Department of Health, Oregon Association of Hospitals and Health Systems, Oregon Office of Health Analytics, Pennsylvania Health Care Cost Containment Council, Rhode Island Department of Health, South Carolina Revenue and Fiscal Affairs Office, South Dakota Association of Healthcare Organizations, Tennessee Hospital Association, Texas Department of State Health Services, Utah Department of Health, Vermont Association of Hospitals and Health Systems, Virginia Health Information, Washington State Department of Health, West Virginia Department of Health and Human Resources, West Virginia Health Care Authority, Wisconsin Department of Health Services, and Wyoming Hospital Association.

DATA AVAILABILITY STATEMENT

The data used for this study were intramural data from the Health care Cost and Utilization Project (HCUP). Publicly available data also are available through the HCUP Central Distributor: [www.hcup-us.](http://www.hcup-us.ahrq.gov/tech_assist/centdist.jsp) [ahrq.gov/tech_assist/centdist.jsp.](http://www.hcup-us.ahrq.gov/tech_assist/centdist.jsp)

ORCID

Thomas A. Hegland \blacksquare <https://orcid.org/0000-0002-2486-6293> Pamela L. Owens D <https://orcid.org/0000-0002-9905-9664> Thomas M. Selden D<https://orcid.org/0000-0003-3448-5838>

REFERENCES

- 1. TDI. The Dartmouth Atlas of Health Care. Dataset. The Dartmouth Institute for Health Policy and Clinical Practice; 2013.
- 2. Cutler DM. The lifetime costs and benefits of medical technology. J Health Econ. 2007;26(6):1081-1100.
- 3. Baicker K, Chandra A, Skinner JS. Geographic variation in health care and the problem of measuring racial disparities. Perspect Biol Med. 2005;48(1 Suppl):S42-S53.
- 4. CDC. Key Updates for Week 23, Ending June 6, 2020. Technical Report. Centers for Disease Control and Prevention. June 2020.
- 5. Centers for Medicare and Medicaid Services (CMS). Preliminary Medicare COVID-19 Data Snapshot. Technical Report. Centers for Medicare and Medicaid Services. December 2020.
- 6. Gordoy M, Wood D. What Do Coronavirus Racial Disparities Look Like State by State?. NPR; 2020.
- 7. Zwanziger J, Melnick GA. The effects of hospital competition and the Medicare PPS program on hospital cost behavior in California. J Health Econ. 1988;7(4):301-320.
- 8. Kanter GP, Segal AG, Groeneveld PW. Income disparities in access to critical care services. Health Aff. 2020;39(8):1362-1367.
- 9. Nguyen TT, Sivakumar AI, Graves SC. Capacity planning with demand uncertainty for outpatient clinics. Eur J Oper Res. 2018;267(1): 338-348.
- 10. Rosenberg BL, Kellar JA, Labno A, et al. Quantifying geographic variation in health care outcomes in the United States before and after risk-adjustment. PLoS One. 2016;11(12):e0166762.
- 11. Cooper Z, Craig SV, Gaynor M, Van Reenen J. The price ain't right? hospital prices and health spending on the privately insured. Q J Econ. 2019;134(1):51-107.
- 12. Cutler DM, Scott Morton F. Hospitals, market share, and consolidation. JAMA. 2013;310(18):1964-1970.
- 13. Chandra A, Kakani P, Sacarny A. Hospital Allocation and Racial Disparities in Health Care. Working Paper 28018. National Bureau of Economic Research. October 2020.
- 14. HCUP State Inpatient Databases (SID). Healthcare Cost and Utilization Project (HCUP). Agency for Healthcare Research and Quality. 2017. Accessed at www.hcup-us.ahrq.gov/sidoverview.jsp
- 15. HCUP. Description of the Data Source, Methodology, and Clinical Criteria - HCUP Summary Trend Tables. Healthcare Cost and Utilization Project (HCUP). Agency for Healthcare Research and Quality.

November 2021. Posted at [https://hcup-us.ahrq.gov/reports/](https://hcup-us.ahrq.gov/reports/trendtables/summarytrendtables.jsp) [trendtables/summarytrendtables.jsp](https://hcup-us.ahrq.gov/reports/trendtables/summarytrendtables.jsp)

- 16. Agency for Healthcare Research and Quality (AHRQ) Quality Indicators. Inpatient Quality Indicators (IQIs) and Patient Safety Indicators (PSIs). v2018. Agency for Healthcare Research and Quality. Accessed at [https://](https://qualityindicators.ahrq.gov/Modules/iqi_resources.aspx#techspecs) qualityindicators.ahrq.gov/Modules/iqi_resources.aspx#techspecs and https://qualityindicators.ahrq.gov/Modules/psi_resources.aspx#techspecs
- 17. CMS. Hospital Compare. Technical Report. Centers for Medicare and Medicaid Services. July 2017.
- 18. Manson S, Schroeder J, Van Riper D, Kugler T, Ruggles S. IPUMS National Historical Geographic Information System: Version 15.0. Dataset. IPUMS; 2020.
- 19. United States Department of Agriculture. Rural Urban Continuum Codes Documentation. 2013. [https://www.ers.usda.gov/data](https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/documentation/)[products/rural-urban-continuum-codes/documentation/](https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/documentation/)
- 20. Braveman P, Egerter S, Williams DR. The social determinants of health: coming of age. Annu Rev Public Health. 2011;32:381-398.
- 21. Alsan M, Wanamaker M. Tuskegee and the health of Black men. Q J Econ. 2018;133(1):407-455.
- 22. Alsan M, Garrick O, Graziani G. Does diversity matter for health? Experimental evidence from Oakland. Am Econ Rev. 2019;109(12): 4071-4111.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Hegland TA, Owens PL, Selden TM. New evidence on geographic disparities in United States hospital capacity. Health Serv Res. 2022;57(5):1006‐1019. doi:[10.1111/1475-6773.14010](info:doi/10.1111/1475-6773.14010)