A Location-based Comparison of Health Care Services in Four U.S. States with Efficiency and Equity

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Abstract:

This paper examines the efficiency and equality in geographic accessibility provided by hospitals. We use the criteria efficiency, availability of the service, and equality. Quantitative measures are defined for all criteria, and are measured using a geographical information system. We then compare existing locations with optimal locations satisfying two objectives, one that minimizes hospital‐patient distance, and another that captures as many patients as possible within a pre-specified time or distance. The results of our study indicate that the existing locations provide near-optimal geographic access to health care. Some potential for improvement is indicated.

Keywords: Hospital location | Efficiency | Accessibility | Equity | Coverage

Article:

1. Introduction

Even if it appears that only recent debates have put health care problems on the (political) agenda, health-related issues have long been the focus of much research. Factors such as the scarcity of recourses (in conjunction with increased expectations), increasing costs of medical personnel and sophisticated equipment, and an ageing population that requires more health care services have brought the topic to the front of the agenda of politicians and practitioners alike.

Considering the aforementioned factors, increased efficiency of available resources is called for. Criteria that are used by the planners as well as the general public to evaluate expenditures will

be the quality of services (a somewhat nebulous concept that needs to be quantified and measured by an appropriate proxy), the accessibility of services, and possibly the fairness of the services. The quality of medical services could be expressed in terms of expected or worst case waiting times for a specific service, the expected success rates of necessary procedures, or others. The accessibility of services is probably easier to measure in terms of distance to a potential patient's home, or the expected coverage of the population at large within a given amount of time. Fairness, another soft concept, could be expressed as the variance of quality and availability of medical services in different regions.

There are many tools to achieve the criteria outlined above. Choice of the size of a facility, the location of a facility, the services offered at a hospital or health post, the hierarchies and referral systems used in the process, incentives to do preventive work, different triage systems, nurses and doctors' schedules can and will all influence the quality and availability of medical services.

This paper investigates one specific aspect of health care management, *viz*., the effects of the location of hospitals on the geographic accessibility of health care. Locating hospitals is a process that must take into consideration many different stakeholders: patients who need ready access to the facility, doctors who want attractive and easy-to-reach workplaces, taxpayers who want value for their dollars, and politicians who want to demonstrate their ability to deliver a quality product. This paper will investigate some of the measures that determine the geographic access of health care. More specifically, it will provide some guidance to policy makers regarding the potential for improvement regarding the locations of the hospitals with respect to a number of criteria relevant in the context.

Many of the studies that deal with hospitals focus either on the correlation between accessibility of the hospital to the population at large and the health of said population, or on the accessibility of hospital care for certain groups. One of the early studies that evaluates the efficiency of hospitals is [27]. In their paper, the authors develop a simulation model to evaluate the efficiency of hospital locations in the Chicago metropolitan area. This paper is one of the earliest to have customers travel on a network from their own location to physicians and hospitals. The authors' model also includes patients' religious and racial choices for the facility they patronize. Because of the technology at the time, the paper's modeling of the network and patient location is somewhat coarse, but they highlight the idea that going to the nearest facility is not always optimal or even feasible due to the type of services needed or racial or religious considerations.

There is a significant number of studies concerning the accessibility of health care facilities. Newhouse et al.[33] measured accessibility as the number of specialists per capita. Rosenthal et al. [35] modeled customer and physicians' locations on a zip code level and modeled accessibility as the number of physicians per capita and the average distance between patients and physicians for rural and urban areas. Using more detail, Love and Lindquist [23] assessed customer and hospital locations at the census block group level for the State of Illinois.

Hare and Barcus [19] followed a different line of research. Their accessibility measure is ultimately the expected time between a customer (approximated by zip code) and the nearest hospital. The road distances and speeds are then used to estimate the travel time. The authors' main results are the correlation with areas of low accessibility of hospitals and (rural) areas of poverty.

Concerning the correlation between accessibility and preventative care, Currie and Reagan [8] find that among inner-city children, each additional mile to the closest hospital (which is used by many in this population group not for emergencies but for routine medical checkups) corresponds to a 3% decrease in the probability that a child has had a medical checkup.[1]

Goodman et al. [40] achieved a similar result in their study. In particular, they determined that patient‑hospital distance is inversely correlated to the likelihood that patients will seek care in discretionary services. Similarly, Nattinger et al.'s [31] study revealed that longer patient‑hospital distances correlated with lower use of follow-up radiation treatment after a lumpectomy. Finally, Buchmueller et al. [4] used a quasi-experimental approach, using actual hospital closures' affects on accessibility on patient outcomes. They find that patient‑hospital distances positively correlate with deaths due to heart attacks and accidental injuries.

After briefly discussing the measurement of average accessibility and equality of accessibility in the next section, we discuss how optimization models may be used to determine a theoretical maximum on the amount of improvement possible in reducing the average or providing a minimum access level while keeping the number of facilities the same. Section 3 applies these criteria to four states in the southeastern US, finding that improving the average (efficiency) usually also improves the lot of those with the worst access. However, if the goal is solely to guarantee a minimum level of service, we see equality of access improve at the expense of efficiency. Section 4 summarizes our findings and suggests future extensions of this research.

2. Development of criteria for the evaluation of hospital locations

This section first describes a number of criteria that are relevant in the evaluation of health care facilities and their location. It then develops measurable proxies for the criteria. The planned evaluation does not only include the direct comparison of a number of U.S. states on the aforementioned criteria, but it also includes the comparison of the situation present in those states and an optimized situation, which is obtained by relocating the existing number of hospitals at locations prescribed by optimization models.

The three main criteria considered in this work are

- the general efficiency,
- the service availability, and
- the equality of the locations.

Clearly, we need proxy expressions for these criteria in order to make them operational. As a measure of general efficiency, we will use the average distance (or time) between any potential patient and his closest hospital. Assigning patients to the hospitals closest to them appears somewhat arbitrary, but is not unusual. As the Dartmouth Atlas [9] states “As a result, when patients are admitted to hospitals, the admission generally takes place within a relatively short distance of where the patient lives.” We will use this assumption of throughout this paper. The service availability may be measured as the proportion of the population (i.e., all potential patients) that is located within a prespecified distance *D* from their nearest facility. This is then the union of the “covering areas” of all hospitals in the state, where a potential patient is considered covered, if he is no farther than *D* from the closest facility. The notion of coverage was first introduced by Toregas et al. [39].

An obvious question is the magnitude of *D*. Many different values have been studied in the literature, depending on whether the time under consideration is a proxy for only the driving time from home to health care facility, or if it includes the entire notification-response-transportation cycle as would be the case when calling an ambulance. Carr et al. [5] provide an excellent analysis of actual times involved in this cycle. For example, 60 minutes from incident to arrival at a trauma center (the “Golden Hour”) has been discussed as a potential time window that is crucial in trauma cases (e.g., [32]). We decided to use 30 minutes in this study as a goal, since our measurements will include only the final transportation phase of an ambulance trip, but can also be a proxy for driving times to seek non-emergent care. Bosanac et al. [3] made an early argument for this standard, providing a comprehensive literature review and application to the state of West Virginia. More recently, Carr et al. [5] examined the proportion of the U.S. population living within 30 minutes of an emergency department or a teaching hospital by modeling travel distances and times based on population density. Forrest and Starfield [15] found that travel times over 30 minutes reduced the likelihood of first contact care with a primary care physician. Frezza and Mazghebe [16] suggest a “golden period” of 30 minutes for the treatment of penetrating chest injuries, finding a dramatic difference in survivability at the 30-minute threshold. Note that all authors use travel time rather than distance, as distance is just a proxy for time. The usefulness of this proxy will be tested below.

Finally consider equity. While some consider equity to be broader than simply equality, also embodying other dimensions of fairness, justice, and neediness (e.g. [30] and [36]) most researchers treat them as equivalent for the purposes of measurement as equivalent, as do we. Refs. [38], [28] and [26] are the earliest works to consider the tradeoffs between efficiency and equity. Mulligan [29] and Marsh and Schilling [25] give excellent discussions of the wide variety of ways that equality (or inequality) has been measured, discussing the strengths and weaknesses of each. Measures such as the range of values and maximum absolute deviation are extremely sensitive to extreme values and ignore the interior of the distribution, while measures such as the variance are not normalized, and are thus incomparable between times or jurisdictions. We use a normalized measure that takes the entire distribution into account (discussed in

both [29] and [25]) that was first suggested by the economist Lorenz [22]. Lorenz derived methods for looking at income distributions from an equality point of view, though it is common to use Lorenz Curves as graphical depictions of inequality for any quantitative study in which inequality is of interest. A traditional two-dimensional Lorenz curve has two lines. First, a diagonal representing the line of equality, where the poorest x% of the population also earn $x = y$% of the income. Second, the empirical line showing the actual % of the income earned (on the y axis) by the poorest x% of the population.

We use this concept to depict inequality in accessibility to hospitals in Virginia in Fig. 1. On the x axis we order the population from lowest distance to highest distance, and plot the cumulative proportion of the total distance traveled on the y axis. As an example, we plot the point (0.75, 0.437) indicating that the 75% of the population with the lowest travel time drive only 43.7% of the total distance, leaving the 25% with the worst travel time to travel the remaining 56.3%.

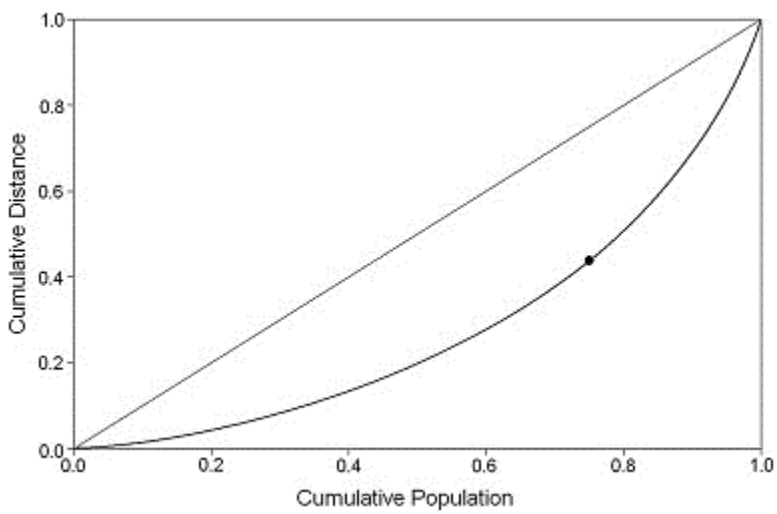

Fig. 1. Lorenz curve for patient‑hospital distances in Virginia.

In order to operationalize the concept as a scalar measure, Gini [17] and [18] introduced what is now known as the Gini index. It denotes the area between the Lorenz curve and the line segment between (0, 0) and (1, 1) in relation to the area of the triangle with vertices (0, 0), (1, 0), and (1, 1). The latter is a constant with value 1/2, which is used exclusively for the purpose of normalization, so that the Gini index will always assume a value between 0 (indicating total equality) and 1 (indicating total inequality).

Below, we present formulations below that deal with the issues at hand. In order to do so, it is necessary to first set the stage and describe the general scenario. Consider a metric space, in which customers are located at well-known points. Let I denote the set of customer locations (i.e., potential patients), and let Jdenote the set of potential facility locations. Suppose that distances between a customer i, $i = 1, \cdots, |I|$ and a facility j, $j = 1, \cdots, |J|$ is denoted by d_{ij}.

Furthermore, we assume that there are w_i customers at point i. In addition, we need to define variables x_{ij}, which express the proportion of customer i ' s demand that is satisfied from facility j, and binary variables y_j that assume a value of one, if a facility is located at site j, and zero otherwise.

A well-known model (see [34], for the original contribution; an up-to-date treatment can be found in Ref. [24]) that addresses efficiency, our first concern, is the p-median formulation. In the context of this study, the problem locates a given number of p hospitals, so as to minimize the average customer-hospital distance. With the above definitions, we can write the *p-median problem* (in its disaggregated form) as

equation(1)

$$P_{p-\mathrm{m}}: \quad \mathrm{Min}\ z = \sum_{i\in I}\sum_{j\in J} w_i d_{ij} x_{ij}$$

$$\text{s.t.} \quad \sum_{j\in J} x_{ij} = 1 \quad \forall i\in I$$

$$x_{ij} \le y_j, \quad \forall i\in I,\ j\in J$$

$$\sum_{j\in J} y_j = p$$

$$x_{ij} \ge 0, \quad \forall i\in I,\ j\in J$$

$$y_j = 0 \text{ or } 1, \quad \forall j\in J.$$

It should be noted that the above formulation assumes that each potential patient must make a separate and special trip to the facility. This assumption appears reasonable in our context.

Our second concern is the availability of hospital services. This issue is addressed by another well-known model in location theory, the maximal covering location problem, due to Church and ReVelle [6]; for a recent survey see Ref. [37]. In order to formulate it, it is necessary to define a covering distance (also referred to as service standard) that indicates within which distance from a hospital a customer is covered.[2] The problem is then to locate p hospitals, so as to ensure that as many potential patients as possible are within D miles of a facility. Details concerning the choice of the value of D are discussed below.

In order to formulate the problem, define the set $N_i = \{j: d_{ij} \le D\}$ as the set of all hospitals that ware no farther away from patient i than the "service level" distance D. Furthermore, we will use the binary variables y_j defined earlier. In addition, we need *coverage variables* x_i, which assume a value of one, if all patients at site i are within distance D of any of the hospitals. We can then formulate the *maximal covering location problem*as

equation(2)

$$P_{\mathrm{mc}}: \quad \text{Max } z = \sum_{i \in I} w_i x_i$$

$$\text{s.t.} \quad \sum_{j \in N_i} y_j \geq x_i, \quad \forall\, i \in I$$

$$\sum_{j \in J} y_j = p$$

$$x_i \geq 0 \text{ or } 1, \quad \forall\, i \in I$$

$$y_j = 0 \text{ or } 1, \quad \forall\, j \in J.$$

It would appear logical to have the two above formulations that optimize efficiency and availability be followed by a formulation that optimizes equality. However, it is very well known that equality objectives often result in meaningless solutions, unless they are coupled with an efficiency objective, e.g., in a bi-objective optimization problem. For details regarding the relations between different classes of objectives, see Ref. [13]. Drezner et al. [11] have described a problem that optimizes the Gini index in a location problem and provides bounds for the problem.

3. Evaluation of hospital locations in the southeastern U.S.

For the purpose of evaluating actual situations on the criteria delineated in the previous section, we have chosen four adjacent U.S. states that are somewhat comparable in size, population density, and cultural background. In particular, we have chosen North Carolina, South Carolina, Tennessee, and Virginia, since, as evident from the basic geographical and demographic information provided in Table 1, these four states in the southeastern USA meet these criteria for comparability. Although the majority of the population lives in urban centers in all four states, the chosen states are predominantly rural with only 6-7% of the land area being classified as urban.

Table 1. Descriptive statistics for states (2000 census).

State	Population	Land Area (Mi^2)	Pop/Mi^2	Block groups (BG)	Pop/BG
NC	8,049,313	48,711	165.25	5261	1530.0
SC	4,012,012	30,109	133.25	2857	1404.3
TN	5,689,283	41,217	138.03	4006	1420.2
VA	7,078,515	39,594	178.78	4733	1495.6

State	%Over 65	%Hisp	%Black	Per capita personal income	% Population in urban areas	% Land in urban areas
NC	12.9	4.7	21.6	27,194	60.2	7.3
SC	12.1	2.4	29.5	24,321	60.5	6.2
TN	12.4	2.2	16.4	26,239	63.6	5.9
VA	11.2	4.7	19.6	31,162	73.0	6.0

For the purposes of measurement, we use block groups in each state as defined by the 2000 census. The population in each such block group is assumed to be concentrated at the centroid of this group, which makes our models tractable. While the numbers of block groups in the different states differ, the number of people per block group is surprisingly uniform for all the four states at about 1,500, for details, see Table 1.

This study restricts itself to "General Medical and Surgical" hospitals as defined by the American Hospital Association [1], including any facility that provides diagnostic and therapeutic services for a variety of conditions, provides X-ray services, has a clinical laboratory, and a staffed operating room [1]. The main reasons for this focus is to avoid possible cross contamination of data due to differences in the behavior of patients who consult other types of hospitals, such as psychiatric, rehabilitation, and chemical dependency hospitals. Even though we are focusing on General Medical and Surgical Hospitals, the methods we employ could readily be applied to other types of health care facilities, given appropriate behavioral assumptions. Taking population counts and population-weighted block group centroids from the 2000 U.S. Census, we measure the minimum travel time to the hospital along the road network. For the sake of brevity, we will call these hospitals the "nearest". These travel times and distances are calculated according to Microsoft MapPoint 2004, where we assume speeds of 65 mph on interstate highways, 60 mph on limited access highways, 50 mph on major roads, 35 mph on minor roads, and 20 mph on city streets. This study does not take the effects of acceleration and deceleration into consideration; for pertinent details, see Ref. [12].

For each census block group we record the time and distance to the nearest hospital, along with the population in that group. We show a histogram of this data for Virginia in Fig. 2, with the solid line for distance and the dotted line for time.

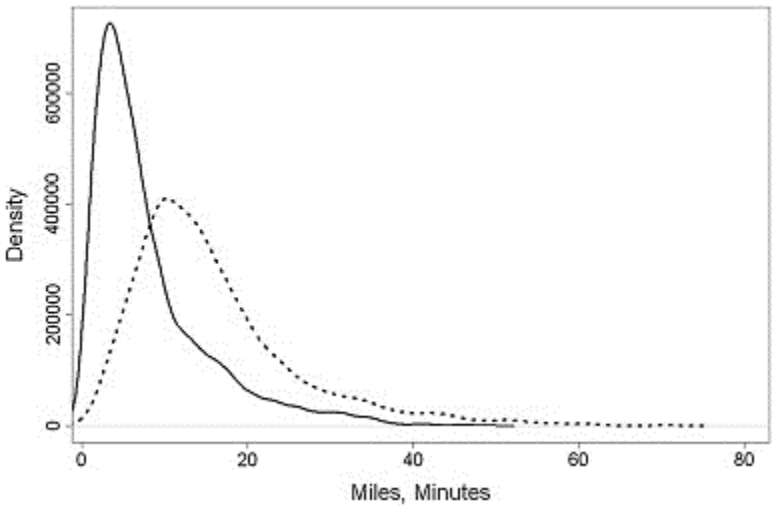

Fig. 2. Smoothed histograms of distances to closest facility (miles solid line, minutes dotted) in Virginia.

It is apparent in Fig. 2 that the distance and time, taken from the same data set, differ significantly. While the patient‑hospital distances show a high kurtosis at a fairly short distance, the distribution of the time is much flatter. Interestingly, we find that the distribution of time–the measure that actually matters, as the patient‑hospital distance is just a proxy for service–is more equal than the distribution of distances.

The population-weighted means, medians, and standard deviations of the criteria examined in this paper for all four states are summarized in Table 2.

Table 2. Optimization results.

Actual state	Distances	Overall mean: 8.30 miles			Times	Overall mean: 15.91 minutes					
	Mean dist.	Median	St. dev.	Gini	Mean time	Median	St. dev	Pop	#<30 min.	%<30 min	Gini
NC	8.42	6.96	6.54	0.3862	15.80	14.38	9.08	8,049,313	7,571,039	94.06%	0.2972
SC	8.92	7.28	6.72	0.4047	15.95	14.35	9.14	4,012,012	3,670,907	91.50%	0.3146
TN	7.86	6.60	5.66	0.3932	16.03	14.60	8.97	5,689,283	5,241,155	92.12%	0.3057
VA	8.16	5.85	7.24	0.4435	15.91	13.55	9.93	7,078,515	6,422,244	90.73%	0.3237
p-Median state	Distances	Overall mean: 7.17 miles			Times	Overall mean: 14.87 minutes					
	Mean dist.	Median	St. dev.	Gini	Mean time	Median	St. dev.	Pop	#<30 Min	%<30 Min	Gini
NC	7.53	6.14	5.42	0.3843	15.24	13.62	8.36	8,049,313	7,564,241	93.97%	0.2959
SC	7.53	6.18	5.47	0.3898	15.04	13.83	8.24	4,012,012	3,790,340	94.47%	0.2977
TN	6.39	4.76	5.16	0.4229	13.82	11.90	8.43	5,689,283	5,371,191	94.41%	0.3230
VA	7.17	4.98	6.28	0.4390	15.20	13.00	9.38	7,078,515	6,490,121	91.69%	0.3180
Max cover state	Distances	Overall mean: 9.40 miles			Times	Overall mean: 18.08 minutes					
	Mean dist.	Median	St. dev.	Gini	Mean time	Median	St. dev.	Pop	#<30 Min	%<30 Min	Gini
NC	9.44	9.33	5.08	0.3004	18.09	18.25	7.53	8,049,313	7,840,948	97.41%	0.2303
SC	9.26	8.92	4.8	0.29	17.8	17.83	7.2	4,012,0	3,930,7	97.98%	0.22

			3	65	4		4	12	97		82
TN	9.06	9.12	4.67	0.2938	17.52	18.03	7.42	5,689,283	5,596,680	98.37%	0.2362
VA	9.70	9.38	5.07	0.2874	18.66	18.55	7.52	7,078,515	6,769,486	95.63%	0.2161

Table 2 indicates that there is a very strong correlation between distance and time. In particular, for most of the populations the average distance/times correspond roughly to an average speed of 30 mph. This makes sense because 60-70% of the populations in the states live in urban areas. So it appears that using distance as a proxy for time is largely a useful procedure as distances are much easier to obtain than real travel times. However, the Gini indexes do tell quite a different story. The Gini index based on distance overestimates the index based on time consistently by about one third (between 28.62% and 38.05%). This is because the average speed traveled in rural areas is much greater, which tend to serve as a partial equalizer when looking at travel times. As a result of analysis of the results will only be based on the actual times rather than the distance. In general, we wish to note that time is the measure of interest to planners. Using distances instead as a proxy will, of course, introduce additional errors. This may be justified if proper conversions from distance to time are not available, but it will still be an approximation. Given the results that show that distance and time are reasonably well correlated, the approximation may be sufficient for the task at hand.

Fig. 3 shows for the state of North Carolina the differences between the access times achieved in the actual solution, the optimized solution with the *p*-median objective, and the optimized solution for the max capture objective. Similar graphs for the other states show very similar curves and are omitted here due to space considerations.

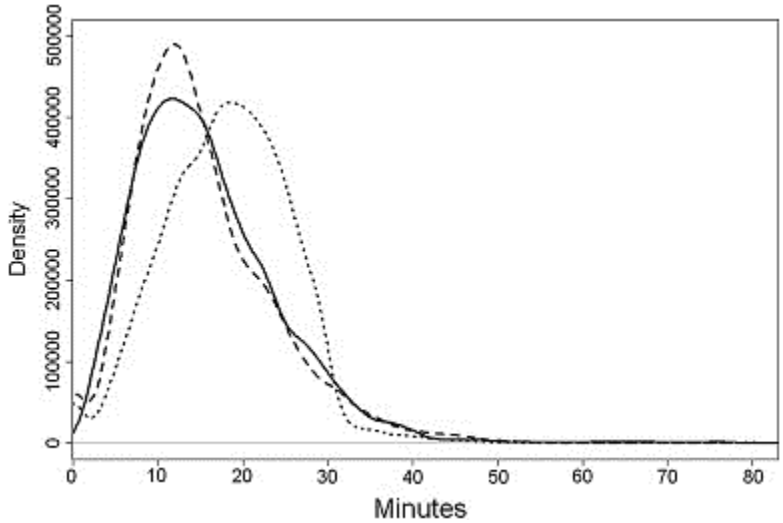

Fig. 3. Functions comparing times for actual solution (solid line), *p*-median solution (broken line), and maximum capture solution (dotted line) for North Carolina.

Fig. 3 clearly shows one of the main results of this investigation: as far as the general efficiency of the solutions is concerned, the actual solution and that of the *p*-median problem are quite similar (with the *p*-median having a larger kurtosis). On the other hand, the max cover solution has a much higher mean access time and the function is located 1.5–2 minutes to the right of the actual solution. Fig. 4 graphically displays the impacts of the optimizations on service availability.

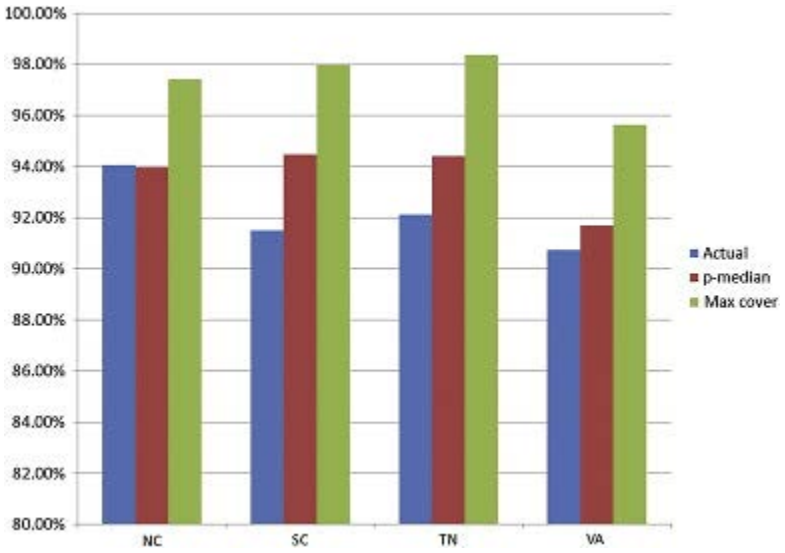

Fig. 4. Service availability in each state for the actual solution, the *p*-median solution, and the maximum set covering solution.

The comparison of the solutions with respect to equality can be seen in Table 3 and Table 4. These tables show the changes that would arise if the *p*-median and the max cover solution, respectively were to replace the actual solution. Note that in both tables, "*x*% more efficient" means *x*% less time. Similarly, "*x*% more equality" refers to a Gini index that is *x*% lower. The comparison results are quite different from those above: here, the actual and *p*-median solutions provide almost identical degrees of equality, while the max cover solution shows a significantly higher degree of equality than either of the other two solutions. The tradeoffs between efficiency and equality are as apparent here as they are in traditional income distributions.

Table 3. Impact of using optimal *p*-median solutions as opposed to the actual solutions.

State	General efficiency (mean)	General efficiency (median)	Service availability	Equality
NC	3.54% More	5.29% More	0.09% Less	0.44% More
SC	5.71% More	3.62% More	3.25% More	5.37% More
TN	13.79% More	18.49% More	2.48% More	5.66% Less
VA	4.46% More	4.06% More	1.06% More	1.76%

				More
Average	6.52% More	7.79% More	1.36% More	0.26% More

Table 4. Impact of using optimal max cover solutions as opposed to the actual solutions.

State	General efficiency (mean)	General efficiency (median)	Service availability	Equality
NC	14.49% Less	26.91% Less	3.57% More	22.51% More
SC	11.85% Less	24.25% Less	7.08% More	27.46% More
TN	9.30% Less	23.49% Less	6.78% More	22.73% More
VA	17.28% Less	36.90% Less	5.41% More	33.24% More
Average	13.66% Less	28.39% Less	5.81% More	26.57% More

The analysis shows that on average, the *p*-median solution is able to improve the actual situation by about 7% as far as efficiency is concerned, while it leaves the service availability and the equality essentially unchanged. The state of Tennessee is an outlier: its efficiency would increase by 14-18% in a *p*-median solution (depending on whether a mean or median measure is used) and its service availability would also increase by more than the average percentage. However, these improvements were to come at the expense of equality which is the only one among the four states that would actually decrease in the *p*-median solution.

On the other hand the max cover solution would change the actual solution in a much more dramatic way. Highly significant decreases of 13-28% in efficiency occur, coupled with increases of 26% in terms of equality and some increase in service availability as well. It appears highly questionable, to say the least, that changes of this magnitude are desirable or realistic as far as their implementation is concerned.

It is important to realize that we do, of course, not advocate closing all existing hospitals and reopen them at new and improved locations. The purpose of our optimization was to provide us with a theoretical optimum that can be used as a benchmark to evaluate the existing locations on. This can be done by either comparing the measures that were devised to assess the quality of the existing and the theoretically optimal solution, or by comparing the actual location patterns. The latter analysis determines that over half (51%) of the existing hospitals are within 2 miles of an optimal *p*-median location, and 85.6% are within 5 miles. In the maximum capture case, we find that 54.9% of existing facilities are within 5 miles of one of the maximum capture optimal locations, and 85.9% are within 10 miles. So, improving efficiency or equity might be done by

either encouraging relocation or additional facilities representing only a small fraction of capacity.

4. Summary & outlook

In this paper we have studied geographic access to hospitals, which is one of many facets of overall accessibility to health care. We calculated travel distances and times at a very fine level using census block groups and road networks for four contiguous U.S. States. We found that measures of equality are very sensitive to whether times or distances are used because of the higher speeds in rural areas relative to urban areas. We argued that travel times are a more justifiable measure of access than distance.

Remarkably, we found that the existing hospital locations in these states are very efficient relative to the optimized set of locations, with three of the four states providing average travel times within 3-6% of the optimal value. Similarly, the existing locations provide a fairly good level of service availability, with 91-94% of the populations in these states having access to a hospital within a 30-minute drive. Stated differently, even if policy makers could go back in time to form a bureaucracy to screen hospital locations to ensure that they were located “optimally,” or invest substantial funds to force/encourage improvements in either efficiency or availability, little improvement could have been made over the pattern that has emerged naturally. The sole exception to this was the state of Tennessee.

An additional corollary of the results presented in this study is that it determines the theoretical limits of improvement in either efficiency (mean time within which a patient can reach the nearest hospital) or service availability (proportion of the population that can reach a hospital within 30 minutes), given the actual locations of the hospitals and the best possible solutions (assuming that all hospitals could be relocated to their optimal sites). As mentioned before, we found that the existing locations provide service levels very close to those that could be attained by using optimal locations. This information will be very helpful to policy makers in that it provides them with an indication of what the potentials for improvements are and how much access and efficiency can be enhanced.

Finally, the study also found that improving efficiency usually had an improvement in availability as a byproduct. However, the opposite was found when the goal was improving availability: an increase in availability served as an equalizing influence, reducing travel times for the worst served, but increasing times for the majority, which decreased efficiency. Thus, we observe the tradeoffs between equity and efficiency seen so often in the economics literature played out in a spatial accessibility analysis. Such tradeoffs will be of particular interest in prescriptive scenarios, i.e., those in which decision makers are actively searching for locations of new or facilities or are seeking replacements of existing facilities.

Future research could focus on a variety of tools to increase efficiency of health care services. Among them are hierarchical systems and the required referral systems (pioneered in location theory by Hodgson [20]). Another important issue deals with congestion [2]. However, many such models are probabilistic, which will any larger instance of these models impossible to solve exactly. Among of the exceptions are deterministic models with backup coverage, see, e.g., [10].

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