Racial, Ethnic, and Affluence Differences in Elderly Patients' Use of Teaching Hospitals

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OBJECTIVE: **To understand the role of race, ethnicity, and affluence in elderly patients' use of teaching hospitals when they have that option.**

METHODS: **Using a novel data set of 787,587 Medicare patients newly diagnosed with serious illness in 1993, we look at how sociodemographic factors influence whether patients use a teaching hospital for their initial hospitalization for their disease. We use hierarchical linear models to take into account differences in the availability of teaching hospitals to different groups. These models look within groups of people who live in the same county and ask what demographic factors make an individual within that county more or less likely to use a teaching hospital.**

RESULTS: **We find that blacks are much more likely than whites to use teaching hospitals (odds ratio [OR], 1.75; 95% confidence interval [95% CI], 1.73 to 1.77). However, Hispanics and Asian-Americans are less likely to use teaching hospitals than are whites (Hispanic OR, 0.92; 95% CI, 0.88 to 0.97; Asian-American OR, 0.89; 95% CI, 0.82 to 0.97). Medicaid patients are less likely to use teaching hospitals (given their opportunities) than are non-Medicaid recipients (OR, 0.91; 95% CI, 0.90 to 0.92). And we find a curvilinear relationship with affluence, with those in the poorest and those in the wealthiest neighborhoods most likely to use a teaching hospital.**

CONCLUSION: **The use of teaching hospitals is more complex that heretofore appreciated. Understanding why some groups do not go to teaching hospitals could be important for the health of those groups and of teaching hospitals.**

KEY WORDS: **inequality; medical education; small area variation; race; resource use.**
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It is well known that the demographics of patients in teaching hospitals differ significantly from those in nonteaching hospitals and from those of the general population. Prior work has been hospital-focused and has described and contrasted the patient populations of teaching and nonteaching hospitals. It has demonstrated that patients of teaching hospitals are disproportionately indigent and poor—whether one looks at outpatient clinics,[1] primary hospitalizations,[1–4] or transfer patients.[5] The proportion of hospitalized patients in teaching hospitals who are black has been shown to be 2 times the corresponding proportion in nonteaching hospitals.[1] Indeed, teaching hospitals have been described as a critical "safety net" for underserved and disadvantaged communities.[1,2] For a variety of purposes—particularly for risk-adjustment for mortality comparisons and reimbursement—this focus on hospitals' "risk" of having certain patient populations is appropriate. However, this is not the only possible focus. Here, we ask the question, "Among those who actually have the option to use a teaching hospital, what sorts of patients are more likely to go to a teaching hospital?"

The difficulty in answering this patient-focused question is defining the denominator correctly. We need to identify patients for whom both teaching and nonteaching hospitals are options. Perhaps particular kinds of individuals choose to go to teaching hospitals even when they have a choice, and not only when they have no choice—a fact that cannot be discerned from studies that compare only hospital-based data. The image of teaching hospitals as a "safety net" carries the idea that many patients in teaching hospitals have "landed" there because they have few or no other options. Undoubtedly, that is the case for some people. However, we might reasonably hypothesize that many patients in teaching hospitals are there despite having other options. For example, past work has shown that perceived hospital quality is identified by patients as a very important part of their decisions to go to a particular hospital and that patients with more experience with hospitals care even more about quality.[6–9] In fact, a study in Maryland showed that even uninsured patients were willing to bypass closer emergency departments to seek help at an institution of their own choosing.[10] However, such "decisions" are only meaningful if more than 1 option exists, and prior studies do not adequately account for the geographical and financial constraints on patients' decision making. A patient may not be able to go to a teaching hospital because of geographical isolation, and a patient may not be able to go to a nonteaching hospital because of financial constraints, particularly those imposed by insurance status. We propose that a good approximation of patients who have an option between teaching and nonteaching hospitals is obtainable by selecting patients for whom: (1) his or her neighbors have gone to a teaching hospital, and (2) the patient has a widely accepted insurance policy.

So, given those patients for whom teaching hospitals are an option, we ask: what characteristics make a patient more likely to go to a teaching hospital? In this initial

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study, we explore the role of fundamental demographic characteristics—race, ethnicity, and affluence—among a nationwide cohort of elderly Medicare beneficiaries.

METHODS

General Approach

More concretely, in order to conduct this study, we exploit a novel data set and a particular statistical methodology that allows the options a patient faces to be taken into account. The data set is the Care after the Onset of Serious Illness (COSI) data, an incidence cohort of elderly individuals newly diagnosed with a serious disease in 1993; this dataset is constructed from Medicare claims and is described in detail below. Because the data are drawn from fee-for-service Medicare, all patients are insured by a common policy that is accepted virtually everywhere. The data allow us to understand the results of patient decisions made without regard for financial constraints. In addition, we use hierarchical linear models (HLM) to estimate the effects in which we are interested.[11] In doing so, we propose that an individual is at risk for going to a teaching hospital if his or her neighbors have gone to a teaching hospital. If no one from a community goes to a teaching hospital, then that community contributes nothing to understanding how personal characteristics influence teaching hospital attendance. But if individuals from a given community do go to a teaching hospital, then we look within that community and ask: given that people from this community go to a teaching hospital, what makes an individual within the community more likely to go to such a hospital?

We therefore looked within counties in which at least 10 people from our cohort went to teaching hospitals. HLM allows us to estimate models that fit a separate intercept term for each community and allows us to look within a community at the effect of individual-level variables. This means that the estimates at the individual level are unbiased by anything that is constant across the entire community—such as, we argue, the availability of teaching hospitals. Moreover, the effects are also unbiased by anything else that is constant at the community level (such as, say, a scandal at a local hospital), without our needing to actually measure what that factor might be. Unlike many other statistical methods, HLM lets us estimate these so-called "fixed effects" and take into account the clustering of patients within communities without violating necessary assumptions about the structure of unobserved variables, and yields both statistically efficient and unbiased standard errors. In order to use HLM in these ways to get reliable estimates, an enormous amount of data is necessary; this is one of the additional benefits of the COSI data set.

Data

The subjects analyzed here are drawn from the COSI dataset, a dataset we have built based on Medicare claims. Medicare data capture 96% of the American population older than 65.[12] COSI contains clinical, demographic, and other information about a population-based cohort of 1,164,790 elderly patients identified at the time of initial diagnosis with a serious illness in 1993. In the first stage of data development, a cohort of all patients newly diagnosed with 1 of the following diseases was identified: cancer of the lung, colon, pancreas, urinary tract, liver or biliary tract, head or neck, or central nervous system, as well as leukemia or lymphoma, stroke, congestive heart failure, hip fracture, or myocardial infarction. To be included in the study, patients were required to be at least 68 years of age to allow for 3 years of claims in order to exclude prevalent cases (see below); we also required that patients live in the 50 United States or the District of Columbia and have valid claims data (including age, gender, ZIP code, admission date, and discharge date) to allow accurate ascertainment of eligibility.

Briefly, the development of the COSI cohort relies initially on 1993 inpatient hospitalization records. Extensive descriptions of our data development methods are available elsewhere.[13] These inpatient records, contained in the MedPAR file, represent a complete enumeration of hospitalizations for Medicare beneficiaries occurring during 1993. For individuals who had a hospitalization with 1 of the above conditions in 1993, we used well-described methods to ascertain whether their condition could be considered incident or prevalent. We included in COSI only those malignancies that were deemed incident at the time of their first hospitalization for 1 of the above conditions after reviewing 3 prior years of claims.[14,15] In the case of heart attack, hip fracture, and stroke, we used similar approaches to include only new events for a patient.[16–18] All other diseases that patients may have had (for example, as noted on prior hospitalizations for other conditions) were also collected and were treated as comorbidities using an implementation of the Charlson score.[19–21]

For the purposes of the current study, we also required that the individual have been initially hospitalized at a hospital that could be linked to the American Hospital Association survey data in order to identify teaching hospitals and have a valid county identifier in the claims; 1,108,060 patients (95.1%) could be analyzed. Of these, 787,587 patients (71.1%) lived in counties in which at least 10 patients went to a teaching hospital. These 787,587 patients are the cohort analyzed in this paper. We confirmed that the exclusion of patients living in counties where almost no one went to a teaching hospital did not bias our results.

Our outcome variable was whether a teaching hospital was used for the patients' initial hospitalization for their serious illness. Teaching hospital status was defined as self-reported membership in the Council of Teaching Hospitals in the 1993 survey.[22]

This research was approved by the University of Chicago Human Subjects Committee.

Covariate Definitions

Medicare data have certain well-known limitations with respect to their racial classification system, and the race codes provided in the claims can only be reliably used for white/nonwhite comparisons.[23,24] However, with access to the names of beneficiaries, it is possible to apply large-scale, well-validated computerized algorithms for identifying Hispanic and Asian-American ethnicities, substantially improving the adequacy of the racial/ethnic classification system we can use here.[25,26] The Asian-American surname algorithm was developed among those born before 1941 and alive in 1990 who had applied for Social Security; using a gold standard of country in which the person was born (for this relatively new immigrant population), the algorithm has a positive predictive value of 0.82 for the groups included. The Hispanic surname algorithm was developed using Hispanic self-identification in the 1990 census as the gold standard in all age groups; it has a positive predictive value of 0.93. Thoughout this manuscript “white” and “black” refer to non-Hispanic white and non-Hispanic black; the shorter words are used for expositional convenience. Medicaid receipt was obtained directly from the Denominator File, as is conventionally done.[27–34] We also linked individuals at the ZIP-code level to 1990 decennial census median incomes (ZIP codes aggregate 25,000 to 50,000 people). This provides a continuous measure that is likely well-correlated with total household financial resources. This approach has been validated[35,36] but has certain important limitations,[37–39] within which we have attempted to abide; foremost, we do so by avoiding interpretations of these coefficients as directly representing the effects of changes in household income.

Statistical Methods

We used 2-level hierarchical modeling for individuals nested within counties.[11] Given the clustering of individuals within counties, hierarchical modeling is required to generate unbiased and efficient estimates, as well as proper standard errors. Such modeling can take into account (1) the influence of different sample sizes across counties, and (2) the dependence among individual outcomes clustered within the same county. As we use it, HLM obtains its analytic leverage by comparing patients within each county to others in the same county, and assumes that if 10 people in a county were able to use a teaching hospital, then some teaching hospitals are available to all members of that county. Strictly, this amounts to the assumption that patients are homogenously distributed within counties with respect to distance to teaching hospitals on the racial, ethnic, and affluence dimensions we highlight.

A logistic model was used at level 1 given that our outcome of interest, use of a teaching hospital (or not) for one's initial admission for a serious disease, was dichotomous. Individual-level variables were entered at the individual level, group-mean centered, and the variance components of their slopes fixed at the county level in order to assess for variation between individuals in odds of teaching hospital use adjusted for differences between counties in all county-level factors. We therefore report unit-specific coefficients. In order to confirm that our results were not biased by the omission of counties in which very few individuals used teaching hospitals, we re-estimated our models using all counties in the sample, regardless of whether any patients living there used teaching hospitals, and the substantive conclusions were unchanged.

Definition of Community

There are a number of difficult methodologic issues involved in defining health care markets. Some have strongly advocated the use of the Hospital Referral Regions (HRRs),[40] others the use of network-based measures,[41–43] and others counties. In this project we have used counties to approximate markets—that is, to approximate the community of people who share similar health care options—as has been done in numerous other studies.[43–54] This was done for a number of reasons: (1) our intuition that counties best approximate the way patients think about where they might go for care; (2) empirical tractability and availability of data; and (3) past work suggesting that results are often (but not always) insensitive to the difference between HRRs and counties (and that these differences are particularly small for medical diagnoses of the type we study here).[55]

RESULTS

Basic descriptive statistics are provided in Table 1. The full cohort consists of 1,108,060 patients newly diagnosed in 1993; they resided in 3,647 counties. Our regressions analyzed the 787,587 (71.1%) patients who lived in 810 counties (22.2% of counties) from which at least 10 cohort members used a teaching hospital. The mean age of the analytic sample was 79.0 (±7.1 SD); 41.5% were male; 87.4% were white; 14.0% received Medicaid benefits at some point during 1993; and the median income of the ZIP code in which patients lived was $32,674. A total of 17.1% of patients overall used a teaching hospital. In the average county included in our sample, 851 patients used a teaching hospital; this ranged from a low of 10 (by construction) to a high of 4,913. Two hundred seventy (6.2%) of the 4,390 hospitals used by our analytic cohort were teaching hospitals; this includes all teaching hospitals used by any patient in the full cohort.

Unadjusted results on the association between race/ethnicity, Medicaid receipt, and teaching hospital use in the entire sample of 1,108,060 people are shown in Table 2. In these uncontrolled associations, blacks and Asian Americans are substantially more likely to use a teaching hospital than are whites or Hispanics. Medicaid recipients are also less likely to go to teaching hospitals

Table 1. Description of Sample at Time of Initial Hospitalization

	Entire COSI Sample (*N* = 1,108,060)	Potential Teaching Hospital Users (*N* = 787,587)
Demographics		
Mean age, y (±SD)	79.1 (6.7)	79.0 (7.1)
Male, %	41.8	41.5
Medicaid recipient, %	15.8	14.0
Income (median of ZIP code)	\$30,078	\$32,674
Race/ethnicity, %		
White	88.3	87.4
Black	7.2	7.8
Asian American	0.5	0.7
Hispanic	2.0	2.2
Other race/ethnicity	1.9	1.9
Primary diagnosis, %		
Noncancers		
Myocardial infarction	17.9	17.7
Congestive heart failure	20.8	20.6
Hip fracture	17.4	17.4
Stroke	20.0	20.0
Cancers		
Central nervous system	0.4	0.4
Head and neck	0.8	0.9
Liver and biliary tract	0.7	0.7
Colon	6.5	6.8
Leukemia	1.7	1.7
Lung	6.7	6.9
Lymphoma	2.6	2.6
Pancreas	1.2	1.2
Urinary tract	3.1	3.1
Went to a teaching hospital, %	12.6	17.1

COSI, Care after the Onset of Serious Illness.

than are individuals who did not qualify for Medicaid in 1993 (before controlling for any differences in any other characteristics).

Table 3 presents the full HLM models; these regressions now take into account the different opportunities that people have to use teaching hospitals depending on where they live and also control for age, gender, primary diagnosis, and comorbidity. Most generally, the results indicate that there was significant variation in rates of teaching hospital use at the county-level—as would be expected if counties appropriately capture the options patients have. Formally, this is shown because the variance component was highly statistically significantly different from zero (value = 1.39, χ^2 = 213,244.8, 809 *df*, $P < .001$); the magnitude of this component has no interpretation in hierarchical linear models with categorical outcome variables.

More pertinently, however, within a given county, older patients and women were less likely to use teaching hospitals. Blacks were 75% (odds ratio [OR], 1.75; 95% confidence interval [95% CI], 1.73 to 1.77) more likely than whites to use a teaching hospital. Asian Americans and Hispanics were both less likely than whites to use teaching hospitals. (For Asian Americans, these results contrast with the uncontrolled associations presented in Table 2; this difference is likely due the extraordinarily high levels [94% in1990] of urbanization of Asian Americans.[56]) These ORs translate to an average patient in an average county having a 9.2% chance of going to a teaching hospital if white, a 15.1% chance if black, an 8.3% chance if Asian American, and an 8.6% chance if Hispanic, holding all else constant. (Because of the skewed distribution of number of patients choosing teaching hospitals across counties, the average county has fewer patients choosing teaching hospitals than does the sample as a whole.)

There are also statistically significant effects of affluence on the choice of teaching hospitals. Medicaid patients are 9% less likely (OR, 0.91; 95% CI, 0.90 to 0.92) to use a teaching hospital, all else constant. The effect of neighborhood income on the odds of using a teaching hospital is nonlinear. Wealthier individuals in a county are progressively less likely to choose a teaching hospital until they reach a certain higher income level, after which they are more likely to choose a teaching hospital. This so-called "inflection point," at which the curve changes direction, is high; it occurs at ZIP codes with a median income \$46,800 above the mean for the county. Some examples may clarify this. Patients with average characteristics living in a neighborhood with an average median income of \$32,700 have a 9.2% chance of using a teaching hospital. An otherwise identical patient living in a very poor neighborhood, with a median income of \$15,000, would have a 17.1% chance of using a teaching hospital; if that patient also received Medicaid, then his or her chance of using a teaching hospital was reduced to 15.9%. Finally, a patient residing in the same county in a quite wealthy neighborhood with a median income of \$100,000 would use a teaching hospital 11.3% of the time. (We emphasize again that these probabilities are adjusted for age, gender, race/ethnicity, primary diagnosis, and comorbidity.)

Table 2. Relationship of Race/Ethnicity and Medicaid Status to Teaching Hospital Use*

	Not a Teaching Hospital, *n* (%)	Teaching Hospital, *n* (%)	Total
White	865,058 (88)	113,804 (12)	978,862
Black	59,804 (75)	19,538 (25)	79,342
Asian-American	5,034 (84)	964 (16)	5,998
Hispanic	19,741 (88)	2,648 (12)	22,389
Other	18,895 (88)	2,574 (12)	21,469
Medicaid recipient	156,312 (90)	18,257 (10)	174,569
No Medicaid	812,220 (87)	121,271 (13)	933,491

* *These results are not adjusted for any possible confounders and are estimated on the full sample of 1,108,060 patients.*

Table 3. Results of HLM Regression Explaining Teaching Hospital Choice

	Unadjusted*		Adjusted†	
	Odds Ratio	95% Confidence Interval	Odds Ratio	95% Confidence Interval
Age (1 y)	0.985	(0.984 to 0.986)	0.983	(0.981 to 0.985)
Male	1.074	(1.061 to 1.087)	1.058	(1.043 to 1.072)
Medicaid	0.908	(0.892 to 0.923)	0.914	(0.894 to 0.934)
ZIP median income ($10,000)	0.752	(0.740 to 0.764)	0.712	(0.699 to 0.727)
ZIP median income squared	1.043	(1.041 to 1.045)	1.037	(1.035 to 1.039)
Race/ethnicity (vs white)				
Black	2.400	(2.356 to 2.444)	1.751	(1.710 to 1.792)
Asian	1.055	(0.984 to 1.131)	0.891	(0.818 to 0.972)
Hispanic	0.924	(0.886 to 0.964)	0.922	(0.876 to 0.970)
Other	1.038	(0.994 to 1.085)	1.024	(0.975 to 1.076)
Primary diagnosis (vs myocardial infarction)				
Noncancers				
Congestive heart failure	0.992	(0.973 to 1.011)	0.982	(0.961 to 1.004)
Hip fracture	0.893	(0.875 to 0.911)	0.978	(0.956 to 1.002)
Stroke	0.890	(0.872 to 0.907)	0.856	(0.838 to 0.875)
Cancers				
Central Nervous System	2.027	(1.882 to 2.183)	2.494	(2.288 to 2.719)
Head and neck	2.311	(2.191 to 2.438)	2.707	(2.543 to 2.883)
Liver and biliary tract	1.450	(1.360 to 1.547)	1.467	(1.361 to 1.580)
Colon	1.128	(1.099 to 1.158)	1.111	(1.079 to 1.144)
Leukemia	1.210	(1.157 to 1.266)	1.307	(1.240 to 1.378)
Lung	1.254	(1.222 to 1.286)	1.264	(1.227 to 1.301)
Lymphoma	1.435	(1.385 to 1.487)	1.504	(1.443 to 1.567)
Pancreas	1.400	(1.332 to 1.472)	1.370	(1.295 to 1.450)
Urinary tract	1.284	(1.241 to 1.328)	1.279	(1.230 to 1.330)

** Unadjusted results do not control for any other variables, and do not adjust for county-level effects. The 4 race/ethnicity variables were run in a single regression compared to white; the 12 primary diagnosis variables were run in a distinct single regression compared to myocardial infarction.*

† These adjusted results use HLM to compare within-county effects. A Charlson Comorbidity Score was also included in the model, implemented using a family of 24 indicator variables,[21] but the parameters are not shown here.

HLM, hierarchical linear model.

DISCUSSION

Most patients do not use teaching hospitals. Even among the seriously ill members of our cohort, all of whom were elderly Medicare beneficiaries, only 17% of patients used a teaching hospital. Despite the long line of research on the performance advantages of teaching hospitals,[57,58] we do not know what sort of patients are more likely to opt out of the usual care that their neighbors get and instead go to a teaching hospital. We found that among elderly patients who are in fee-for-service Medicare (that is, patients facing few financial constraints on their choice) and who reside in counties where at least some people are able to use teaching hospitals, several patterns emerged. We found first that younger (within the elderly) and male patients were more likely to opt for teaching hospitals. We found that blacks were most likely to opt for teaching hospitals, followed by whites, followed by Asian Americans and Hispanics. We found that patients who were poor enough to also qualify for Medicaid (the so-called "dually entitled") were less likely to go to a teaching hospital. However, there was a curvilinear relationship with affluence—those in the poorest and the wealthiest neighborhoods were most likely to choose a teaching hospital rather than the conventional care of their neighbors.

This work has relevance for 2 growing literatures. First, it contributes to research showing the inadequacy of binary racial categories (e.g., "white/nonwhite") as an approach to racial and ethnic classification. There appear to be important differences among ethnic groups in their health and health care utilization patterns; these differences have been noted and reviewed extensively elsewhere.[59] This work often finds that whites represent an extreme case, and other groups array to one side of whites; in contrast, in the case of our results, some groups were less likely to opt for teaching hospitals and others were more likely than were whites. Second, this work can be brought to bear on the question of whether teaching hospitals are targeting particular patient populations for "exploitation." Physician and medical historian Dr. Ken Ludmerer has noted that sometimes teaching hospitals are perceived as "towering complexes that dominated the urban landscape—symbols, to many, of white imperialism and racism in increasingly black and Hispanic neighborhoods ... viewed by their community with hostility and resentment."[2] (page 262). Our data suggest that this concern may be misplaced. If teaching hospitals were exploiting people of color, it seems likely that they would not strongly differentiate between blacks and Hispanics (although such differentiation is not implausible). Likewise, teaching hospitals would likely draw in the poorest from any given neighborhood—those with Medicaid. In neither case was this true in our sample. Instead, a more complex picture emerges, with teaching hospitals being the destinations for some people of color but not others, and for both those living in poor neighborhoods and in the wealthiest neighborhoods. Of course, the rich and the poor may exercise their choice to go to teaching hospitals under very different circumstances; those differences may include important differences in the quality of the nonteaching hospitals that are available. Nevertheless, other evidence suggests that teaching hospitals provide better care than nonteaching hospitals. Indeed, it has been argued that the mortality of blacks would be even higher relative to that of whites if it were not for the greater use of teaching hospitals by blacks.[60]

Our results have certain limitations. For our purposes, we were interested in the characteristics of individuals who use teaching hospitals for their initial care for a serious disease—when they are likely quite ill. Yet, an important part of the mission of teaching hospitals is to serve as referral centers; we have not examined that role in these data. Likewise, our data apply only to the elderly in Medicare's general insurance policy; the associations might be different among the younger population or under incentive regimes that steer patients toward or away from certain hospitals. However, our results demonstrate the choices people make in the absence of financial pressures and therefore may suggest the ways in which health care contracts can be designed to facilitate patients' preferences, rather than hinder them. We have looked only at initial diagnoses with serious illnesses; we have done so because these are illnesses for which teaching hospitals may be most advantageous and because they account for a significant fraction of the most expensive hospital stays. However, there may be different patterns of choice for less-ill patients. Finally, given that our data are of administrative origin, we do not have self-reported race and ethnicity data; it would be useful to confirm these findings against self-identified classifications.

Hopefully, future work in this field will continue to explore patients' perspectives while examining the influence of many potential intervening variables. We have not done detailed mapping in order to examine the constraints of distance within a given county; however, since both the poor and the rich seem able to use teaching hospitals within a county, it seems unlikely that the relative distances within a county are playing a central role in altering choices for care among the seriously ill. Certainly, differences in distance to teaching hospitals may be compounded by differences in access to transportation. Throughout, we have only used data available in the claims. While this gives us rich medical detail and adequate sample size to estimate HLM models, it limits our ability to ask certain types of questions. We have not been able to explore the effects of variables such as education and family structure that are likely important. A key question, we believe, would address the ways in which differential proximity, differential travel times, differential educational levels, and differential access to familial and other social support mediate these racial, ethnic, and affluence effects. Understanding such mediators is important, insofar as they are the most likely targets for feasible interventions in the near term.

Our results suggest that, while teaching hospitals may serve as part of a safety net for the poor, within any given county they are less likely to be the destination hospital for Medicaid patients. A similarly subtle picture appears with regard to the racial and ethnic preferences for teaching hospitals. Thus, blacks are more likely to go to teaching hospitals than are whites, but Hispanics and Asian Americans (once one correctly takes into account their different opportunities) are less likely than whites to go to teaching hospitals. This has several implications. First, students of health services utilization need to account for this complexity, and many conventional modeling strategies (e.g. black/white race dichotomies, linear income effects) may miss important differences in patterns of behavior. Second, the patterns our study uncovers emphasize the importance of looking at how patients choose their health care, rather than merely looking at who has ended up in particular types of hospitals. This offers the opportunity to separate the hospital choices made from the frequency with which groups need hospital care. What is more, distinct processes may occur for initial diagnosis and for referral care. This may explain the variation between our results on Medicaid and conventional findings of increased Medicaid use of teaching hospitals. Third, these results raise questions about why teaching hospitals seem relatively less attractive to newer immigrant groups than to the black and white populations. Clearly, additional work is necessary to understand this phenomenon—both from the perspective of the health of those populations (since teaching hospitals appear to provide better care, which those populations are not utilizing) and the health of teaching hospitals (since those groups represent a rapidly growing fraction of the patient population).

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