This PDF is a selection from a published volume from the National Bureau of Economic Research

Volume Title: Perspectives on the Economics of Aging

Volume Author/Editor: David A. Wise, editor

Volume Publisher: University of Chicago Press

Volume ISBN: 0-226-90305-2

Volume URL: http://www.nber.org/books/wise04-1

Conference Date: May 17-20, 2001

Publication Date: June 2004

Title: Area Differences in Utilization of Medical Care and Mortality among U.S. Elderly

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URL: http://www.nber.org/chapters/c10349

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Area Differences in Utilization of Medical Care and Mortality among U.S. Elderly

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10.1 Introduction

The two most important, most enduring questions in health economics are (1) what are the determinants of expenditures? and (2) what are the determinants of health? Extensive research over the last thirty-five years has produced a variety of answers to these questions, depending in large part on the specific context within which the questions are posed. One crucial distinction is between explaining changes over time and explaining cross-sectional differences at a given time. With regard to secular changes in the United States in recent decades, most health economists now believe that advances in medical technology provide the major explanation for both increases in expenditures and improvements in health.[1] With regard to cross-sectional differences, the focus of this paper, there is less agreement. By exploiting a rich body of data from the Centers for Medicare and Medicaid

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For development of the variables used in this paper we are indebted to Jeffrey Geppert, Chris Kagay, Hoon Byun, and Sarah Rosen. We also thank Deborah Kerwin-Peck and Sarah Rosen for preparation of the tables and Dan Gottlieb for additional research assistance. Financial support was provided to Fuchs by the Robert Wood Johnson and Kaiser Family Foundations and to Mark McClellan and Jonathan Skinner by the National Institute on Aging. Helpful comments from David Cutler, Angus Deaton, Ed Glaeser, and especially Joseph Newhouse are gratefully acknowledged.

1. See, for example, Cutler et al. (1998), Pardes et al. (1999), Currie and Gruber (1996), and Schneider (1999).

Services (formerly HCFA), the U.S. Census of Population, and other sources, we hope to narrow that disagreement, at least with respect to area differences in utilization of care and mortality of the elderly.

Our focus on the elderly is motivated in part by the fact that they account for a disproportionate share of national health care expenditures and an even greater share of government health care expenditures. Moreover, the elderly experience the bulk of the major health problems of the population. Approximately one-half of all deaths occur between ages sixty-five and eighty-four, and another one-fourth occur at ages eighty-five and above. These shares are based on the current age distribution of the U.S. population. For a stationary population experiencing current age-specific mortality rates, deaths at ages sixty-five–eighty-four would still account for almost one-half the total; the share at eighty-five and above would rise to one-third. The focus on the elderly is facilitated by the fact that the Medicare program generates a large, detailed body of data on utilization and mortality.

One reason for focusing on area differences is that the large number of metropolitan and nonmetropolitan areas in the United States provide a convenient framework for aggregating individual data in the search for variables that may be related to utilization and mortality. Moreover, many health policy analysts believe that an understanding of area differences may suggest opportunities to limit expenditures and/or improve health (for example, Wennberg, Fisher, and Skinner 2002).

This paper has two main sections: utilization and mortality. In most markets an interest in expenditures would require attention to prices as well as quantities, but given universal insurance coverage through Medicare and administrative price setting by HCFA, utilization is a natural subject for study. Mortality is only one of many possible measures of health, but there are several reasons to concentrate on it. First, mortality is by far the most objective measure. Second, it is, for most people, the most important health outcome. Third, it is probably significantly correlated with morbidity because most deaths are preceded by illness.

In this paper we focus on whites, aged sixty-five–eighty-four, or more specifically, those people not identified as African-American. We exclude blacks because at those ages both utilization and mortality of blacks are higher than for whites, and the percentage black in an area is correlated with other variables of interest. Moreover, preliminary research by Donald Nichols suggests that the relationship between those other variables and utilization and mortality may be significantly different for blacks than for whites. We exclude anyone eighty-five and over because it is more difficult to obtain accurate measures for self-reported variables such as education and income. About one-half the population eighty-five and over suffer from some form of dementia, and about one-fifth are in nursing homes where measurement of income is particularly problematic. Moreover, most nursing home utilization is not covered by Medicare, the source of our data on utilization.

Briefly, we find wide variation in the utilization of health services across regions. It is not simply that some regions are higher along all dimensions of care, but that in some regions (Florida, for example) there is much more diagnostic testing, even while per capita inpatient services are comparable to the national average. In general, utilization is strongly positively associated with mortality across areas—in other words, areas with more sick elderly use more health care, other things being equal. There remains, however, substantial variation in utilization after controlling for factors such as education, income, and mortality.

Cross-area variations in mortality rates among this elderly group are not as large as variations in utilization, but they are still substantial. The 10 percent of metropolitan statistical areas (MSAs) with the highest mortality (age-sex adjusted) have an average death rate 38 percent greater than the 10 percent of MSAs with the lowest mortality. The comparable differential between the high and low utilization areas is 49 percent.

Education, real income, cigarettes, obesity, air pollution, and the percent black account for more than half of the variation in mortality across areas, but there is still substantial differences across regions unexplained by these variables. Florida, in particular, has death rates significantly below the national average; the differential is particularly large for areas in the southern portion of the state. The final section of the paper explores two puzzles revealed by regression analyses: (1) why Florida is so different from the rest of the country with respect to utilization and mortality; and (2) why the presence of more blacks in an area should be associated with higher mortality among elderly whites. We considered several possible solutions to these puzzles, including differential migration patterns of the elderly, but ultimately we are left with conjectures rather than robust explanations.

10.2 Previous Studies

10.2.1 Spatial Variations in Health Care Utilization

There is an extensive literature on geographic variations in health care spending and how it might be explained; we consider here a selective overview of these studies.

Researchers have documented variations across regions in health care utilization beginning with the studies by Glover in the 1930s, the work by Wennberg and associates in the 1970s and 1980s, and more recent studies by a wide variety of researchers.[2] There is a general consensus that the variations are real and persistent over time. The *Dartmouth Atlas of Health*

2. For an excellent review of some of this earlier literature, see Eisenberg (1986). More recently, see Wennberg and Cooper (1999), Escarce (1992), Green and Becker (1994), Chassin et al. (1986), and references therein.

Care provides extensive documentation of the differences across regions for a variety of utilization measures (Wennberg and Cooper 1999). In the *Atlas* studies, regions are defined based on Hospital Referral Regions (HRRs), each of which has at least one hospital with a tertiary cardiovascular or neurological surgical center. The geographical boundary of the HRR is based on the migration patterns of Medicare patients who use the hospitals inside the HRR, of which there are 306 in the United States. Average 1995–96 fee-for-service Medicare per capita expenditures ranged from $3,506 in Eugene, Oregon, $3,700 in Minneapolis, $7,783 in Miami, to $9,033 in McAllen, Texas; these are all adjusted for age, sex, race, and regional price differences using a variant of the part B price adjuster. Utilization rates of specific interventions that are not subject to the difficulties of price adjustment also show dramatic variations across regions. These differences are therefore best thought of as differences in quantities—hospital admissions, physician visits, and procedures—for the enrollees who live in each region, regardless of where they actually get their care.

Most of the controversy comes in how these variations can be interpreted. One clear possibility is factors related to demand; a sicker population, for example, should lead to greater demand for health care. Health status is clearly a critical determinant of health care utilization. Average annual spending for Medicare beneficiaries with "poor" self-assessed health is $8,743, but only $1,656 for those in excellent health (Wennberg and Cooper 1996).

While regional differences in health status are clearly important determinants of health care spending (as we demonstrate in the following), they do not fully explain the two-fold differences in Medicare spending across regions. Even after accounting for differences across regions in underlying health measures such as stroke, heart attacks, hip fractures, cancer incidence, income, poverty rates, and behavioral factors such as the percentage of smokers and seatbelt users, one cannot explain more than 42 percent of the overall variation across regions in expenditures (Skinner and Fisher 1997; Skinner, Fisher, and Wennberg 2001). Longitudinal cohort studies also reveal differences in resource use across both hospitals and regions after controlling for patient health status and function.[3]

A related "demand" based explanation is that patient preferences (ow-

3. Cutler and Sheiner (1999) found that regional measures of the age/sex/race composition of the population explained 70 percent of regional differences in (age-sex-race adjusted) Medicare expenditures. The factors providing the additional explanatory power included the age-composition of deaths in the region and the age-specific mortality rates. Here we raise a cautionary note about "ecological fallacy" in which aggregated data are used to make inferences about individual causal pathways, a concern of particular importance to any research on geographic variation (Susser 1994a,b). For example, the percentage of the elderly population that is Hispanic is predicted to increase regional Medicare expenditures (Cutler and Sheiner 1999), yet average Medicare expenditures for Hispanics is roughly equal to expenditures for non-Hispanics.

ing to unmeasured illness or preferences for care, holding illness constant) determine health care utilization, so that health care resources move to areas with the greatest demand as measured by initial physician visits or other indicators, such as health (Escarce 1992; Escarce 1993; Folland and Stano 1989; Green and Becker 1994). In many of these studies, demand is inferred by the frequency of initial visits to the physician (as opposed to subsequent referrals, which are viewed as supply-driven). It remains an interesting, and largely untested, question as to whether visits to physicians reflect demand (patient preferences) or supply (how often the physician schedules office visits). Clearly, these demand-related factors can potentially explain some of the variation we observe, particularly in Florida where rates of utilization are higher than the rest of the country.

Another explanation is based on the supply of health care resources. The earliest incarnation of this link is "Roemer's Law," which states that if a hospital bed is built, it will be filled. In this view, the preexisting resource capacity of the area, which arose out of historical accident, in turn determines the intensity of care in the region. In regions with greater supplies of hospital beds, inpatient expenditures are higher. A similar story holds for physician supply; larger populations of physicians per capita are associated with higher levels of per capita physician expenditures (Wennberg and Cooper 1996, 1999).

However, correlation does not establish causation. One could expect more hospital beds to be built where there is greater demand, and one would expect physicians to move to regions where the demand of physician services is high. Furthermore, the correlations are not very strong. For example, using *Dartmouth Atlas* data, just one-quarter of the variation in part B (physician) expenditures across the United States can be explained by physician supply. And while the supply of specialists in Miami is 45 percent higher than the supply in Minnesota, the number of visits by specialists to people in their last six months of life in Miami is more than four times larger. In other words, there appear to be significant nonlinearities in treatment patterns across regions that cannot be explained solely by differences in resource supply.

Another hypothesis, closely related to Wennberg's "practice style" theory is that some physicians show greater "enthusiasm" for specific procedures (Wennberg, Barnes, and Zubkoff 1982; Chassin 1993). A recent study surveyed both orthopedic surgeons and referring physicians with regard to their propensity to perform surgery (in the former case) and their perceptions of outcomes and propensity to refer (in the latter case), and found that these factors were highly significant in explaining overall knee replacement rates in the population, even after controlling for the underlying clinical conditions of the patients (Wright et al. 1999). The study did not, however, test patient preferences conditional on health needs.

A number of studies seeking to explain physician behavior have examined associations between specific physician psychosocial attributes or physician training or practice characteristics (years in practice, diversity of diagnoses managed, specialty) and measures of utilization (Allison et al. 1998; Franks et al. 2000; Pearson et al. 1995; Selby et al. 1999). Although associations were generally weak, physicians with greater fear of malpractice, anxiety due to uncertainty, and less willingness to take risks were more likely to spend more per patient or more likely to refer. However, the magnitudes of these differences are not large enough to explain, by themselves, the wide regional variation in utilization.

As a statistical proposition, differences in physician enthusiasm by themselves are not enough to generate regional variations. Most regions include a large number of physicians, and if physicians are endowed with differing but randomly distributed levels of enthusiasm, they would average out over the large number of physicians in the area. (Of course, for some surgical procedures, one or two specialists could exert a strong influence on regional rates.) The interesting question therefore is why enthusiasm should be correlated across physicians within a given region.

Finally, factors that operate at the level of the hospital and market are also known to influence spending. Teaching status, membership in multihospital chains, degree of competition, and hospital ownership (for example, for-profit ownership) have all been associated with differences in resource use (Gray and McNerney 1986; Kessler and McClellan 1999; Silverman, Skinner, and Fisher 1999; Taylor, Whellan, and Sloan 1999). The extent to which these factors contribute to regional differences in spending is not well understood.

10.2.2 Spatial Variations in Mortality

Spatial variations in mortality have not been studied as extensively as variations in utilization, and many studies have focused heavily on the influence of one or two variables such as air pollution or income inequality. The earliest investigations typically used states or a limited number of MSAs as the units of observation, thus suffering from the problem of few degrees of freedom (Auster, Leveson, and Sarachek 1969; Silver 1972). Considerable effort has been devoted to studying the effects of income and education and to sorting out the relative importance of these closely related variables. Both variables are usually found to be related to mortality, but their importance can vary greatly with age and cause of death. Income, for instance, is much more highly correlated with infant mortality than with deaths at other ages.

Attempts to discover the impact of medical care have produced mixed results (Fuchs and Kramer 1972; Hadley 1988). More recently, Skinner, Fisher, and Wennberg (2001) used as an instrument physician visits in the last six months. This geographical variable was highly correlated with overall Medicare expenditures but uncorrelated with predicted survival based on regional measures of health. This study found "flat of the curve" effects of Medicare expenditures on survival, at least for the expenditures explained by physician visits in the last six months. Similar results were found using cohort data of heart attack patients controlling for detailed chart data using the Cooperative Cardiovascular Project data (Fisher et al. 2003).

Several studies have found a positive association between air pollution and mortality.[4] More recently, numerous investigators have focused on income inequality (rather than low income per se) as a major cause of higher mortality.[5] In two comprehensive reviews of this literature Deaton (2001) and Deaton and Paxson (1999) critique the theoretical foundations of these studies and their empirical implementations. In a study of changes over time in Britain and the United States, Deaton and Paxson (2001) find no support for an effect of income inequality on mortality. Deaton and Lubotsky (2001) find that when they control for percent black, the effect of income inequality is eliminated. They also find that percent black is positively related to white mortality at nearly all ages.

10.3 Data and Estimation Strategy

In this paper utilization is measured using a weighted index of quantities of services. We adopt this approach, instead of using Medicare expenditures, because it sidesteps the difficult problem of deflating Medicare expenditures across regions to "undo" differential payments made by Medicare for the same service in different areas. These differentials are introduced to offset differences in costs experienced by the providers of care and for other reasons. Deflated expenditures are also problematic to the extent that the residents of an area receive services in another area. In such cases, the price index of the area of residence is not the appropriate deflator.[6]

We count the number of specific services received by the resident of an area, regardless of the area where the services were provided. Each detailed service is then weighted by the national reimbursement rate for that service; the sum of the weighted quantities divided by the number of Medicare enrollees is the total utilization for each area. Because this approach relies on billing codes for thousands of detailed services, systematic differences across areas in coding could introduce inaccuracies into this measure. Also, services not covered by Medicare are not included.

The year of the study is 1990, with the utilization and mortality measures based on an average of 1989–91. Many of the other measures are obtained

4. See Evans, Tosteson, and Kinney (1984), Chappie and Lave (1982), and Ozkaynak and Thurston (1987).

5. See Kennedy, Kawachi, and Prothrow-Stith (1996), Kaplan et al. (1996), and Lynch et al. (1998).

6. The Medicare records define residence as the location where the individual receives Social Security retirement checks.

from the 1990 Census of Population. There are 224 MSAs with populations exceeding 100,000.[7] In addition, residents of MSAs with less than 100,000 are aggregated to one group within each state and residents outside MSAs are also aggregated to one group per state. The result is 313 areas.[8]

In this paper the areas are aggregated into seven regions:

Region	Census Divisions and States
North	New England, Middle Atlantic, and East North Central
Upper South	Delaware, Maryland, Washington, D.C., Virginia, and West Virginia
Deep South	North Carolina, South Carolina, Georgia, and East South Central
Florida	Florida
West South	West South Central
Big Sky	West North Central, Montana, Idaho, Wyoming, and Colorado
West	Pacific, Arizona, New Mexico, Utah, and Nevada

This regional breakdown was developed by a geographer, Ge Lin, who found it to be more useful than the conventional census regions, or divisions, in studying disability among the elderly (Lin 2000). We find this breakdown intuitively appealing, especially for the distinctions it makes among the southern states and among the mountain states and its treatment of Florida as a separate region.

We also aggregate areas according to their total population size in the following manner: (1) over 500,000, (2) 250,000 to 500,000, (3) 100,000 to 250,000, (4) under 100,000 (aggregated to a single area within a state), and (5) non-MSAs (aggregated to a single area within each state). When regions and population size are used as dummy variables, the omitted categories are "North" and "over 500,000."

10.4 Results

Table 10.1 presents a list of variables included in this paper, giving the short name, definition, and source. For a fuller explanation of the derivation of the utilization measures, see the appendix. The utilization measure, mortality, percent high school dropout (LOED), and real income have all been adjusted for age and sex. Cigarette use and obesity are state measures; the same value is assigned to every area within each state. Particulate concentration (Pollution) is only available for MSAs > 100,000.

Table 10.2 provides summary statistics for each variable. The means and standard deviations are calculated by weighting each area by its share of the population white aged sixty-five–eighty-four. Looking first at the

7. One other MSA > 100,000, St. Cloud, Minnesota, was excluded from the study because of problems with the mortality data.

8. Some states do not have any MSAs with less than 100,000 or do not have any non-MSA residents.

Table 10.1 Names, Definitions, and Sources of Variables

Variable	Definition	Source
TOTUTIL	Total health care utilization, per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,f,g] (1989–1991)
INUTIL	Inpatient utilization (including institutional reimbursement and physician services), per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,f,g] (1989–1991)
OUTUTIL	Outpatient utilization (including institutional reimbursement for same day services, physician, and miscellaneous services), per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,f,g] (1989–1991)
TOTADM	Weighted total hospital admissions, per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,f] (1989–1991)
MEDADM	Weighted hospital medical admissions, per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,f] (1989–1991)
SURGADM	Weighted hospital surgical admissions, per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,f] (1989–1991)
TOTPHYS	Total physician utilization (inpatient and outpatient), per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,g] (1989–1991)
EANDM	Physician utilization for evaluation and management services (inpatient and outpatient), per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,g] (1989–1991)
DIAG	Physician utilization for diagnosis (inpatient and outpatient), per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,g] (1989–1991)
TREAT	Physician utilization for procedures/treatment (inpatient and outpatient), per white Medicare enrollee 65–84[a] (1989–1991)	HCFA[e,g] (1989–1991)
MORT	Deaths, per 1,000 whites 65–84[a] (average 1989–1991)	HCFA[e] (1989–1991)
LOED	Percent of whites 65–84[a] with less than 12 years of schooling (1990)	U.S. Census of Population (1990)
REALINC	Mean income for whites aged 65–84[a] (1990) deflated by cost of living index[c] (1991)	U.S. Census of Population (1990)
CIGS	Per capita sales by state (packs) (average 1984–1989)	Tobacco Institute (1998)
OBESE	Percent obese[d] by state, adjusted for race (1991)	Mokdad et al. (1999)
POLUTN	Mean PM-10 concentration (particulate matter 10 microns or smaller in diameter, $\mu g/m^3$; average	Shprentz (1996)
BLACK	Percent of total population black (1990)	Area Resource File (1992)

[a]Standardized for age and sex.

[b]HCFA 5 percent samples (MEDPAR, Outpatient SAF, BMAD, HHA SAF, Hospice SAF).

[c]COL predicted from a regression of U.S. Chamber of Commerce cost-of-living index for 109 metropolitan areas (1991) on standardized wage index and median property values (1990).

[d]Body mass index (weight divided by square of height) ≥ 30 kg/m^2.

[e]Hiskew 20 percent random sample.

[f]MEDPAR 20 percent random sample.

[g]BMAD 5 percent random sample.

Table 10.2 Summary Statistics

	Mean[a]	SD[a]	CV[a]	Percentile 25th	50th	75th	Minimum	Maximum
				Part A: All Areas (N = 313)				
TOTUTIL	3,265	368	11.3	2,870	3,088	3,375	2,316	4,368
INUTIL	2,132	207	9.7	1,903	2,063	2,231	1,576	2,931
OUTUTIL	1,133	254	22.4	930	1,051	1,169	691	1,998
TOTADM	1,783	178	10.0	1,589	1,735	1,888	1,352	2,423
MEDADM	933	138	14.8	793	904	1,004	567	1,518
SURGADM	849	65	7.7	789	840	889	615	1,083
TOTPHYS	1,195	237	19.9	975	1,096	1,226	797	1,976
EANDM	400	82	20.5	318	359	397	235	660
DIAG	210	61	29.2	157	185	222	100	460
TREAT	585	120	20.6	488	546	637	377	1,011
MORT	38.3	3.1	8.1	36.1	38.8	41.1	29.2	51.8
LOED	0.382	0.098	25.7	0.318	0.388	0.459	0.134	0.691
REALINC	14,022	1,570	11.2	12,772	13,995	15,373	9,473	21,105
CIGS	114.7	16.2	14.1	107.3	112.6	124.3	62.4	193.4
OBESE	0.118	0.018	15.1	0.103	0.120	0.132	0.082	0.158
BLACK	0.108	0.088	81.0	0.018	0.061	0.143	0.001	0.425
				Part B: MSAs > 100,000 (N = 224)				
TOTUTIL	3,340	388	11.6	2,880	3,113	3,484	2,316	4,368
INUTIL	2,136	215	10.1	1,874	2,056	2,238	1,576	2,931
OUTUTIL	1,204	267	22.2	955	1,084	1,218	691	1,998
TOTADM	1,766	179	10.1	1,567	1,710	1,889	1,352	2,423
MEDADM	906	126	13.9	777	872	980	567	1,518
SURGADM	859	71	8.3	787	850	914	615	1,083
TOTPHYS	1,274	243	19.1	1,012	1,132	1,273	797	1,976
EANDM	430	83	19.3	328	373	410	235	660
DIAG	230	63	27.2	165	195	235	117	460
TREAT	613	127	20.8	503	566	652	377	1,011
MORT	38.2	3.1	8.2	36.2	38.9	41.3	29.2	51.8
LOED	0.345	0.080	23.2	0.305	0.368	0.425	0.167	0.691
REALINC	14,464	1,536	10.6	13,221	14,402	15,679	9,473	21,105
CIGS	112.9	13.8	12.2	107.3	112.6	124.3	62.4	193.4
OBESE	0.116	0.017	14.8	0.103	0.120	0.133	0.082	0.151
POLUTN	29.3	6.1	20.9	23.7	26.4	29.1	17.2	60.4
BLACK	0.124	0.077	62.2	0.028	0.076	0.154	0.001	0.425

Notes: SD = standard deviation; CV = coefficient of variation; *N* = number of observations; MSA = metropolitan statistical area. For explanations of variables, see table 10.1.

[a]Weighted by population: whites aged sixty-five to eighty-four.

means, we see that inpatient utilization accounts for about two-thirds of the total and outpatient utilization one-third. Admissions are approximately evenly divided between medical and surgical. Approximately one-half of total physician utilization is accounted for by treatment (procedures), about one-third by evaluation and management, and about one-sixth by diagnostic interventions.

The utilization measure shows considerably more variation across areas than does mortality. The relative variation in outpatient utilization is more than double that for inpatient utilization. As between medical admissions and surgical admissions, the former has twice the variation of the latter. Diagnosis has the most variation of the three types of physician services; all three have much greater variation than hospital admissions. This difference may be explained in part by more random variation in the measure of outpatient utilization, which has a smaller mean and is calculated from a smaller sample.

10.4.1 Utilization Indexes by Region and Population Size

Tables 10.3 and 10.4 show indexes of utilization for areas grouped by region or population size for various types of utilization. All indexes are based on U.S. = 100. All are adjusted for age and sex, and areas are weighted by their population of whites sixty-five–eighty-four. The first column of table 10.3 shows that total utilization is much greater in Florida than in the rest of the country. Utilization is lowest in Big Sky. Across areas grouped by population size, total utilization is highest in the areas with over 500,000 population, and the 250,000–500,000 population group is second highest. The other three categories all have below-average utilization, with little difference among them.

Comparisons between indexes for inpatient (INUTIL) and outpatient (OUTUTIL) utilization (table 10.3 columns [2] and [3]) show many substantial differences, both for regions and population size. Most noteworthy is Florida, where the inpatient index is slightly below the national average, but outpatient utilization is approximately 55 percent above. In Big Sky the direction of difference is reversed; the inpatient index exceeds the outpatient index by more than 20 percentage points. Areas of large population size tend to show relatively more utilization of outpatient care; the reverse is true for MSAs < 100,000 and the areas that are not MSAs.

Substantial regional and population size differences in the indexes for medical admissions and surgical admissions can be seen in table 10.4. In Florida, the index for surgical admissions is 15 percentage points higher than for medical admissions; the West region also has relatively more surgical admissions. In the three southern regions, medical admissions tend to be relatively higher than surgical admissions, but the only big differential is in the Deep South.

The final utilization comparisons in table 10.4 are among three types of

Table 10.3 **Utilization Indexes, by Region and Population Size (U.S. = 100)**

	TOTUTIL	INUTIL[a]	OUTUTIL[b]
	Part A: All Areas (N = 313)		
Region			
North	96.8	97.8	95.1
Upper South	101.2	102.4	98.9
Deep South	102.7	104.8	98.6
Florida	117.5	97.4	155.3
West South	101.8	104.9	95.9
Big Sky	91.8	99.3	77.7
West	101.8	100.3	104.5
Population size			
>500,000	103.6	101.4	107.9
250,000–500,000	99.5	95.8	106.4
100,000–250,000	94.8	95.7	93.2
<100,000	96.9	100.3	90.5
Not MSA	94.9	99.2	86.7
U.S. expenditure per enrollee	3,265	2,132	1,133
	Part B: MSAs > 100,000 (N = 224)		
Region			
North	96.1	98.1	92.5
Upper South	100.1	99.2	101.8
Deep South	100.5	102.3	97.1
Florida	116.0	97.2	149.3
West South	101.6	104.9	95.8
Big Sky	93.1	101.6	78.1
West	102.2	102.2	102.0
U.S. expenditure per enrollee	3,340	2,136	1,204

Notes: All indexes standardized for age and sex. Area values weighted by population: whites aged sixty-five to eighty-four. N = number of observations; MSA = metropolitan statistical area. See table 10.1 for explanations of variables.

[a]Includes hospital and physician.

[b]Includes hospital, physician, and miscellaneous services.

physician services: evaluation and management, diagnosis, and treatment (surgical and nonsurgical procedures). The differences for Florida are huge, with the index for diagnostic tests 63 percent above the U.S. average, while evaluation and management is only 27 percent above. The procedures/treatment index is intermediate at 45 percent above the U.S. average. When only the areas above 100,000 are compared, the differentials are slightly smaller. In Big Sky the diagnostic test index is particularly low: 14 percentage points below the procedures/treatment index in the same region.

10.4.2 Correlations among the Different Measures of Utilization

Most measures of utilization are positively correlated, suggesting that the forces that influence variation in utilization across areas are stronger

Table 10.4 Hospital Admissions Indexes, by Region and Population Size (U.S. = 100)

	TOTADM	MEDADM	SURGADM	TOTPHYS[a]	EANDM[a]	DIAG[a]	TREAT[a]
Part A: All Areas (N = 313)							
Region							
North	98.5	98.8	98.2	94.0	100.1	95.4	89.3
Upper South	102.2	105.4	98.8	98.5	99.6	95.5	98.9
Deep South	107.3	113.5	100.4	92.7	91.0	91.0	94.5
Florida	92.3	84.8	100.7	142.0	126.6	162.8	145.0
West South	105.8	107.0	104.4	97.5	91.7	99.0	101.0
Big Sky	101.1	101.9	100.2	85.3	80.5	77.2	91.6
West	97.8	94.4	101.4	111.2	110.3	104.9	114.0
Population size							
>500,000	100.0	98.4	101.7	109.0	111.6	112.8	105.8
250,000–500,000	95.4	91.1	100.1	102.7	96.6	104.4	106.2
100,000–250,000	96.2	94.0	98.6	92.4	87.7	92.1	95.7
<100,000	102.1	105.2	98.6	89.5	88.5	83.3	92.4
Not MSA	101.6	105.5	97.3	86.3	84.2	80.5	89.8
U.S. expenditure per enrollee	1,783	933	849	1,195	400	210	585
Part B: MSAs > 100,000 (N = 224)							
Region							
North	99.4	100.8	98.0	91.7	97.7	93.3	86.9
Upper South	97.7	98.1	97.3	102.1	100.0	101.6	103.8
Deep South	104.6	106.7	102.2	91.5	86.4	90.1	95.6
Florida	92.6	86.3	99.2	136.4	121.7	153.6	140.3
West South	105.7	105.9	105.6	97.6	91.1	97.1	102.3
Big Sky	103.3	105.2	101.4	85.3	81.7	77.6	90.8
West	100.3	99.0	101.7	108.3	108.1	100.7	111.3
U.S. expenditure per enrollee	1,766	906	859	1,274	430	230	613

Note: See table 10.3.

[a]Includes inpatient and outpatient.

than the possibilities for substitution between various types of utilization. For example, the coefficient of correlation between inpatient and outpatient utilization is 0.27, even though there are surely some opportunities for substitution between inpatient and outpatient care. Similarly, although some health problems can be treated either medically or surgically, the correlation between medical admissions and surgical admissions is 0.47. The largest negative correlation, –0.13, is between medical admissions and physicians' diagnostic services. (For a full set of correlation coefficients see 10A.1.)

10.4.3 Mortality Indexes

Table 10.5 presents mortality indexes for areas grouped by region or by population size. As in the utilization tables, all indexes have been adjusted for age and sex, and areas are weighted by the population of whites aged sixty-five–eighty-four in those regions. The most striking result is the low mortality in Florida, which is slightly more than 10 percent below the U.S.

Table 10.5 **Mortality Indexes, by Region and Population Size (U.S. = 100)**

	MORT	Ages 65–74	Ages 75–84	Men	Women
Part A: All Areas (N = 313)					
Region					
North	102.2	102.3	102.0	101.9	102.5
Upper South	106.4	107.4	105.5	106.3	106.5
Deep South	108.5	109.7	107.5	112.0	104.5
Florida	89.5	90.0	89.2	90.3	88.7
West South	103.9	104.0	103.8	104.3	103.4
Big Sky	94.0	93.2	94.6	95.4	92.4
West	94.0	92.8	94.9	91.0	97.3
Population size					
>500,000	99.8	99.7	99.9	98.7	101.1
250,000–500,000	98.1	97.1	98.8	97.8	98.4
100,000–250,000	100.7	100.6	100.8	101.4	100.0
<100,000	101.7	102.0	101.4	102.8	100.4
Not MSA	99.8	100.1	99.5	101.6	97.7
Deaths per 1,000	38.31	26.16	59.68	48.95	30.72
Part B: MSAs > 100,000 (N = 224)					
Region					
North	102.9	103.4	102.6	103.1	102.8
Upper South	104.4	103.8	104.8	103.6	105.2
Deep South	108.7	110.2	107.6	112.0	105.1
Florida	88.9	89.8	88.2	90.5	87.1
West South	104.7	103.5	105.6	105.4	103.9
Big Sky	97.7	96.8	98.3	98.1	97.2
West	94.5	93.4	95.3	92.2	97.1
Deaths per 1,000	38.20	26.03	59.60	48.41	30.92

Note: See table 10.3.

average. Also below the U.S. average are Big Sky and West regions. The other four regions all have above average mortality, with the Deep South experiencing the highest rate at more than 8 percent above the U.S. average. When areas are grouped by population size, the most notable result is that the mortality indexes are approximately the same across all the groups. Apparently despite the many socioeconomic and other differences that exist between the large and the small metropolitan and nonmetropolitan areas, white death rates at ages sixty-five–eighty-four do not vary with population size.

The second and third columns of table 10.5 allow comparisons of mortality between ages sixty-five–seventy-four and seventy-five–eighty-four (adjusted for sex mix). On the whole, the indexes are very similar. The regional rankings of mortality for the two age groups are almost identical. There is a slight tendency for the regional differentials to be smaller at ages seventy-five–eighty-four than at sixty-five–seventy-four. When age-adjusted mortality rates for men and women are compared (columns [4] and [5] of table 10.5), two substantial regional differentials are evident. In Deep South the relative mortality index is more than 7 percentage points higher for men than for women. In West, the index for men is 6 percentage points lower than for women.

10.4.4 Socioeconomic and Other Indexes

Differentials in socioeconomic and other indexes across areas grouped by population size and region are shown in table 10.6. Florida again stands out from the rest of the country in several respects. The percentage of high school dropouts is the lowest and real income the highest of all the regions. Only the West rivals Florida in having a low percentage of elderly with less than twelve-years schooling. By contrast, the percent of dropouts is particularly high in the Deep South. Across the population size groups, the patterns for the percentage of high school dropouts and real income are quite systematic, with the former indexes rising and the latter falling as population size falls.

Regional differences in cigarette use and obesity are not as large as for the percentage with low education and have distinctive patterns of their own. Cigarette use is highest in the Deep South and lowest in the West. Obesity is highest in the North and West South and lowest in Florida. Both cigarette use and obesity are lowest in the two largest population size groups and highest in the three other groups. In this respect, the pattern is similar to that for low educational attainment.

The reasons for including the percent of total black population in 1990 (BLACK) in the study will become apparent in discussion of the mortality regressions. For the present, we note that this variable has great regional variation, with extremely high rates in the Upper South and Deep South and extremely low rates in Big Sky and West. The index is much above av-

Table 10.6 **Socioeconomic and Other Indexes, by Region and Population Size (U.S. = 100)**

	LOED[a]	REALINC[a]	CIGS	OBESE	BLACK	POLUTN
Part A: All Areas (N = 313)						
Region						
North	102.2	95.6	102.0	108.0	94.1	
Upper South	109.6	107.5	105.9	95.9	167.8	
Deep South	131.0	96.3	118.3	97.6	195.2	
Florida	73.3	112.3	106.4	83.0	121.6	
West South	115.4	104.0	97.3	105.3	126.0	
Big Sky	100.1	104.1	94.8	101.0	38.5	
West	75.9	100.7	83.9	88.1	48.9	
Population size						
>500,000	88.4	103.3	97.9	98.0	125.5	
250,000–500,000	95.1	103.1	99.4	98.9	78.8	
100,000–250,000	100.4	101.8	100.9	102.2	74.1	
<100,000	116.0	94.0	104.1	102.8	77.4	
Not MSA	119.6	94.2	102.2	102.9	68.3	
U.S. average	0.382	14,022	114.7	0.118	0.108	
Part B: MSAs > 100,000 (N = 224)						
Region						
North	109.7	94.8	102.6	109.1	106.6	97.2
Upper South	95.6	118.0	107.1	90.5	203.0	90.2
Deep South	121.4	101.9	118.3	98.3	168.3	99.0
Florida	79.8	108.5	108.1	84.2	105.3	81.7
West South	110.9	108.8	97.6	107.9	118.9	87.3
Big Sky	94.9	103.8	98.8	97.3	64.7	96.4
West	80.9	99.0	85.4	89.1	49.2	120.8
U.S. average	0.345	14,464	112.9	0.116	0.124	29.3

Note: See table 10.3.

[a]Standardized for age and sex.

erage in the largest metropolitan areas and considerably below average in all the others.

The last variable in table 10.6, pollution, is only measured for the MSAs greater than 100,000. The index for the West is 21 percent above the U.S. average; all other regions are below the U.S. average, with the lowest rate in Florida. Across population size groups, the pollution index declines steadily from the largest to the smallest.

10.4.5 Correlations among Variables

Some variables, such as low education and real income, are highly correlated with one another; the coefficient is –0.61. Low education is also significantly correlated with cigarettes (0.38) and obesity (0.37). All three variables are significantly correlated with mortality: low education (0.49), cigarettes (0.44), and obesity (0.41). For a full matrix of correlation coefficients among all the variables, see 10A.2.

10.4.6 Regression Analysis: Utilization

In this section, we consider what factors appear to explain the various measures for utilization. All variables are in natural logs except for the region and population size dummy variables. All regressions are run across the 313 areas and across the 224 MSAs > 100,000. At a theoretical level, the relation between low education and utilization is uncertain. It might be negative because individuals with less than twelve years of schooling might lack information about health care or might have less easy access to care. On the other hand, the relationship might be positive to the extent that those with less education are in worse health and require more care.

The predictive relation between income and utilization is also uncertain. If higher-income individuals are in better health, the relationship might be negative, but the relationship could be positive if there is a strong positive income elasticity of demand for care. Among other considerations, higher-income individuals are more likely to have private insurance that supplements Medicare.

Finally, because poor health usually results in increased utilization of health care, we expect mortality to be positively related to utilization to the extent that mortality is a good indicator of poor health. The relationship could be negative if this effect is outweighed by a reverse causality running from greater utilization to lower mortality. Because of the possibility of reverse causality, the parameter estimate for deaths per 1,000 whites aged sixty-five–eighty-four, average 1989–91 (MORT) should be regarded as a lower-bound estimate of the true coefficient.

Table 10.7 presents regression results for our measure of total utilization for three specifications. The first includes only the region and population size dummies, the second the two socioeconomic variables and mortality, and the third all the variables together. The results for the 224 MSAs are similar to those for the 313 areas and are available in table 10A.3. Probably the most striking result is the large coefficient for MORT: With all variables included, it is 0.51 (0.08). Under the reasonable assumption that the mortality rate is a good indicator of the health of the population, we infer that variation in health status across areas is a major determinant of health care utilization among whites aged sixty-five–eighty-four. Another notable result is the large increase in the Florida coefficient when the other variables are added to the regression. All the population size dummies have significant negative coefficients; that is, utilization is greater in MSAs larger than 500,000 than in any of the other areas. One likely interpretation is that patients in large metropolitan areas find it easier to obtain care (because of closer proximity to hospitals and physicians and the availability of a wide range of specialists).

Table 10.7 Utilization Regression Results, OLS

	Ln TOTUTIL			Ln INUTIL	Ln OUTUTIL
R^2	0.366	0.090	0.450	0.343	0.652
Upper South	0.053		0.029	0.022	0.036
	(0.025)		(0.025)	(0.024)	(0.037)
Deep South	0.080		0.040	0.027	0.063
	(0.018)		(0.019)	(0.018)	(0.027)
Florida	0.193		0.270	0.113	0.496
	(0.021)		(0.023)	(0.022)	(0.034)
West South	0.064		0.049	0.064	0.021
	(0.019)		(0.020)	(0.019)	(0.029)
Big Sky	–0.028		0.014	0.092	–0.148
	(0.018)		(0.019)	(0.018)	(0.028)
West	0.038		0.091	0.094	0.087
	(0.015)		(0.017)	(0.016)	(0.025)
250,000–500,000	–0.064		–0.058	–0.053	–0.065
	(0.020)		(0.019)	(0.018)	(0.027)
100,000–250,000	–0.090		–0.090	–0.074	–0.118
	(0.021)		(0.020)	(0.019)	(0.029)
<100,000	–0.061		–0.060	–0.027	–0.117
	(0.016)		(0.016)	(0.015)	(0.024)
Not MSA	–0.082		–0.079	–0.041	–0.152
	(0.014)		(0.015)	(0.015)	(0.022)
Ln LOED		–0.080	0.036	0.043	0.020
		(0.033)	(0.036)	(0.034)	(0.052)
Ln REALINC		0.151	0.026	–0.032	0.147
		(0.072)	(0.074)	(0.071)	(0.108)
Ln MORT		0.361	0.515	0.694	0.216
		(0.086)	(0.084)	(0.080)	(0.122)
Intercept	8.086	5.247	5.986	5.458	4.853
	(0.009)	(0.730)	(0.763)	(0.729)	(1.113)

Notes: MSA = metropolitan statistical area. See table 10.1 for explanations of variables. Numbers in parentheses are standard errors. Number of observations = 313.

Table 10.7 also presents regression results for inpatient utilization and outpatient utilization for the specification that includes all the variables. The coefficient for mortality is very large for inpatient care, but much smaller for outpatient care. For Florida, the reverse is true, with a huge coefficient for outpatient care and a much smaller (but still statistically significant coefficient) for inpatient care. In contrast, the Big Sky region has a large, statistically significant positive coefficient for inpatient care and a negative one for outpatient care. Clearly, regions differ both with regard to overall utilization as well as with respect to specific components of care. Neither low education nor real income are significantly related to utilization after controlling for the other variables. This result may reflect the offsetting theoretical considerations discussed previously.

Table 10.8 Utilization Regression Results, by Type of Service, OLS

	Ln MEDADM	Ln SURGADM	Ln EANDM	Ln DIAG	Ln TREAT
R^2	0.526	0.261	0.549	0.570	0.609
Upper South	0.024	–0.019	0.035	0.025	0.076
	(0.031)	(0.020)	(0.040)	(0.054)	(0.037)
Deep South	0.046	0.001	–0.029	0.033	0.064
	(0.023)	(0.015)	(0.030)	(0.040)	(0.028)
Florida	0.058	0.077	0.264	0.499	0.464
	(0.029)	(0.018)	(0.037)	(0.049)	(0.034)
West South	0.063	0.051	–0.030	0.080	0.112
	(0.025)	(0.016)	(0.032)	(0.042)	(0.029)
Big Sky	0.139	0.064	–0.115	–0.138	0.042
	(0.024)	(0.015)	(0.030)	(0.041)	(0.028)
West	0.081	0.067	0.078	0.062	0.242
	(0.021)	(0.013)	(0.027)	(0.036)	(0.025)
250,000–500,000	–0.067	–0.013	–0.156	–0.140	–0.039
	(0.023)	(0.015)	(0.030)	(0.040)	(0.028)
100,000–250,000	–0.087	–0.036	–0.213	–0.184	–0.083
	(0.025)	(0.016)	(0.032)	(0.042)	(0.029)
<100,000	0.007	–0.023	–0.196	–0.254	–0.060
	(0.020)	(0.013)	(0.026)	(0.034)	(0.024)
Not MSA	0.009	–0.039	–0.235	–0.280	–0.110
	(0.019)	(0.012)	(0.024)	(0.032)	(0.022)
Ln LOED	0.084	0.013	–0.009	0.064	0.043
	(0.044)	(0.028)	(0.057)	(0.076)	(0.053)
Ln REALINC	–0.147	0.083	–0.126	0.170	0.304
	(0.092)	(0.059)	(0.118)	(0.157)	(0.109)
Ln MORT	1.100	0.466	0.190	–0.116	0.106
	(0.104)	(0.067)	(0.133)	(0.178)	(0.123)
Intercept	4.272	4.250	6.560	4.239	3.046
	(0.945)	(0.605)	(1.212)	(1.618)	(1.122)

Notes: See table 10.7.

Table 10.8 presents similar regression results for medical and surgical admission and the three types of physician services. The coefficient for mortality is extremely large for medical admissions, no doubt reflecting the severe illness of many patients with neoplastic, cardiovascular, and cerebrovascular diseases who are admitted to medical services with little hope of altering the final outcome. The mortality coefficient for surgical admissions is less than half that for medical admissions, but still highly significant. In contrast, none of the three types of physician utilization has a mortality coefficient that is significantly different from zero.

The relationship between mortality and utilization reported in this paper is echoed in a study by Frohlich, Fransoo, and Roos (2001) of twelve communities in Winnipeg, Manitoba. They found that age-sex adjusted deaths before age seventy-five, their Premature Mortality Rate (PMR), was positively correlated with most types of care. However, PMR was not correlated with visits to specialists and negatively correlated with "high profile" procedures such as magnetic resonance imagings (MRIs), coronary artery bypass grafts (CABGs), hip and knee replacements, and preventive services.

The coefficients for Florida are particularly large for diagnostic and treatment services, smaller but still highly significant for evaluation and management, and smallest for hospital admissions. The Big Sky region has notably large negative mortality coefficients for evaluation and management and diagnostic services and a notably large positive coefficient for medical admissions. In comparisons of utilization across areas grouped by population size, the most striking result is the much higher utilization of evaluation and management and diagnostic services in MSAs > 500,000 relative to those with 250,000–500,000, and especially in areas with less than 250,000 or areas not classified as MSAs. The only significant result for the socioeconomic variables is a large, positive relation between real income and treatment. Result of regressions similar to those in table 10.8 but restricted to MSA > 100,000 are presented in table 10A.4.

Because there may be some causality running from utilization to mortality, we also ran two-stage least squares regressions. The results are reported in table 10A.5. The coefficients for predicted Ln mortality are typically much larger than in the ordinary least squares (OLS) regressions, but the standard errors are also much larger, raising questions about the reliability of the estimates.

10.4.7 Regression Analysis: Mortality

In addition to the dummy variables for region and population size, the mortality regressions include the percentage of individuals who did not finish high school and mean real income. Education and income have been shown to exhibit strong associations with mortality. Similarly, the harmful effects of cigarettes and obesity on health have been well established. Finally, given the Deaton and Lubotsky results, we also include a variable measuring the fraction of the population that is African American.

The mortality regression results are presented in table 10.9 in three specifications similar to those shown for utilization. First we note that the R^2s are considerably higher for mortality than for utilization regressions. This is despite the fact that none of the population-size dummies are significantly different from zero either when just the geographical dummies are included or when the other variables are entered into the regression. This is unlike the utilization regressions where there is a significant differential between the largest areas and the others.

Inclusion of the other variables results in a significant reduction in the negative coefficients for Big Sky and West. There is also a small reduction in the negative coefficient for Florida. Nevertheless, even after controlling

Table 10.9 **Mortality Regression Results, All Areas**

	(1)	(2)	(3)
R^2	0.485	0.521	0.627
Upper South	0.041		0.045
	(0.017)		(0.016)
Deep South	0.064		0.025
	(0.012)		(0.013)
Florida	–0.134		–0.096
	(0.014)		(0.015)
West South	0.019		0.020
	(0.013)		(0.013)
Big Sky	–0.079		–0.026
	(0.012)		(0.012)
West	–0.085		–0.009
	(0.010)		(0.012)
250,000–500,000	–0.013		0.001
	(0.013)		(0.012)
100,000–250,000	–0.004		0.009
	(0.014)		(0.013)
<100,000	–0.009		–0.004
	(0.011)		(0.011)
Not MSA	–0.016		–0.010
	(0.009)		(0.011)
Ln LOED		0.076	0.036
		(0.018)	(0.023)
Ln REALINC		–0.141	–0.121
		(0.042)	(0.049)
Ln CIGS		0.098	0.133
		(0.027)	(0.031)
Ln OBESE		0.148	0.111
		(0.024)	(0.025)
Ln BLACK		0.027	0.021
		(0.003)	(0.004)
Intercept	3.671	4.992	4.507
	(0.006)	(0.428)	(0.510)

Note: Number of observations = 313.

for all the other variables, Florida has a coefficient (relative to North) of –0.096 (0.01). It is the region with by far the lowest mortality. After controlling for the other variables, the highest regional mortality is in the Upper South.

Looking at the other variables we find that the percentage of high school dropouts has a positive coefficient until the geographic variable dummies are entered into the equation. Then the coefficient, while still positive, is not significantly different from zero. In the full regression, real income has a negative coefficient that is significantly different from zero. Cigarette use has the expected positive coefficient, which becomes larger when the geographic dummies are included. Obesity has the expected positive coefficient, but it becomes smaller when the geographic dummies are included. Finally, the percent black has a positive coefficient and also remains relatively unchanged by inclusion of the geographic dummies. In the regressions across the 224 MSAs > 100,000, shown in table 10A.7, the results are similar. In addition, the pollution index has the expected positive coefficient and remains relatively unchanged in the presence of the geographic dummies.

Preliminary efforts to find an effect of income inequality were unsuccessful. In fact, in a variety of specifications, the coefficient for inequality was always negative. Similarly, we found no evidence of a relationship between religiosity and mortality whether measured by percent of religious adherents or by frequency of church attendance.

10.5 Two Puzzles

Here we consider two specific puzzles regarding patterns of mortality and utilization. The first puzzle is why the percentage of African Americans in an area is positively related to the mortality of whites aged sixty-five–eighty-four. The second puzzle concerns the unusually low mortality and unusually high utilization in Florida relative to the rest of the country.

10.5.1 Percent Black and Mortality

Why should the mortality of whites aged sixty-five–eighty-four be significantly positively related to the percent of the total population of an area that is black? The possible answers fall into two main categories. First, there may be health differences *among the elderly whites* that are correlated with BLACK, differences that are not accounted for by the other variables in the mortality regression. Such differences could arise as a result of selective in- and out-migration under the reasonable assumption that the movers are healthier than the stayers.

Second, there may be differences *among the areas* that are correlated with the white mortality. Some of these differences could take the form of fewer, *locally* provided services or a different mix of services that affect white mortality. Some differences could be psychosocial, such as racial tension or the fear of crime.

In order to learn more about the relationship between percent black and percent white mortality, we tested to see whether it is stronger in areas of high or low segregation. Using three Cutler-Glaeser measures of segregation—centralization, isolation, and dissimilarity—we divided the areas into equal groups of high segregation and low segregation and ran the basic mortality regression for each group. In none of the three trials did the coefficient for Ln BLACK differ significantly between the high- and the low-segregation group. The mean coefficient for the three high-segregation groups regressions was 0.018 and for the low segregation groups 0.022. It appears that the relation between BLACK and MORT is about the same for areas of high and low segregation.

Another attempt to gain insight into the percent black effect produced more significant results. We divided the 224 MSAs > 100,000 into two equal groups based on the percentage change in the population of whites aged sixty-five–seventy-four between 1980 and 1990. The two groups are designated as "high-growth" and "low-growth," respectively. We then ran identical, full specification regressions for each group with the following results for the percent black coefficient: In the high-growth areas, the coefficient is 0.051 (0.010); in low-growth areas, the coefficient is 0.008 (0.009). The fact that percent black is not significantly related to mortality in the low-growth areas suggests rejection of explanations that rely on *differences among the areas.* If such differences were causal, it is not easy to see why they would not also be operative in the low-growth areas.

The large coefficient in the high-growth areas suggests the possibility of unmeasured differences in selective migration, with the healthier (or more health conscious) migrants moving to the areas with lower percent blacks. However, if there is also a selective out-migration, why doesn't that produce a significant coefficient for BLACK in the low-growth areas? One possible answer is that much of the out-migration probably comes from a relatively few, very large areas such as New York, Chicago, Philadelphia, Boston, and Detroit, whereas the destination of the migrants is more dispersed with many going to areas with relatively small populations. This means that the effect of out-migration on the mortality rates of the remaining populations could be much less than the effect of in-migration on mortality rates in the high-growth areas.

10.5.2 Floridian Exceptionalism

The data examined in this paper reveal that Florida is exceptional in three respects: (1) Among whites aged sixty-five–eighty-four utilization of care is much higher than in any other region, and the differential increases when other variables are introduced as controls; (2) mortality is by far the lowest in the country; (3) the positive relation between mortality and utilization that is evident in the rest of the country is not present in Florida.

Above-average Medicare spending in Florida has been well established in previous studies, for example, Wennberg and Cooper (1999). Our direct, detailed measures of utilization of services (rather than nominal or deflated Medicare spending) show that the Florida differential from the North of 0.193 (0.021) when only population size is controlled for rises to 0.270 (0.023) when education, real income, and mortality are included in the regression. Depending on the type of care, the size of the Florida differential varies enormously, from 0.058 (0.029) for medical admissions to 0.499 (0.049) for diagnostic services.

With respect to mortality the introduction of other variables reduces the negative coefficient for Florida from –0.134 (0.014) to –0.096 (0.015), but it still remains much larger than Big Sky, the region with the next lowest mortality of –0.026 (0.012).

The combination of low mortality and high utilization is one of the most intriguing aspects of Floridian exceptionalism. When total utilization in Florida is regressed on mortality (controlling for education and income, all variables in logs) the coefficient is slightly negative albeit not significantly different from zero. For the country as a whole, including Florida, the coefficient is 0.515 (0.084); when Florida is excluded the coefficient rises to 0.636 (0.092).

In order to gain some insight into Floridian exceptionalism, we examined each Florida MSA > 100,000 separately as shown in table 10.10. Predicted levels of utilization and mortality, obtained for each MSA from regressions that exclude Florida, are compared to actual levels, and the percent differential between actual and predicted calculated. We see that utilization is above predicted in every Florida MSA, but the differentials

Table 10.10 Percent Differential between Actual and Predicted Values for Florida MSAs > 100,000

Degrees North Latitude		TOTUTIL		MORT		Percent Differential	
		Actual	Predicted	Actual	Predicted	TOTUTIL	MORT
30.26	Pensacola	3,724	3,197	41.1	37.9	16.5	8.4
30.2	Jacksonville	4,084	3,310	40.5	37.8	23.4	7.0
29.4	Gainesville	3,548	3,190	42.7	36.7	11.2	16.4
29.11	Daytona Beach	3,342	2,524	30.7	37.4	32.4	–17.9
29.1	Ocala	3,331	2,610	33.1	38.8	27.6	–14.7
28.33	Orlando	4,074	3,120	37.8	37.7	30.6	0.3
28.04	Melbourne	3,858	2,843	35.8	36.9	35.7	–2.8
28.02	Lakeland	3,129	2,814	35.0	38.5	11.2	–8.9
27.58	Tampa	3,874	2,992	35.7	37.5	29.5	–4.7
27.29	Bradenton	3,442	2,800	36.3	36.7	23.0	–1.1
27.28	Fort Pierce	3,661	2,690	33.3	37.1	36.1	–10.4
27.2	Sarasota	3,667	2,478	30.1	35.3	48.0	–14.6
26.42	West Palm Beach	4,030	2,607	30.2	35.7	54.6	–15.4
26.39	Fort Meyers	3,769	2,435	29.3	36.9	54.8	–20.5
25.45	Miami	4,130	2,820	33.0	37.7	46.5	–12.5

Notes: MSA = metropolitan statistical area. See table 10.1 for explanations of variables. Percent differential is calculated by running regressions across 209 MSAs > 100,000 (Florida excluded), then predicting utilization and mortality for each Florida MSA using the regression equations and the MSA values, then calculating the percentage differential between observed and predicted.

tend to be largest in the southern portion of the state. The mortality differentials also tend to be greatest in the southern MSAs; indeed, the three most northern MSAs have actual mortality that is above the levels predicted from the regression. Two exceptions to the North versus South differences are Daytona Beach and Ocala; these relatively northern MSAs have utilization and mortality differentials that resemble those of the southern MSAs.

Is Florida the only state with exceptional results? To answer this question we examined several other states that have been mentioned in health policy discussions as being unusual with respect to utilization or mortality or both. With methods analogous to those used to obtain the results presented in table 10.10, we calculated percentage differentials between actual and predicted values for MSAs > 100,000 in Arizona, Minnesota, Nevada, Oregon, and Utah. The results presented in table 10.11 show some differentials, but nothing that comes close to challenging the characterization of Florida as "exceptional."

Another possible explanation for the low mortality rates in Florida is migration. Suppose that people who move to Florida are, on average,

Table 10.11 Percent Differential between Actual and Predicted Values for MSAs > 100,000 in Selected States

	TOTUTIL	MORT
Arizona		
Phoenix	17.8	–3.6
Tucson	5.7	6.0
Yuma	4.7	1.2
Minnesota		
Duluth	–5.8	10.9
Minneapolis	–5.5	–0.7
Rochester	19.5	–4.1
Nevada		
Las Vegas	–5.0	6.5
Reno	–5.4	0.2
Oregon		
Eugene-Springfield	–6.8	–7.1
Medford	–9.7	–10.3
Portland-Vancouver	–13.6	7.0
Salem	–12.6	–7.4
Utah		
Provo-Orem	–12.8	7.2
Salt Lake City-Ogden	–24.6	10.5

Notes: MSA = metropolitan statistical area. See table 10.1 for explanations of variables. Percent differential is calculated for each state by running regressions across MSAs > 100,000 (excluding the state in question), then predicting utilization and mortality for each MSA in that state using the regression equations and the MSA values, then calculating the percentage differential between actual and predicted.

healthier than their counterparts who did not move. Given the large share of Florida residents who have moved from other states, one would expect that Florida would be a very healthy region simply because of this selection effect.

To test this hypothesis, we used the Medicare claims database for 1998 in Miami and Tampa, Florida, two regions with large populations of retirees. We first compared mortality rates of current residents of these areas as a function of where they were living three years previously. The sample was limited to nonblacks aged sixty-eight–eighty-four, with a cutoff age of sixty-eight to ensure that we could match Medicare denominator information on zip code of residence from three years before when they were sixty-five. Migrants from the North experience a lower mortality probability (odds ratio equal to 0.80, 95 percent confidence interval of 0.71 to 0.91), which is consistent with the hypothesis that migrants tend to be somewhat healthier than nonmigrants. Migrants from other parts of the country, however, showed if anything slightly elevated mortality rates, although individually the effects were not significant. In any case, the overall influence of recent migrants (during the past three years) is minimal with regard to overall mortality rates because the proportion of recent movers—just 4.2 percent of the sample—is so small. Weighting the odds ratios by the proportion of people who migrated implies that the influence of this recent migration on overall mortality rates in the region is to reduce it by only about 0.5 percent.

The three-year window is probably too restrictive. Another approach is to use the first three digits of the individual's Social Security number. For this cohort, Social Security numbers were most likely issued while in their adult years, particularly during the 1940s through the 1960s when eligibility of Social Security gradually expanded to cover most employment sectors. This approach runs the risk of including in the "migrant" category individuals who may have been living in Florida for several decades. In any case, the results do not support the migration explanation; the one-third of the sample who received their Social Security number in Florida had slightly lower mortality than those who received their number in some other region.

If selective in-migration does not explain low mortality in the southern Florida MSAs, there are two other possibilities that need to be explored. First, the relatively benign climate for most of the year allows the elderly residents to pursue a great deal of physical activity, including golf, tennis, swimming, walking, and so on. Such activity is undoubtedly conducive to better health. Second, the low mortality in the southern Florida MSAs may result from a high level of social interaction among the elderly, as well as public services directed toward this very large voting bloc. Many of them live in communities populated primarily by other elderly where there is a great deal of eating out together, participating in social functions, and helping one another at times of physical or emotional stress.

Many social critics deplore age-restricted living arrangements and argue that the elderly would derive health and other benefits from interactions with members of younger generations. Reconciliation of these two points of view could lie in the classic quantity-quality trade-off. Holding the quantity of social interaction constant, the social critics may be correct that interactions across generations are more beneficial. But it also may be true that the greater quantity of social interactions in the elderly segregated communities more than offsets the lower value of a given unit of interaction.

As is apparent from the previous discussion, it is much easier to document Floridian exceptionalism than it is to explain it. We do not think that the high utilization is the cause of the low mortality because there is no support for this view in data for the rest of the country. When we tried utilization as a right-hand-side (RHS) variable in the mortality regression, the coefficient was positive in both OLS and two-stage least squares (2SLS) specifications. Nor do other studies find in comparisons between Florida and other regions that reductions in mortality are attributable to greater levels of care (Skinner, Fisher, and Wennberg 2001). One "demand-driven" explanation for both high utilization and low mortality is that Floridians are very concerned about health, and this concern may also be expressed in exercise, diet, and other behaviors that are demonstrably linked to longevity, as well as increased demand for medical care.

10.6 Summary

This paper examines 313 U.S. areas for differences in medical care utilization and mortality of whites aged sixty-five–eighty-four in 1990. Areas are grouped into seven regions and five groups based on population size. Utilization is measured by direct count of detailed services, weighted by the national reimbursement for each service.

Probably the most noteworthy result of the utilization regressions is the extent to which cross-area variation in utilization is related to variation in mortality. For total utilization, the elasticity is 0.515 (0.084) after controlling for region, population size of area, education, and real income. This is a lower-bound estimate; the true coefficient would be larger to the extent that there is a negative relationship running from utilization of care to mortality. The elasticity is especially large for medical admissions and especially small for physicians' diagnostic services and treatments.

Also noteworthy is the extent to which the well-known propensity for higher utilization in Florida is even larger after controlling for socioeconomic variables and mortality. The coefficient for Florida is 40 percent (8 percentage points) higher when the other variables are in the regression.

A third result worthy of comment is the much higher utilization in MSAs of over 500,000 population relative to other areas. The average differential is about 8 percent. Among the other areas there is no strong pattern related to population size. Similarly, there is no consistent pattern for the socioeconomic variables in their relationship to total utilization of care (although see McClellan and Skinner 1999).

The mortality regressions produced several noteworthy results. First, we find no relationship between mortality and population size. Elderly residents of large MSAs enjoy no advantage in life expectancy over their peers who live in small MSAs or outside MSAs, despite the well publicized differentials in the availability of medical care. Secondly, we find a very large negative coefficient for Florida. This region has by far the lowest mortality of any large region regardless of whether other variables are controlled for. Cigarette smoking, air pollution, and obesity have their expected positive coefficients. Last, we note a robust positive relationship between percent black and mortality of whites aged sixty-five–eighty-four. This relationship is particularly strong among areas with above-average growth of the elderly population between 1980 and 1990. Among low-growth areas, the coefficient is not significantly different from zero. This puzzle, and the exceptional results for Florida for utilization and mortality, requires further investigation.

Appendix

Procedures for Estimating Total Health Care Utilization (TOTUTIL) and Its Components

Inpatient Hospital Utilization

The hospital admissions measures of utilization are created using the Medicare Provider Analysis and Review File (MEDPAR) 20 percent sample. They are 1989–91 averages for nonblack Medicare enrollees, aged sixty-five–eighty-four.

Hospital admissions claims are weighted by the national average cost of the diagnosis related group (DRG). (There are over 500 diagnosis related groups, as coded using the International Classification of Diseases, 9th revision.) This average cost is calculated for each DRG by dividing the total national charges for a given DRG by the number of claims. Charges include the DRG price (sum of the reimbursement, primary payor reimbursement, primary payor amount, coinsurance amount, inpatient deductible, and blood deductible noncovered charges), the total per diem amount, and the amount paid over the DRG allowance.

The measure of utilization is calculated by summing the weighted number of claims for each area and dividing by the total number of enrollees in that area. The index is adjusted for sex and age using the indirect method. Each claim is classified as "medical" or "surgical" based on its DRG code.

Physician Utilization

The physician utilization measures are created using the part B Medicare Annual Data (BMAD) Procedure File 5 percent sample. They are 1989–91 averages for nonblack Medicare enrollees, aged sixty-five–eighty-four.

The physician claims are weighted by the national Medicare reimbursement amount, based on the HCFA Common Procedure Coding System (HCPCS) code. (This coding system is used primarily for billing Medicare for supplies, materials, injections, and services performed by health care professionals. There are over 12,000 HCPCS codes.) Four Medicare payment schedules are used to determine the reimbursement amount:

- Anesthesiology uniform relative value guide, 1999: The weight is set as the prevailing charge conversion factor (16.0) multiplied by the sum of the uniform base unit plus time units.
- Clinical Diagnostic Laboratory Fee Schedule (CLAB), 1999: The weight is set as the 60 percent national limitation amount (equal to 74 percent of the 1999 median) and adjusted to 1992 for inflation.
- Durable Medical Equipment, Prosthetics/Orthotics, and Supplies Fee Schedule (DMEPOS), 1999: The weight is set as the maximum fee schedule amount (equal to the midpoint of the statewide fee schedule amounts) and adjusted to 1992 for inflation.
- Relative Value Unit (RVU), 1992: The weight is set as the total relative value unit with a conversion factor of 31.001.

Some of the HCPCS codes in the claims data were adjusted because the earliest RVU schedule was published in 1992; however, many HCPCS codes changed between 1991 and 1992. In order to match the 1989–1991 BMAD data to the 1992 RVUs, we reassigned some of the HCPCS codes in the claims data to their respective 1992 codes. This reassignment was based on a crosswalk published by HCFA in the *Federal Register* (Vol. 56, No. 227).

The measure of utilization is calculated by summing the weighted number of claims for each area and dividing by the total number of enrollees. The index was adjusted for sex and age using the indirect method. Using the 1999 Berenson-Eggers Type of Service (BETOS) Public Use File, the physician claims were classified into four categories: evaluation & management; procedures/treatment; diagnosis (imaging and tests); and miscellaneous (durable medical equipment and other).

Hospital Outpatient

The utilization measure for institutional expenditures on outpatient care is extrapolated by calculating the ratio of national outpatient (outpatient hospital and freestanding surgery centers) physician expenditures to national institutional expenditures for outpatient care. This ratio is applied to the area outpatient physician expenditures to obtain area institutional outpatient utilization.

Denominator

The enrollment numbers, used as a denominator for all of the utilization measures, are calculated from the Health Insurance Skeleton Eligibility Write-Off File (hiskew) 20 percent sample. They are 1989–91 averages of nonblack people aged sixty-five–eighty-four who were ever enrolled in Medicare.

In order to remove HMO members, we delete anyone who has "ever been enrolled in an HMO" as reported in the hiskew file. This measure alone, however, removes too many people. To obtain a more accurate count of enrollees in an HMO at a moment in time, we use HCFA statistics published in the 1995 *Health Care Financing Review Statistical Supplement* for the percent of Medicare enrollees in an HMO for each state. This measure cannot be used alone because of the large difference in HMO membership between large and small cities in states with a high HMO rate.

To correct these problems, we combine the published HCFA state rates with the variation across MSAs in a given state as calculated from hiskew. We calculate the ratio of the HCFA state HMO rate to the hiskew state rate (a weighted average of the MSA HMO rates). We then apply this ratio to the individual MSA HMO rates. Finally, the utilization measures are adjusted by dividing by the percent of Medicare enrollees not in an HMO.

Table 10A.1 **Coefficients of Correlation[a] among Ten Measures of Utilization**

	TOTUTIL	INUTIL	OUTUTIL	TOTADM	MEDADM	SURGADM	TOTPHYS	EANDM	DIAG	TREAT
					Part A: All Areas (N = 313)					
TOTUTIL	1.000	0.748	0.842	0.562	0.420	0.651	0.836	0.728	0.738	0.778
INUTIL	0.748	1.000	0.272	0.947	0.856	0.780	0.338	0.352	0.222	0.314
OUTUTIL	0.842	0.272	1.000	0.046	–0.086	0.310	0.938	0.770	0.890	0.873
TOTADM	0.562	0.947	0.046	1.000	0.947	0.730	0.058	0.103	–0.014	0.051
MEDADM	0.420	0.856	–0.086	0.947	1.000	0.472	–0.087	0.027	–0.134	–0.122
SURGADM	0.651	0.780	0.310	0.730	0.472	1.000	0.346	0.227	0.250	0.400
TOTPHYS	0.836	0.338	0.938	0.058	–0.087	0.346	1.000	0.873	0.910	0.915
EANDM	0.728	0.352	0.770	0.103	0.027	0.227	0.873	1.000	0.807	0.630
DIAG	0.738	0.222	0.890	–0.014	–0.134	0.250	0.910	0.807	1.000	0.736
TREAT	0.778	0.314	0.873	0.051	–0.122	0.400	0.915	0.630	0.736	1.000
					Part B: MSAs > 100,000 (N = 224)					
TOTUTIL	1.000	0.751	0.847	0.588	0.484	0.623	0.861	0.727	0.724	0.813
INUTIL	0.751	1.000	0.285	0.954	0.888	0.828	0.391	0.411	0.213	0.373
OUTUTIL	0.847	0.285	1.000	0.086	–0.011	0.238	0.935	0.725	0.879	0.880
TOTADM	0.588	0.954	0.086	1.000	0.950	0.833	0.141	0.192	0.006	0.141
MEDADM	0.484	0.888	–0.011	0.950	1.000	0.619	0.051	0.193	–0.056	–0.002
SURGADM	0.623	0.828	0.238	0.833	0.619	1.000	0.267	0.143	0.117	0.359
TOTPHYS	0.861	0.391	0.935	0.141	0.051	0.267	1.000	0.857	0.892	0.911
EANDM	0.727	0.411	0.725	0.192	0.193	0.143	0.857	1.000	0.776	0.601
DIAG	0.724	0.213	0.879	0.006	–0.056	0.117	0.892	0.776	1.000	0.706
TREAT	0.813	0.373	0.880	0.141	–0.002	0.359	0.911	0.601	0.706	1.000

Notes: N = number of observations; MSA = metropolitan statistical area. See table 10.1 for explanations of variables.

[a]Weighted by population: whites aged sixty-five to eighty-four.

Table 10A.2 **Coefficients of Correlation[a] among Utilization, Mortality, and Other Variables**

	TOTUTIL	MORT	LOED	REALINC	OBESE	BLACK	CIGS	POLUTN
				Part A: All Areas (N = 313)				
TOTUTIL	1.000	0.119	–0.145	0.191	–0.158	0.383	0.055	
MORT	0.119	1.000	0.490	–0.275	0.411	0.398	0.443	
LOED	–0.145	0.490	1.000	–0.610	0.366	0.067	0.379	
REALINC	0.191	–0.275	–0.610	1.000	–0.193	0.287	–0.136	
OBESE	–0.158	0.411	0.366	–0.193	1.000	–0.081	0.209	
BLACK	0.383	0.398	0.067	0.288	–0.081	1.000	0.262	
CIGS	0.055	0.443	0.379	–0.136	0.209	0.262	1.000	
				Part B (N = 224)				
TOTUTIL	1.000	0.001	–0.170	0.143	–0.153	0.244	0.096	0.302
MORT	0.001	1.000	0.526	–0.216	0.531	0.395	0.403	0.086
LOED	–0.170	0.526	1.000	–0.547	0.474	0.127	0.336	–0.012
REALINC	0.143	–0.216	–0.547	1.000	–0.149	0.287	0.048	–0.214
OBESE	–0.153	0.531	0.474	–0.149	1.000	0.085	0.311	–0.040
BLACK	0.244	0.395	0.127	0.287	0.085	1.000	0.391	–0.047
CIGS	0.096	0.403	0.336	0.048	0.311	0.391	1.000	–0.273
POLUTN	0.302	0.086	–0.012	–0.214	–0.040	–0.047	–0.273	1.000

Notes: N = number of observations. See table 10.1 for explanations of variables.

[a]Weighted by population: whites aged sixty-five to eighty-four.

Table 10A.3 Utilization Regression Results, OLS, MSAs > 100,000

		Ln TOTUTIL		Ln INUTIL	Ln OUTUTIL
R^2	0.309	0.043	0.418	0.343	0.581
Upper South	0.037		0.021	0.003	0.058
	(0.036)		(0.037)	(0.034)	(0.055)
Deep South	0.053		0.011	0.006	0.022
	(0.027)		(0.027)	(0.025)	(0.040)
Florida	0.197		0.289	0.121	0.533
	(0.024)		(0.028)	(0.026)	(0.041)
West South	0.063		0.043	0.063	0.010
	(0.026)		(0.028)	(0.026)	(0.042)
Big Sky	–0.020		0.012	0.090	–0.146
	(0.028)		(0.027)	(0.025)	(0.040)
West	0.056		0.115	0.108	0.130
	(0.017)		(0.021)	(0.019)	(0.031)
250,000–500,000	–0.062		–0.055	–0.049	–0.062
	(0.021)		(0.019)	(0.018)	(0.029)
100,000–250,000	–0.087		–0.083	–0.066	–0.116
	(0.022)		(0.021)	(0.019)	(0.031)
Ln LOED		–0.090	0.025	–0.004	0.073
		(0.047)	(0.048)	(0.044)	(0.072)
Ln REALINC		0.093	0.066	–0.035	0.232
		(0.094)	(0.102)	(0.095)	(0.153)
Ln MORT		0.186	0.627	0.799	0.343
		(0.114)	(0.106)	(0.099)	(0.159)
Intercept	8.083	6.441	5.172	5.053	3.624
	(0.010)	(0.921)	(1.019)	(0.948)	(1.526)

Notes: MSA = metropolitan statistical area. See table 10.1 for explanations of variables. Number of observations = 224.

Table 10A.4 Utilization Regression Results, by Type of Service, OLS, MSAs > 100,000

	Ln MEDADM	Ln SURGADM	Ln EANDM	Ln DIAG	Ln TREAT
R^2	0.452	0.289	0.410	0.443	0.615
Upper South	–0.017	–0.041	0.040	0.034	0.137
	(0.044)	(0.029)	(0.061)	(0.079)	(0.052)
Deep South	0.006	0.003	–0.091	–0.037	0.057
	(0.032)	(0.021)	(0.044)	(0.058)	(0.038)
Florida	0.046	0.091	0.274	0.511	0.527
	(0.033)	(0.022)	(0.045)	(0.059)	(0.039)
West South	0.056	0.050	–0.036	0.022	0.132
	(0.033)	(0.022)	(0.046)	(0.060)	(0.039)
Big Sky	0.129	0.060	–0.130	–0.170	0.060
	(0.032)	(0.021)	(0.044)	(0.058)	(0.038)
West	0.085	0.084	0.107	0.089	0.284
	(0.024)	(0.016)	(0.034)	(0.044)	(0.029)
250,000–500,000	–0.060	–0.011	–0.154	–0.131	–0.038
	(0.023)	(0.015)	(0.032)	(0.041)	(0.027)
100,000–250,000	–0.073	–0.033	–0.205	–0.171	–0.085
	(0.025)	(0.016)	(0.034)	(0.045)	(0.029)
Ln LOED	–0.001	–0.002	0.012	0.078	0.072
	(0.056)	(0.038)	(0.078)	(0.102)	(0.067)
Ln REALINC	–0.144	0.109	–0.105	0.293	0.244
	(0.120)	(0.080)	(0.167)	(0.217)	(0.142)
Ln MORT	1.162	0.613	0.174	0.081	0.330
	(0.125)	(0.084)	(0.174)	(0.226)	(0.148)
Intercept	3.924	3.447	6.436	2.371	2.815
	(1.200)	(0.803)	(1.672)	(2.173)	(1.422)

Notes: See table 10A.3.

Table 10A.5 Utilization Regression Results for Total Health Care, Inpatient, and Outpatient Utilizations, Two-Stage Least Squares

	Part A: All Areas (N = 313)			Part B: MSAs > 100,000 (N = 224)		
	Ln TOTUTIL	Ln INUTIL	Ln OUTUTIL	Ln TOTUTIL	Ln INUTIL	Ln OUTUTIL
R^2	0.422	0.246	0.637	0.381	0.260	0.528
Upper South	0.018	0.022	0.009	0.000	–0.007	0.017
	(0.027)	(0.025)	(0.040)	(0.041)	(0.036)	(0.065)
Deep South	0.028	0.027	0.032	–0.022	–0.009	–0.043
	(0.021)	(0.020)	(0.031)	(0.031)	(0.027)	(0.049)
Florida	0.295	0.114	0.557	0.369	0.156	0.687
	(0.029)	(0.027)	(0.043)	(0.038)	(0.033)	(0.060)
West South	0.045	0.063	0.011	0.031	0.058	–0.013
	(0.020)	(0.019)	(0.031)	(0.031)	(0.027)	(0.049)
Big Sky	0.030	0.092	–0.109	0.036	0.100	–0.098
	(0.022)	(0.021)	(0.033)	(0.030)	(0.026)	(0.048)
West	0.105	0.094	0.122	0.153	0.124	0.204
	(0.020)	(0.019)	(0.030)	(0.025)	(0.022)	(0.040)
250,000–500,000	–0.054	–0.053	–0.054	–0.042	–0.043	–0.038
	(0.019)	(0.018)	(0.029)	(0.022)	(0.019)	(0.034)
100,000–250,000	–0.087	–0.074	–0.111	–0.072	–0.061	–0.095
	(0.020)	(0.019)	(0.030)	(0.023)	(0.020)	(0.037)
<100,000	–0.053	–0.027	–0.100			
	(0.017)	(0.016)	(0.025)			
Not MSA	–0.070	–0.041	–0.128			
	(0.017)	(0.016)	(0.025)			
Ln LOED	0.015	0.042	–0.031	–0.048	–0.036	–0.067
	(0.039)	(0.037)	(0.058)	(0.056)	(0.049)	(0.089)
Ln REALINC	0.034	–0.032	0.166	0.063	–0.037	0.225
	(0.075)	(0.071)	(0.112)	(0.112)	(0.097)	(0.177)
Predicted Ln MORT	0.758	0.703	0.811	1.332	1.106	1.702
	(0.185)	(0.174)	(0.276)	(0.229)	(0.198)	(0.362)
Intercept	5.000	5.424	2.438	2.549	3.907	–1.438
	(1.020)	(0.961)	(1.525)	(1.339)	(1.160)	(2.116)

Notes: First stage used to predict regressions can be found in table 10.9. See table 10.1 for explanations of variables. N = number of observations; MSA = metropolitan statistical area. Numbers in parentheses are standard errors.

Table 10A.6 Utilization Regression Results for Hospital Admissions and Physician Utilizations, Two-Stage Least Squares

	Ln MEDADM	Ln SURGADM	Ln EANDM	Ln DIAG	Ln TREAT
		Part A: All Areas (N = 313)			
R^2	0.450	0.204	0.544	0.564	0.608
Upper South	0.023	–0.029	0.019	0.001	0.080
	(0.033)	(0.021)	(0.043)	(0.057)	(0.039)
Deep South	0.044	–0.010	–0.047	0.007	0.069
	(0.025)	(0.017)	(0.033)	(0.044)	(0.030)
Florida	0.060	0.100	0.301	0.551	0.455
	(0.035)	(0.023)	(0.046)	(0.061)	(0.042)
West South	0.063	0.048	–0.036	0.071	0.114
	(0.025)	(0.016)	(0.032)	(0.043)	(0.030)
Big Sky	0.141	0.079	–0.091	–0.105	0.036
	(0.027)	(0.018)	(0.035)	(0.047)	(0.032)
West	0.082	0.080	0.099	0.092	0.236
	(0.024)	(0.016)	(0.031)	(0.042)	(0.029)
250,000–500,000	–0.067	–0.009	–0.150	–0.131	–0.040
	(0.024)	(0.015)	(0.031)	(0.041)	(0.028)
100,000–250,000	–0.086	–0.033	–0.208	–0.178	–0.084
	(0.025)	(0.016)	(0.032)	(0.043)	(0.030)
<100,000	0.008	–0.017	–0.186	–0.240	–0.063
	(0.021)	(0.014)	(0.027)	(0.036)	(0.025)
Not MSA	0.010	–0.030	–0.220	–0.260	–0.114
	(0.021)	(0.013)	(0.027)	(0.036)	(0.024)
Ln LOED	0.082	–0.006	–0.039	0.021	0.051
	(0.047)	(0.031)	(0.062)	(0.082)	(0.056)
Ln REALINC	–0.147	0.090	–0.115	0.187	0.301
	(0.092)	(0.060)	(0.119)	(0.159)	(0.109)
Predicted Ln MORT	1.123	0.684	0.553	0.392	0.011
	(0.225)	(0.147)	(0.293)	(0.391)	(0.268)
Intercept	4.181	3.366	5.087	2.176	3.432
	(1.246)	(0.812)	(1.617)	(2.162)	(1.481)
		Part B: MSAs > 100,000 (N = 224)			
R^2	0.358	0.229	0.394	0.419	0.587
Upper South	–0.024	–0.053	0.012	–0.008	0.111
	(0.044)	(0.031)	(0.065)	(0.086)	(0.056)
Deep South	–0.004	–0.015	–0.136	–0.102	0.016
	(0.034)	(0.023)	(0.050)	(0.065)	(0.043)
Florida	0.071	0.133	0.380	0.666	0.626
	(0.041)	(0.028)	(0.060)	(0.079)	(0.052)
West South	0.052	0.044	–0.052	–0.002	0.117
	(0.033)	(0.023)	(0.049)	(0.065)	(0.042)
Big Sky	0.137	0.073	–0.097	–0.121	0.090
	(0.033)	(0.023)	(0.048)	(0.064)	(0.042)
West	0.098	0.105	0.158	0.164	0.331
	(0.027)	(0.019)	(0.040)	(0.053)	(0.034)
250,000–500,000	–0.056	–0.004	–0.137	–0.107	–0.023
	(0.023)	(0.016)	(0.035)	(0.046)	(0.030)
100,000–250,000	–0.069	–0.027	–0.191	–0.150	–0.072
	(0.025)	(0.017)	(0.037)	(0.049)	(0.032)
Ln LOED	–0.024	–0.041	–0.085	–0.064	–0.018
	(0.061)	(0.042)	(0.090)	(0.118)	(0.077)

Table 10A.6 (continued)

	Ln MEDADM	Ln SURGADM	Ln EANDM	Ln DIAG	Ln TREAT
Ln REALINC	–0.145	0.107	–0.110	0.285	0.240
	(0.121)	(0.084)	(0.178)	(0.235)	(0.153)
Predicted Ln MORT	1.385	0.989	1.113	1.456	1.199
	(0.247)	(0.172)	(0.365)	(0.481)	(0.313)
Intercept	3.096	2.044	2.941	–2.750	–0.423
	(1.445)	(1.005)	(2.132)	(2.815)	(1.833)

Notes: First stage used to predict regressions can be found in table 10A.7. See text for explanations of variables. N = number of observations; MSA = metropolitan statistical area. Numbers in parentheses are standard errors.

Table 10A.7 Mortality Regression Results, MSAs > 100,000

	(1)	(2)	(3)
R^2	0.473	0.517	0.645
Upper South	0.011		0.055
	(0.022)		(0.023)
Deep South	0.056		0.043
	(0.017)		(0.018)
Florida	–0.147		–0.088
	(0.015)		(0.017)
West South	0.017		0.051
	(0.016)		(0.016)
Big Sky	–0.053		0.004
	(0.017)		(0.016)
West	–0.087		–0.008
	(0.011)		(0.016)
250,000–500,000	–0.012		0.008
	(0.013)		(0.012)
100,000–250,000	–0.006		0.016
	(0.014)		(0.013)
Ln LOED		0.115	0.021
		(0.025)	(0.029)
Ln REALINC		–0.031	–0.178
		(0.055)	(0.064)
Ln CIGS		0.088	0.142
		(0.039)	(0.044)
Ln OBESE		0.169	0.138
		(0.032)	(0.036)
Ln POLUTN		0.057	0.045
		(0.021)	(0.024)
Ln BLACK		0.024	0.026
		(0.005)	(0.006)
Intercept	3.672	3.879	4.900
	(0.006)	(0.578)	(0.692)

Notes: MSA = metropolitan statistical area. See table 10.1 for explanations of variables. Numbers in parentheses are standard errors. Number of observations = 224.

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Comment Joseph P. Newhouse

Fuchs, McClellan, and Skinner (FMS) have several findings:

1. Using metropolitan and rural areas as units of observation, mortality is an important explanatory variable for both Medicare spending and

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use of services among whites aged sixty-five–eighty-four, and is quantitatively more important in explaining the variation in that spending than are economic and demographic variables.

2. Florida is very different from the remainder of the country in having observed rates of use that are much higher than predicted and observed mortality that is much lower than predicted.

3. There is a city size gradient in use; metropolitan areas with populations between 250,000 and 500,000 have higher rates of use than smaller cities and nonmetropolitan areas, and areas with more than 500,000 people have still higher use.

4. Even with measures specific to whites aged sixty-five–eighty-four, the following three variables do not exert an important or robust effect on use or on mortality: real income; a measure of inequality or dispersion in income; and the proportion of individuals with less than a high school education.

5. Even with measures not specific to whites aged sixty-five–eighty-four, and indeed measured at the state level, cigarette consumption, obesity, and air pollution affect mortality measured across metropolitan areas.

6. The percentage of the area's total population that is black is significantly associated with elderly white mortality.

This paper is in the tradition of literature from some of the earliest days of health economics, including several papers by the first author (for example, Fuchs and Kramer 1972; Bombardier et al. 1977; Fuchs 1978; Auster, Leveson, and Sarachek 1969). The canonical paper in that literature made use of data at the state level, and the variation was mostly or entirely cross-sectional. Much of the older literature, however, was more concerned with explaining use of medical services than explaining mortality. Utilization was typically measured in partial or crude fashion, such as a count of physician visits or hospital admissions. If mortality was measured, it was usually total mortality or infant mortality. The standard finding was that the marginal unit of medical service had little effect on mortality but that lifestyle variables did importantly affect mortality; the classic paper in this genre was Fuchs' comparison of Nevada and Utah, showing large differences in mortality relating to lifestyle (Fuchs 1974).

This paper makes several advances over the earlier literature, primarily exploiting the availability of detailed information on the use of services from Medicare claims data. Such data enable one to measure the intensity of services per medical encounter (for example, per visit or per hospital admission), and it is the change in intensity that has driven the sustained increase in medical spending. Real per capita spending on medical care rose on average 4.4 percent per year in the United States between 1940 and 1998, a factor of 12. It rose 4.2 percent per year between 1980 and 1998, a factor of 2. Virtually the entire rise has been in increased services per encounter. For example, the rise in total spending since 1980 occurred despite a decline of hospital days per person by about one-third and approximately unchanged physician visit rates (U.S. Department of Health and Human Services 2000). Thus, the measures of utilization used in the older literature are simply not helpful in understanding why spending rose.

Fuchs, McClellan, and Skinner also use the detailed claims data to disaggregate spending into finer categories. For example, they classify physician services into evaluation and management services, surgical and other treatment procedures, and diagnostic interventions. Finally, unlike most all of the earlier literature, FMS restrict their measure of mortality to the elderly, where mortality is believed to be more sensitive to medical care.

I begin my comments with some additional or different interpretations of the results then add some caveats. I next comment on possibilities for future extensions along the lines of this paper, but I conclude with a skeptical comment on the overall research strategy for the questions at issue that are posed at the outset of the paper: What determines medical spending? What determines health?

Other Interpretations

I think more can be said about four results: the positive effect of mortality rates on spending; the smoking and obesity results; the city size gradient; and the relationship between the percentage black and elderly white mortality rates.

Mortality and Spending

Some of the relationship between mortality and spending represents a mechanical effect of spending at the end of life. Between 5 and 6 percent of the Medicare beneficiaries die each year (these numbers include those aged over eighty-five, who are excluded from FMSs results), and decedents spend about five to six times as much as nondecedents (Lubitz and Riley 1993; Hogan et al. 2000). Using these figures, one can show that at the mean a 1 percent rise in the mortality rate adds about 0.13 percent to spending. Because the FMS estimated elasticity of spending with respect to mortality is 0.82, well above 0.13, this solidifies their conclusion that mortality is a proxy for general health status. That is, the estimated relationship is not simply additional spending at the end of life.

Disproportionate spending at the end of life, however, is consistent with FMSs findings that mortality has much greater effects on medical than on surgical spending, on inpatient than on outpatient spending, and on evaluation and management services rather than procedures, because surgical procedures and aggressive treatment are less likely among the terminally ill or those predictably near the end of life.

Smoking, Obesity, and Pollution

FMS's estimated elasticities for mortality with respect to smoking, obesity, and pollution variables are in the range of 0.05 to 0.15. But there is surely large random measurement error in these variables because the smoking and obesity variables pertain to both the elderly and nonelderly, are statewide rather than specific to the metropolitan or rural area, and do not account for migration (for example, the nonsmoker from Massachusetts who retires to North Carolina is given the smoking habits of a North Carolinian). As a result, the estimated elasticities understate the true elasticities, potentially by a large amount.

The City Size Gradient

The city size gradient may partly reflect the location of most teaching hospitals in larger cities. Teaching hospitals treat given cases more intensively than community hospitals, and most of their patients are from the local area. I do not suppose that this could account for all of the city size effect, but it may be possible to control for the share of teaching hospital use with the Medicare claims data. I have more to say about the city size gradient in the following.

One result in table 10.10 is provocative; Gainesville, whose medical delivery system is dominated by a major teaching hospital, has much higher predicted mortality than other Florida metropolitan areas. There is no obvious explanation for why a primarily university town should have high mortality, and one wonders whether this might have something to do with the teaching hospital or whether it is simply a random event from small numbers of deaths. Fuchs, McClellan, and Skinner attribute mortality to place of residence, and not to place of death, which raises the question of how residence is determined. For example, if someone moves to Gainesville for an extended period to undertake an experimental cancer treatment, does that person's measured residence change?

The Black Variable

Fuchs, McClellan, and Skinner treat the black variable as more causally related to race than I would. They divide areas with many blacks into those with high and low segregation, but find an approximately equal effect in both kinds of areas. This, of course, simply shows that the black variable is not measuring the effect of segregation. They also hypothesize that migrating whites may avoid metropolitan areas with a large black population. They test this by omitting California, Arizona, and Florida from their sample, but their result is robust, contrary to the migration hypothesis.

These results leave open that the black variable is simply a proxy for omitted variables (or possibly functional form misspecification) that are correlated with the within-region variation in the black variable. Any omitted variable that affects mortality in those areas within a region that have a high percentage of blacks and that are also extreme on the omitted variable will load onto the black variable. Furthermore, if these areas have extreme values for several of the variables that are included, any nonlinearity in the functional form will also be picked up by the black variable.

Possibilities for Future Extensions

Fuchs, McClellan, and Skinner's data are from the 1989–1991 period. In its mix of services Medicare was unstable in the 1990s; for example, postacute care grew from less than 2 percent of total spending to around 15 percent of spending between 1988 and 1997. I show in figures 10C.1 and 10C.2 the time series for skilled nursing facility days and home health visits per 1,000 beneficiaries. Moreover, reimbursement for physician services, hospital outpatient departments, and postacute care providers all changed markedly in the 1990s (Newhouse 2002). Although it is possible that the distribution of services across areas remained relatively invariant to these changes, it seems improbable. Thus, if this line of work is pursued further, it would be worthwhile reestimating these equations on data from a decade later. One problem in doing so is that in the 1990s enrollment in managed care roughly tripled, from 3 to 15 percent, and detailed claims data for that group are not available.

Problems

Deflators

Despite its correlation of 0.8 with the quantity variable, the measure of deflated spending has substantial measurement error, stemming from the deflator used, the Geographic Practice Cost Index (GPCI) for the area. The GPCI is a measure of physician office input costs. Half of total physician spending is the professional component (that is, physician take-home pay), but the GPCI underweights this by a factor of four for political reasons. Thus, even for physician spending the weights are in error. And physicians account for only about 30 percent of Medicare spending, a figure that includes their in-hospital services; the market basket of inputs for institutional providers differs.

Furthermore, nonlabor input shares, many of which do not vary in price locally, differ across providers. For example, hospitals and skilled nursing facilities differ by about 10 percentage points in their nonlabor share. This error introduces a systematic bias in an unknown direction. Suppose there are some inputs purchased in local markets, primarily labor, and some inputs purchased in national markets, such as supplies and drugs. These pro-

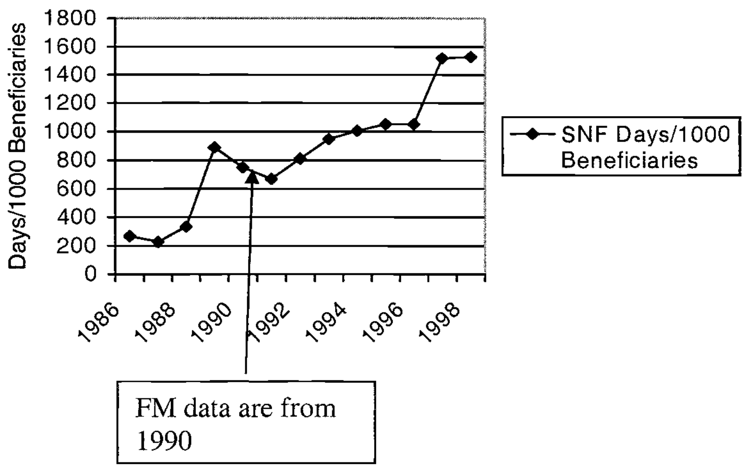

Fig. 10C.1 Skilled nursing facility (SNF) days per 1,000 Beneficiaries, 1986–1998
Source: Newhouse 2002.

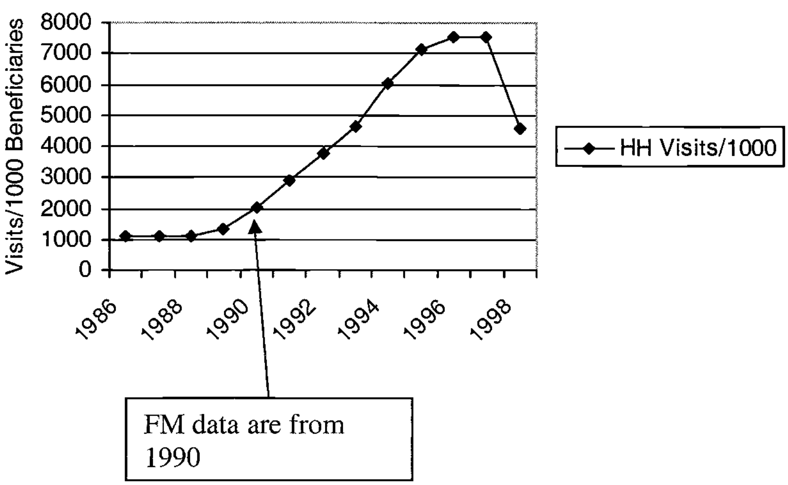

Fig. 10C.2 Home health visits per 1,000 beneficiaries
Source: Newhouse 2002.

portions of local and national inputs will differ across types of providers. Only that portion of costs attributable to the local inputs should be deflated.

To bring out the problem, suppose the weight on the portion that is local errs by treating all dollars as local. Thus, the variable used in this hypothetical example is ln(Total$/*D*), where *D* is the deflator, and the deflator only measures local prices. The proper variable is ln(Local$/$D$ + National$), where Local$ and National$ are spending on locally and nationally purchased inputs, respectively. One can manipulate this latter expression to show that it equals $\ln[D(1 - L) + L]$ + ln(Total$/$D$), where L is the proportion of inputs purchased locally.

If one uses ln(Total$/$D$) as a dependent variable instead of ln(Local$/$D$ + National$), $\ln[D(1 - L) + L]$ is in the error term. But the D will cause the error term to covary with a number of right-hand-side variables. For example, larger cities have higher values of D. In this example the deflator overweights local inputs and one can sign the bias; in the FMS regression it is not clear whether the GPCI over- or underweights local inputs, and that will determine the direction of the bias.

Furthermore, as FMS say, this deflator is incorrect for out-of-area services, which are also systematic by city size, being more prevalent in nonmetropolitan areas. Among nonmetropolitan residents, physician visits are twice as likely to be outside the country of residence as among metropolitan residents (25 versus 13 percent); 12 percent of visits by nonmetropolitan residents were to metropolitan physicians, but only 1 percent of visits by metropolitan residents were to nonmetropolitan physicians (Kleinman and Makuc 1983). I suspect the data for hospitalization are even more disparate. Thus, nonmetropolitan area spending is overdeflated, and consequently the city size gradient is overstated. This is consistent with the gradient's being smaller in the total quantity regression than in the deflated spending regression.

Another issue related to the deflator is whether real income of the elderly should be deflated for property values. To the degree that the elderly own their own homes, they are receiving a stream of housing services from home equity, which should be imputed to their income. This income will generally be greater in areas with higher property values. As a result, I am not persuaded the income of the elderly should be deflated for property values. After deflating for variation in wages, an elderly person who owns her own home with a $25,000 income in Palo Alto may be as well-off as a similar person in Dubuque.

Exclusion of the Nursing Home Population

Fuchs, McClellan, and Skinner excluded the nursing home population. I would not have done this because of possible selection bias. Given that they were excluded, it would be useful to show that this proportion does not vary much across their areas.

The Research Strategy

Although this paper follows in a long tradition of work to explain area differences—indeed, the words *Area Differences* are in the title—I am not persuaded that this is the best strategy to use to answer the questions of what affects health care spending and mortality. Rather, I think person- or household-level data are more suitable.

My guess is that the health economics literature started with area data three decades ago largely because of data availability. Additionally, one of the burning questions at that time was whether physicians induced demand, and for that question area data lost little to person- or household-level data.

But for purposes of understanding the relationship between health status and lifestyle habits, price (including for Medicare beneficiaries the presence of supplementary insurance), and income, person- or household-level data would seem superior. Otherwise one loses all the within-area variation, which is where much of the variation is. Person-level data are now available through the Medicare Current Beneficiary Survey and through the Medical Care Expenditure Survey. I suspect that in the future these data would be more fruitful to exploit.

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