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**Labor Force Participation, Income, and the Use of Short-Term Hospitals by the Elderly**

**David A. Weaver\***

**Division of Economic Research**

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**Social Security Administration  
Office of Research and Statistics**

**\*Suite 211, 4301 Connecticut Ave., N.W., Washington, D.C. 20008**

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## ABSTRACT

Between 1970 and 1983, the rate at which the elderly were hospitalized grew by over 40 percent while the rate of hospitalization for the younger population was fairly stable. Past attempts to explain the different patterns among the young and the old have focused on technology, insurance, health status, and the supply of hospital services. These attempts have been largely unsuccessful. In this article, I examine other possible explanations, namely, that the elderly, who experienced a decline in the rate of participation in the labor force and an increase in income over this period, used increases in available time (i.e., nonwork time) and increases in income to seek out and receive greater amounts of health care.

Using an empirical strategy that adequately controls for the health status and insurance status of the subjects under study, I analyze small area data from the state of North Carolina. This approach yields results that indicate labor force status and income are important determinants of hospital use among the elderly.



## **1. Introduction**

Between 1970 and 1983, the rate at which the elderly (those 65 or older) were hospitalized grew by over 40 percent. A similar, though less dramatic, trend occurred for those aged 45 to 64. These changes in short-term hospital use occurred during a period in which the rate of hospitalization for those under 45 was fairly stable. The rate of hospitalization for each of these age groups has generally declined since 1983, a result likely due to the growth in outpatient procedures. For a description of hospital utilization trends during the period from 1965 through 1986 see U.S. Department of Health and Human Services (1989). Hospital utilization data for more recent years can be found in U.S. Department of Health and Human Services (1991, 1993).

The pronounced increase in the use of hospital services by the elderly during the 1970s and early 1980s has received attention from health care researchers. Lubitz and Deacon (1982) and Valvona and Sloan (1985) analyze a number of factors that could possibly explain why the elderly, in particular, had begun to seek out and receive greater amounts of health care during this period. Among other things, these authors concluded that the trend toward greater hospitalization was **not** driven by changes in the insurance status of the elderly, changes in the supply of hospital services, or changes in the age distribution of those over 64. Further, both studies find that technological change can account for only some of the increase in hospital utilization. Neither study analyzed in detail the health status of the elderly over this period, but other researchers have. Palmore (1986) argues that the health status of the elderly actually improved over this period, which suggests the trend toward increased utilization was not driven by a decline in the health status of the elderly.

Lubitz and Deacon believe that, for various reasons, hospitals and physicians found it increasingly profitable to admit patients over this period. Thus, part of the explanation for the increased use of short-term hospitals by the elderly may be that physicians and hospitals actively promoted more hospital stays. Even if this were true, it is still odd that only the elderly, and not the young, were affected.

Lubitz and Deacon suggest that the elderly may have been differentially affected because the elderly have more time available (because of less time committed to work) to seek out and receive health care. This is a plausible explanation because the physician visits, the hospital stay, and the recovery period associated with a hospital admission all involve a substantial commitment of time on the part of the patient. Individuals who work may be less able or less willing to make such commitments of time.

Although not discussed by Lubitz and Deacon, it is also true that the amount of time available to the elderly to acquire health care has been growing. Between 1970 and 1983 the amount of time committed to work by the elderly fell sharply. During this period, labor force participation rates by the elderly (the percentage of elderly working or actively looking for work) dropped by about a third, falling from 17 percent in 1970 to 11.7 percent in 1983. The participation rate for those aged 45 to 64 also fell during this period, though not as sharply. In contrast, the younger (under 45) population experienced an increase in labor force participation during this period. Data on labor force participation can be found in U.S. Department of Labor (1989).

It is important to note that changes in nonwork time might especially affect the elderly. While a majority of all workers (roughly 3 in 5) have paid sick leave, only a minority of elderly

workers (roughly 1 in 3) have paid sick leave (based on 1988 data reported in Employee Benefit Research Institute 1992). Thus, for the elderly in particular, work does impose time constraints with regard to health care and, consequently, exit from work does represent an increase in available time.

Work status measures or value of time measures are frequently used as explanatory variables in models of the demand for physician care (examples include Acton 1976, Colle and Grossman 1978, Shapiro and Roos 1982, Coffey 1983, Boaz and Muller 1989) but are only rarely used in models of the demand for hospital care (Davis and Reynolds 1976, Pauly 1980, and Shapiro and Roos 1982). Davis and Reynolds find, holding health status constant, that the working elderly do use hospitals less frequently than the nonworking elderly. Using a sample not restricted to the elderly, Pauly also finds, holding health status constant, that working individuals use hospitals less frequently than nonworking individuals. Shapiro and Roos find that the retired elderly use hospitals more frequently than the working elderly but conclude that this result is due to the greater incidence of health problems among the retired elderly.

The decline in the labor force participation rate during the 1970s and early 1980s was not the only change in the economic circumstances of the elderly. During this period, the real income of the elderly generally increased. For families headed by an elderly person, real mean per capita family income in 1982 was 20.2 percent higher than it was in 1970. For elderly persons living alone or with nonrelatives, real mean income in 1982 was 31 percent higher than it was in 1970. The real mean per capita income of nonelderly families and the real mean income of nonelderly persons living alone or with nonrelatives also increased over this period but at a much more modest rate. For a description and a discussion of income trends, see Grad

(1984). The increase in hospital use by the elderly may partly be a result of improvements in the elderly's ability to afford hospital care.

In this article, I test whether economic factors, specifically work status and income, are determinants of hospital use by the elderly. The approach taken here is to analyze variations in hospital use and in economic conditions across small geographic areas. Some recent evidence suggests such an approach is likely to be fruitful. McLaughlin et al. (1989) find that socioeconomic variables are important in explaining variation in hospital utilization across small areas. One of the key contributions of my study is the use of an empirical approach that allows for an economic interpretation of the effects of variables such as work status and income. This is an important contribution because it is often believed that economic variables are correlated with health care utilization because they proxy for underlying health conditions and not because they are economic determinants of health care utilization.

The data, the relationship to be estimated, and the method of estimation are discussed in Section 2 of this article. Empirical results are presented and discussed in Section 3. Concluding comments appear in the fourth and final section of this article.

## **2. Empirical Approach**

### **2.1 The Data**

In this article, I analyze variation in short-term hospital discharge rates across small areas of North Carolina. The discharge data pertain to the elderly (65 or older) and were collected for the period October 1, 1980 to September 30, 1981. All individuals who are admitted to a hospital are discharged, including those who die while in the hospital. Thus, measuring



discharge rates is analogous to measuring admission rates.

The discharge data used in this study were originally collected to help state agencies carry out regulatory functions. As examples, these data were used to determine whether certificates of need (certificates allowing hospitals to expand services or facilities) should be issued and to determine whether new hospital licenses should be issued. These data are based on hospital reports provided to the state as part of the hospital licensure process (each hospital in the state must renew its license each year). Specifically, on the license renewal application each short-term hospital in the state reports discharge information broken down by age of the patient and place of residence. The discharge data used in this study are published in Hospital Patient Origin Report, 1981 Data (State Center for Health Statistics 1982a).

It is important that the discharge data be accurate and one way to gauge the accuracy of the state-collected data is to compare these data with data from other sources. For the 65 or older population (the focus of this study), this is possible. This is because the Health Care Financing Administration (HCFA) maintains discharge data for Medicare patients aged 65 or older. The HCFA data pertain to short-term hospital discharges and are based on claims submitted by these hospitals for reimbursement under Part A of the Medicare program.<sup>1</sup>

During the period of October 1, 1980 to September 30, 1981, the state data indicate that there were 217,925 short-term hospital discharges among the elderly residents of North Carolina. The Bureau of the Census estimates that as of April 1, 1980 there were 601,831 elderly residents of North Carolina (U.S. Department of Commerce, Bureau of the Census 1983b). Thus, over the period under consideration, the state and Census data imply that the elderly residents of

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<sup>1</sup>The HCFA data are unpublished.

North Carolina were discharged at a rate of 362.1 per 1000 elderly. HCFA data indicate that during the calendar years of 1980 and 1981, respectively, there were 203,260 and 213,470 elderly Medicare discharges among the residents of North Carolina. Assuming that 1/4 of the 1980 Medicare discharges occurred between October 1 and December 31 and assuming 3/4 of the 1981 discharges occurred between January 1 and September 30, there were 210,918 elderly Medicare discharges among residents of North Carolina during the period October 1, 1980 to September 30, 1981. HCFA reports that as of July 1, 1980 there were 576,746 elderly Medicare (Part A) enrollees among the residents of North Carolina. Thus, HCFA data imply a discharge rate of 365.7 per 1000. That two very different data sources yield almost identical utilization statistics (differing by less than 1 percent) is striking and it suggests that the state-collected data are of high quality.<sup>2</sup>

For this study, the unit of analysis will be the county. The selection of the county as the unit of observation is dictated by data availability (the discharge data are only available at the county level). However, recent research by McLaughlin et al. (1989) indicates that the unit of observation in small area analysis is not crucial. These authors find socioeconomic variables have similar effects on utilization rates regardless of whether the unit of observation is the county or the hospital market community.

Total discharges by the elderly are multiplied by 1000 and divided by the number of elderly, at the time of the 1980 Census, to form a measure of the discharge rate (discharges per 1000 elderly) (DISRATE) for each of the 100 North Carolina counties. Note that in forming

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<sup>2</sup>One reason the two discharge estimates will differ slightly is that the elderly Medicare population is a subset of the total elderly population (roughly 96 percent of North Carolina's elderly population was covered by Part A of Medicare in 1980).

DISRATE, discharges are assigned based on county of residence and not necessarily the county where the hospital care occurred. See the Appendix for a complete description of DISRATE.

Figure 1 presents a map of the 100 North Carolina counties. The counties are shaded according to whether their discharge rate is "low," "average," or "high," based on whether the value of DISRATE is among the lowest third, middle third, or highest third of all DISRATE values in the state (the highest "third" contains 34 counties). Even though there is substantial variation in discharge rates (DISRATE varies from a low of 186.6 to a high of 633.5), Figure 1 indicates that high or low utilization is not concentrated in particular regions of the state (i.e., eastern (coastal), central (piedmont), or western (mountain) areas of the state).

The utilization data are matched with county level data drawn mainly from the 1980 Census (see Appendix for complete information on data sources). One of the advantages of using small area data from North Carolina is that, across small areas, there is a great deal of variation in the characteristics of the small areas. For example, Census data reveal that among the 100 counties of North Carolina the county unemployment rate, which is a fairly broad indicator of the economic activity in each county, ranges from a low of 3.0 percent to a high of 17.1 percent. This type of heterogeneity is important in small area studies because previous work has shown that socioeconomic variables tend to be important predictors of hospital utilization when the areas under study are fairly heterogenous (McLaughlin et al. 1989).

DISRATE is postulated to be a function of the following variables: LABOR (the percentage of the elderly population that is in the labor force), INCOME (the per capita income of the elderly population), HOSP (a dummy variable with a value of one if a short-term hospital is located within the county, zero otherwise), NOHIGH (the percentage of elderly without a high

school diploma), BLACK (the percentage of the elderly who are black), MALE (the percentage of the elderly who are male), YOUNG (the percentage of the elderly between ages 65 and 74), LOCAL (the percentage of the employed civilian population working for a local government), PDIS (the percentage of the noninstitutionalized elderly who report a disability that prevents or limits them from using public transportation, such as buses and cabs), and INFMR (the five-year infant mortality rate). Generally, variables reflect conditions at the time of the Census (April 1980). See the Appendix for a complete description of each variable and Table 1 for descriptive statistics.

With regard to short-term hospital utilization and labor force participation, North Carolina's elderly are fairly representative. For the U.S. elderly in 1980, DISRATE and LABOR had values of 383.7 and 12.5, respectively (U.S. Department of Health and Human Services 1989, U.S. Department of Labor 1989). The values for North Carolina's elderly were 362.1 and 13.8. With regard to income, North Carolina's elderly are somewhat less representative. In 1979, the mean family income of families headed by an elderly person in North Carolina was 82.5 percent of the national mean. The mean income of elderly persons living alone or with nonrelatives in North Carolina was also 82.5 percent of the national mean (U.S. Department of Commerce, Bureau of the Census 1983a, 1984). However, prices of goods and services are likely to be lower in North Carolina, which would make the cost-of-living-adjusted income of North Carolina's elderly more comparable to that of the Nation's elderly. For example, the average daily charge for a semiprivate hospital room in North Carolina in January of 1980 was only 69.3 percent of the average daily charge for the Nation as a whole (Health Insurance Institute 1981).

One of the main variables of interest is LABOR. If individuals in the labor force have less time available to seek out and receive hospital care, LABOR should be negatively related to DISRATE. The inclusion of INCOME as an explanatory variable enables one to interpret the effect of LABOR as a time effect. That is, while individuals in the labor force do have less time, they generally have more income (because of earnings). Thus, without controlling for INCOME, the coefficient on LABOR would represent a mix of two effects. INCOME, which measures the elderly's ability to afford hospital care, should be positively related to DISRATE.

Two direct measures of health status are included. Areas with a high percentage of disabled elderly (PDIS) and areas with high infant mortality rates (INFMR) are counties where socioeconomic conditions have produced individuals with poor health. Thus, all else equal, these areas should have higher utilization of medical services. Poor health, also, is often concentrated among individuals with low levels of education. Thus, counties with high values of NOHIGH are likely to have higher utilization rates. Age, race, and sex variables are also likely to proxy for health status and thus are included as controls.

Seventeen counties are without short-term hospitals. The elderly of these counties must incur higher travel costs (in terms of both time and money) to receive hospital care. Thus, one would expect HOSP to be positively associated with utilization rates. LOCAL is included because local government workers are not always covered under Medicare and counties with a high incidence of this type of employment may have a number of elderly individuals whose primary insurance plan is very different from that of the general elderly population.

## 2.2 Estimation Strategy

Given the control variables available at the county level, ordinary least squares estimation (OLS) of the relationship between DISRATE and LABOR might reveal the influence of other variables and not the influence of time or labor force participation per se. For example, even with direct and indirect measures of health status (PDIS, INFMR, NOHIGH, YOUNG, MALE, BLACK) as control variables, it is possible that the incidence of participation in the labor force reflects unobserved health status (individuals in good health may be more likely to participate in the labor force). Although health status is the most obvious example, there are clearly other unobservables that could generate a spurious correlation between LABOR and DISRATE. Labor force participation might be correlated with the level of insurance coverage among the county's elderly. Medicare coverage is nearly universal but some elderly are without any insurance and some who have Medicare have no supplemental insurance. Employers play a major role in providing health insurance and thus the incidence and extent of insurance coverage might be correlated with the labor force participation rate. It is also possible that preferences for work (embodied in the value of LABOR) could be correlated with preferences for health care (embodied in the value of DISRATE).

For these reasons, I use an instrumental variables approach in the estimation, treating LABOR as an endogenous regressor. Essentially, this estimation approach differs from OLS in that actual values of the endogenous regressor (LABOR) are replaced with predicted values based on a linear combination of exogenous variables. The set of variables that forms the predicted values consists of all exogenous variables that affect DISRATE (e.g., PDIS, HOSP, NOHIGH) plus additional variables that identify the relationship between the endogenous

regressor and DISRATE. By selecting variables that are correlated with LABOR but uncorrelated with the unobservables, the effect of LABOR can be viewed as a health status, insurance status, and preference constant effect. If, however, the identifying variables correlate with the unobservables, then the predicted values will proxy for the unobservables and the effect of LABOR cannot be viewed as a health status, insurance status, and preference constant effect. It is possible, through specification testing, to determine which interpretation of the identifying variables is correct.

It is plausible that INCOME, which should be correlated with LABOR because income is partly determined by labor market earnings, is also subject to the influence of the same types of unobservables. For this reason, INCOME is also treated as an endogenous regressor.

Four exogenous variables are used for identification: URATE (the local unemployment rate), URATESQ (the local unemployment rate squared), FED (the percentage of employed civilian workers who are employed by the Federal Government), and ASSET (the per capita value of dividends, interest, and rents for 1980). The unemployment rate terms are used because high unemployment rates have been consistently shown to discourage elderly labor force participation (see, e.g., Bowen and Finegan 1969, and Quinn 1977). FED is used because the early retirement options and the generous benefits of the Civil Service Retirement System (this system was in place in 1980) are likely to have discouraged work past age 65 for Federal workers (see Hartman 1983). ASSET is used as a measure of property (nonwork) income.

### 2.3 Specification Tests

It is possible to test for the exogeneity of LABOR and INCOME. This test reveals

whether LABOR and INCOME are correlated with unobserved variables, such as the unobserved health characteristics of a county's elderly. If a correlation exists, exogeneity will be rejected. Rejection of exogeneity implies that OLS estimates will be biased, with the OLS coefficient estimates for LABOR and INCOME partly measuring the influence of the unobserved variables. When exogeneity is rejected, the appropriate empirical approach is instrumental variables estimation, which produces unbiased results because the influence of unobservables on LABOR and INCOME is removed. Thus, rejection of the exogeneity of LABOR and INCOME is an indication that the instrumental variables approach taken in this article is the appropriate empirical approach.

It is also possible to test the overidentifying restrictions of the model. This is an important test because it provides information on whether the variables that were excluded from the DISRATE equation (URATE, URATESQ, FED, ASSET) were appropriately excluded. If the test of overidentifying restrictions fails, it implies at least one of the excluded variables belongs in the DISRATE equation. For example, the unemployment rate has been linked to poor health in a number of studies (see Gravelle 1984 for a discussion of unemployment rates and mortality). If the direct and indirect measures of health status (PDIS, INFMR, NOHIGH, YOUNG, MALE, BLACK) in the DISRATE equation do not adequately control for the adverse health effects of the unemployment terms, then URATE and URATESQ should be included in the DISRATE equation as other health status controls and their exclusion will lead to a rejection of the overidentifying restrictions. Both the exogeneity of LABOR and INCOME and the validity of the overidentifying restrictions will be tested (sections 3.2 and 3.3).



## 2.4 Structural Relationship

In the estimation that follows, I specify a linear relationship between the natural logarithm of DISRATE and the explanatory variables:

$$\ln(DISRATE)_i = \beta_0 + \beta_1 LABOR_i^E + \beta_2 INCOME_i^E + \beta_3 HOSP_i + \beta_4 INFMR_i + \beta_5 PDIS_i + \beta_6 LOCAL_i + \beta_7 NOHIGH_i + \beta_8 BLACK_i + \beta_9 MALE_i + \beta_{10} YOUNG_i + \epsilon_i \quad (1)$$

The  $\beta$ s ( $\beta_0, \dots, \beta_{10}$ ) represent the parameters to be estimated, the subscript  $i$  denotes the  $i^{th}$  county, the superscript  $E$  denotes the variables that are treated as endogenous regressors (see section 2.2), and the  $\epsilon$  is a random error term.

In the above form, each parameter estimate, after being multiplied by 100, reveals the percentage change in DISRATE due to a unit change in the explanatory variable. For example, if LABOR increases by 1, reflecting a 1 percentage point increase in the labor force participation rate, then the resulting percentage change in DISRATE is measured by  $(100 \times \beta_1)$ .

## 2.5 Method of Estimation

Because the observations used to estimate equation 1 are drawn from geographic areas that vary in population size and other characteristics, it is plausible to believe that the error term in equation 1 is heteroskedastic (i.e., the  $\epsilon_i$  have unequal variances). In general, equation 1 specifies a relationship between county averages (in essence, average discharges for the population of the  $i^{th}$  county depend on average values of the explanatory variables for the

population of the  $i^{th}$  county). In this formulation, it makes sense to view the error term,  $\epsilon_i$ , as being an average of individual error terms over the population of the  $i^{th}$  county. This has implications for the variance of  $\epsilon_i$ . Even if the underlying individual error terms are homoskedastic (have equal variance), averages over populations of varying size are heteroskedastic. Specifically, averages based on larger populations have lower variance (see Wallace and Silver 1988, p. 261). In addition, error variance may be related to other county characteristics, such as per capita income (INCOME). Across counties where per capita income is low, one might expect that the level of hospital care fluctuates only mildly around a level of hospital care that could be viewed as necessary (extreme fluctuations below this necessary amount would not occur because it would result in high death rates and extreme fluctuations above this amount would not occur because of the lack of discretionary income). Across counties where per capita income is high, however, there might be sharp fluctuations in the level of hospital care. This type of relationship between income and error variance (i.e., a positive relationship) is often found in studies of expenditures on food items (see, e.g., Prais and Houthakker 1971) which are similar to expenditures on health care in the sense that some expenditures on each commodity can be viewed as necessary and some can be viewed as discretionary. Heteroskedasticity, caused by variation in county characteristics such as population and income, can lead to inconsistent standard errors of the parameter estimates and improper inference unless an appropriate estimation procedure is used.

The parameters of equation 1 are estimated using the two-stage instrumental variables (TSIV) estimator developed by White (1982). TSIV estimation produces standard errors of the parameter estimates that are consistent regardless of the presence of heteroskedasticity. Further,

TSIV estimation has two important advantages over other methods of instrumental variables estimation. First, TSIV estimation does not require assumptions about the functional form of the heteroskedasticity or the sources of the heteroskedasticity. Second, when the model is overidentified, as it is in equation 1, TSIV estimation exploits the correlation between the cross-products of the instrumental variables and the square of the error term to more efficiently estimate the structural relationship. In fact, White (1982) shows that in the presence of heteroskedasticity of unspecified form, the TSIV estimator is the most efficient instrumental variables estimator.

### **3. Results of Estimation**

#### **3.1 TSIV Estimation**

Table 2 column 1 presents the results of the TSIV estimation (see Table 3 for regressions of LABOR and INCOME on all the exogenous variables in the system). Four of the structural coefficients are statistically different from zero based on two-tailed tests and a 10 percent level of significance: LABOR, HOSP, INFMR, and NOHIGH.

For the elderly, lower rates of labor force participation are in fact associated with greater hospital utilization, which is consistent with the time availability hypothesis. The coefficient estimate indicates that a 1 percentage point decline in the labor force participation rate (i.e., a change in LABOR of -1) results in a 6.32 percent increase in DISRATE. A decline in LABOR equal to its standard deviation (a decline of 2.784) would lead to a 17.6 ( $17.6 = 2.784 \times 6.32$ ) percent increase in DISRATE (see Table 1 for standard deviations of the explanatory variables). It is clear that differences in participation rates across small areas are capable of generating

substantial variation in discharge rates.

As expected, HOSP is positively associated with DISRATE. The empirical results indicate that the discharge rate of the elderly is 29.1 percent higher in counties with a short-term hospital present. This suggests that the elderly in counties without hospitals are quite sensitive to the travel costs (in terms of both time and money) associated with hospital care.

INFMR, which likely proxies for poor health status among a county's population, including the elderly population, is also positively related to DISRATE. A 1 standard deviation increase in the INFMR is associated with a 6.6 percent increase in the elderly discharge rate.

The educational characteristics of a county's elderly have an important effect on hospital utilization. A 1 standard deviation increase in NOHIGH (the percentage of elderly without a high school diploma) increases the discharge rate by 19.7 percent. This result is consistent with results from other studies. Fuchs (1986) and McLaughlin et al. (1989) find that there is a negative relationship between surgical utilization and level of education. McMahon et al. (1993) find that the surgical and medical discharge rates of hospital market communities in Michigan are negatively related to the percentage of the population in these communities that has finished high school. It is likely that those with low levels of education are in poorer health, but there are other possible reasons for the relationship. For example, Fuchs argues that physicians may operate less on the highly educated because physicians are more confident that these individuals will carry through on nonsurgical treatments.

While the coefficient of INCOME is not significant at the 10 percent level of a two-tailed test, it is significant at the 10 percent level of a one-tailed test. That is, if the null hypothesis is that INCOME has no effect and the alternative hypothesis is that INCOME has a positive

effect, the null hypothesis would be rejected. The coefficient estimate implies a large effect on the discharge rate. A 1 standard deviation increase in INCOME leads to approximately a 17 percent increase in the discharge rate. High income elderly are not only more likely to have supplemental insurance, but they are also more likely to be able to meet deductibles and co-payments associated with medical care.

No demographic variable is individually significant. However, BLACK, MALE, and YOUNG, are jointly significant at the 5 percent level (based on a Wald statistic proposed by White 1982). Said differently, if the null hypothesis is that all three coefficients are equal to zero and the alternative hypothesis is that at least one of the coefficients is different from zero, one would reject the null. The coefficient estimates indicate that the discharge rate is lower for blacks, higher for males, and higher for elderly between the ages of 65 and 74. Increasing BLACK by its standard deviation results in a 5.6 percent decline in the discharge rate. Similar magnitudes, but of an opposite direction, occur when MALE and YOUNG are increased by their respective standard deviations. It is interesting that the demographic effects are substantially smaller than the effects of the economic variables (LABOR and INCOME).

The above discussion has focused on partial effects (i.e., the effects of given variables holding other variables constant). However, as noted earlier, there is a relationship between the two endogenous variables, LABOR and INCOME, because income is partly determined by labor market income. Labor force withdrawal increases the amount of time available for health care but reduces the amount of income available to purchase health care. Thus, in general, labor force withdrawal sets off competing effects on the demand for health care. These competing effects can be illustrated by considering the effects of a change in the county unemployment rate,

which is a determinant of both LABOR and INCOME. Results from Table 3 imply that a 1.47 percentage point increase in the unemployment rate would lower the elderly labor force participation rate (LABOR) by 1 percentage point and lower elderly per capita income (INCOME) by \$121.9.<sup>3</sup> It is plausible that the effect of the unemployment rate on income is mainly due to the effect of the unemployment rate on labor force participation. That is, increases in the unemployment rate discourage labor force participation by the elderly and as a result reduce their labor market earnings and their per capita income. Thus, in this view, changes in the unemployment rate set off the competing time and income effects described above. If LABOR were to decline by 1 percentage point and, simultaneously, INCOME were to decline by \$121.9, the parameter estimates of equation 1 indicate that the discharge rate would rise by 3.8 percent. Note that this is significantly lower than the income-constant effect of a 1 percentage point decline in LABOR which, as mentioned above, would result in a 6.32 percent increase in the discharge rate.

The coefficient estimates imply that socioeconomic variables have large effects on hospital utilization, which is consistent with other small area studies. For example, consider the effect of the unemployment rate. A 1 percentage point increase in the unemployment rate would lower LABOR by 0.6805 and lower INCOME by 82.9276, which would have the net effect of

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<sup>3</sup>A change in the unemployment rate affects both the variable URATE and the variable URATESQ. Coefficient estimates in Table 3 indicate that the change in LABOR due to a 1 percentage point increase in URATE,  $\partial LABOR/\partial URATE$ , is equal to  $-1.2284 + (0.0413)(2)(URATE)$ , which equals  $-0.6805$  when URATE is set at its average value ( $URATE=6.633$ ). Thus, an increase in URATE of 1.47 percentage points would lower LABOR by 1 (i.e.,  $1.47 \times -0.6805$ ). The change in INCOME due to a 1 percentage point increase in URATE,  $\partial INCOME/\partial URATE$ , is equal to  $-200.593 + (8.8697)(2)(URATE)$ , which equals  $-82.9276$  when URATE is set at its average. An increase in URATE of 1.47 would lower income by 121.9 (i.e.,  $1.47 \times -82.9276$ ).

increasing the discharge rate by 2.6 percent. McMahon et al. (1993) find, for hospital market communities in Michigan, that a 1 percentage point increase in the unemployment rate increases the medical discharge rate by 2.75 percent. McLaughlin et al. (1989) also find that the unemployment rate has a large, positive effect on the medical discharge rate.

The large effects of socioeconomic variables in small area analysis may result from the role of these variables in determining medical practice styles within communities. For example, physicians and hospitals in communities with high per capita income may develop a hospital-intensive style of practice because the bulk of their patients can readily afford hospital care. Even individuals with low income in these affluent communities may have high utilization rates because of a general style of practice that is established. Thus, socioeconomic variables may have amplified effects because they help to determine medical practice styles within communities. Although this explanation of the large effects is speculative, it is consistent with the frequently-held view that community medical practice styles have large effects on utilization rates.

### 3.2 Exogeneity of LABOR and INCOME

Wooldridge (1992) has developed a heteroskedasticity-robust procedure to test the exogeneity of regressors. Under the null hypothesis of exogeneity, the test statistic produced by this procedure is drawn from a chi-square distribution with degrees of freedom equal to the number of tested regressors. To test the null hypothesis, one compares the test statistic to the critical value associated with a chosen significance level. Values in excess of the critical value lead to a rejection of the null hypothesis.

Wooldridge's procedure was implemented to test the exogeneity of LABOR and INCOME. For a 5 percent significance level test, the critical value for the chi-square distribution with 2 degrees of freedom is 5.991. Wooldridge's procedure yielded a test statistic equal to 7.553 and thus the null hypothesis of exogeneity is rejected. This indicates that the approach adopted in this article, namely, the treatment of LABOR and INCOME as endogenous variables, is the appropriate empirical approach.

Table 2 column 2 presents estimates of the relationships between  $\ln(\text{DISRATE})$  and the explanatory variables when LABOR and INCOME are treated as exogenous. That is, column 2 presents Ordinary Least Squares (OLS) estimates of the parameters of equation 1. The LABOR coefficient is positive and not statistically different from zero. INCOME has a negative and significant relationship with DISRATE. One possible interpretation of these results is that the TSIV estimation successfully purges unobserved health status and unobserved insurance coverage. Consider the role of INCOME. It is possible that in the OLS framework INCOME proxies for unobserved health status (hence, the negative coefficient) but in the TSIV framework unobserved health status is purged (hence, the positive coefficient). With regard to LABOR, it is possible that in the OLS framework LABOR generates both a negative time effect and a positive insurance effect (hence, no net effect) but in the TSIV framework unobserved insurance coverage is purged (hence, the negative time effect). The success of the TSIV approach in purging unobserved insurance coverage could be related to the use of FED as an instrumental variable. Federal workers are eligible to carry their employer provided insurance into retirement, where it acts as either basic health insurance (if the individual is not eligible for Medicare) or supplemental insurance (if the individual is eligible for Medicare) (U.S. General



Accounting Office 1978). Thus, while high values of FED are associated with lower labor force participation rates among the elderly (see Table 3), high values of FED do not necessarily predict weak insurance coverage among a county's elderly.

There are other interpretations consistent with the biased estimate of LABOR in the OLS framework. For example, if individuals who have an unobservably strong preference for work also have an unobservably strong preference for health care then the OLS estimate of the LABOR effect would be biased toward zero.

### 3.3 Overidentifying Restrictions

Wooldridge (1992) has also developed a heteroskedasticity-robust test of overidentifying restrictions. The null hypothesis is that the overidentifying restrictions are valid. Failure to reject the null implies that the identifying instrumental variables are valid, in the sense that they were properly excluded from the structural equation. Rejection of the null implies that at least one of the excluded variables (URATE, URATESQ, FED, ASSET) was inappropriately excluded. Under the null, the test statistic is drawn from a chi-square distribution with degrees of freedom equal to 2 (the degree to which the structural equation is overidentified). As noted above, for a 5 percent significance level test, the critical value for the chi-square distribution with 2 degrees of freedom is 5.991. Wooldridge's procedure yielded a test statistic equal to 0.995 and thus the null hypothesis is not rejected. In fact, the null is not close to being rejected. This indicates that the identifying instrumental variables were properly excluded from the structural equation.

#### **4. Conclusion**

Using small area data on the elderly of North Carolina, I find that labor force participation and income have important effects on the utilization of short-term hospital services. Areas where the elderly are less likely to participate in the labor force and areas where the elderly have high per capita income are areas where the elderly are more likely to use short-term hospital services. These results were uncovered using an empirical strategy that appropriately controlled for unobservables such as health status, insurance coverage, and preferences. The cross sectional results of this study are consistent with recent labor force participation, income, and hospital utilization trends associated with the elderly.

On a somewhat narrow level, these results suggest future research on the relationships between labor force participation, income, and the demand for health care is warranted. Future research should analyze not only the effects of participation and income on general measures of health care demand (such as the discharge rate used in this study), but also the effects on different types of medical procedures. It seems likely that economic variables primarily affect the use of medical procedures that in some sense could be viewed as discretionary. Also, research that takes a longitudinal view of the demand for health care would be valuable. With this approach, it would be possible to address such important issues as whether individuals in the labor force are merely postponing the use of hospital services until retirement, rather than foregoing these services completely.

On a broader level, the results of this research suggest that more attention needs to be paid to the role socioeconomic variables play in the demand for health care. In this study, two variables with purely economic interpretations (LABOR, INCOME) were clearly capable of

generating substantial variation in discharge rates across small areas. These results, as well as results from other studies that analyze the role of socioeconomic variables, suggest that socioeconomic variables may have the ability to explain much of the observed variation in health care utilization across small areas.

FIGURE 1

ELDERLY DISCHARGE RATE 1980 - NORTH CAROLINA

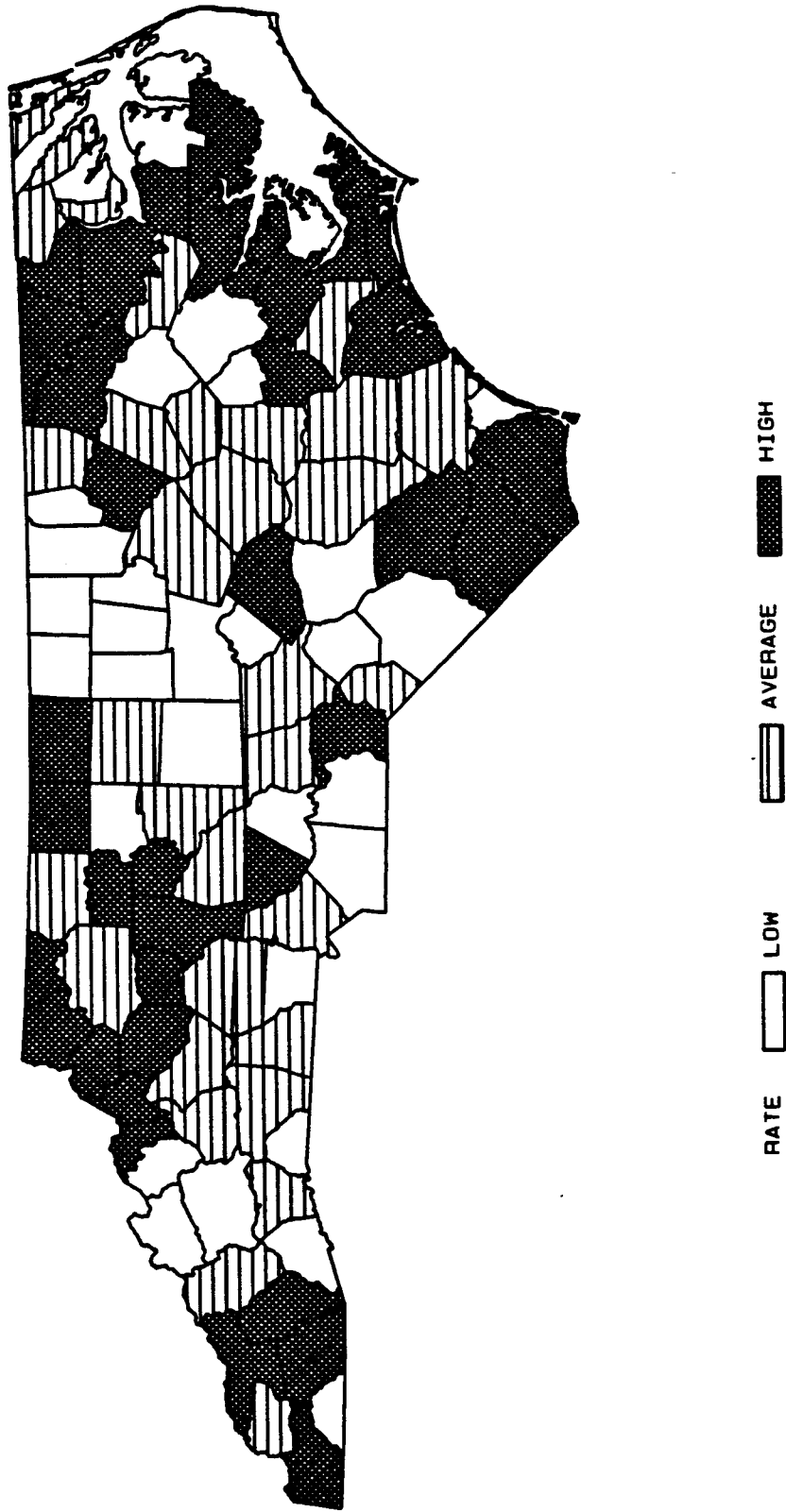


Table 1

Descriptive Statistics  
The 100 Counties of North Carolina, 1980

VARIABLE	MEAN	STD.DEV.
ASSET	1483	498.9
BLACK	19.92	14.10
DISRATE	371.6	76.15
FED	3.059	2.693
HOSP	0.830	0.378
INCOME	5298	811.5
INFMR	159.1	38.67
LABOR	12.78	2.784
LOCAL	6.989	1.522
MALE	40.37	2.646
NOHIGH	78.46	8.328
PDIS	18.45	3.937
URATE	6.633	2.405
URATESQ	49.72	42.00
YOUNG	64.56	3.523

Table 2

## TSIV and OLS Estimates of the Parameters in the Discharge Rate Equation

Dependent Variable:	ln(DISRATE)	
Estimation Method:	TSIV (1)	OLS (2)
Independent Variable	Coefficient <sup>a</sup> ( t-ratio )	Coefficient <sup>a</sup> ( t-ratio ) <sup>b</sup>
CONSTANT	1.9147 (1.034)	4.6749*** (6.812)
LABOR	-0.0632** (2.325)	0.0021 (0.222)
INCOME	0.00021 (1.436)	-0.000089** (2.117)
HOSP	0.2912*** (4.010)	0.2915*** (4.806)
INFMR	0.0017** (2.082)	0.0009* (1.832)
PDIS	0.0065 (1.081)	0.0030 (0.554)
LOCAL	-0.0008 (0.031)	-0.0152 (0.785)
NOHIGH	0.0237* (1.885)	0.00018 (0.047)
BLACK	-0.0040 (1.477)	-0.0020 (0.918)
MALE	0.0114 (0.769)	0.0192** (2.203)

Table 2 (continued)

Dependent Variable:	ln(DISRATE)	
Estimation Method:	TSIV (1)	OLS (2)
Independent Variable	Coefficient <sup>a</sup> ( t-ratio )	Coefficient <sup>a</sup> ( t-ratio ) <sup>b</sup>
YOUNG	0.0123 (1.296)	0.0091 (1.477)
N	100	100
R <sup>2</sup>	0.2950 <sup>c</sup>	0.4060

a. \* denotes significance at the .10 level, \*\* at the .05 level, \*\*\* at the .01 level.

b. The t-ratios are based on White-corrected standard errors (White 1980).

c. The R<sup>2</sup> reported for the TSIV estimation is the two-stage least squares R<sup>2</sup>, as defined in Wallace and Silver (1988, p. 354).

Table 3

## Regressions of LABOR and INCOME on Exogenous Variables

Dependent Variable:	LABOR	INCOME
Estimation Method:	OLS (1)	OLS (2)
Independent Variable	Coefficient <sup>a</sup> ( t-ratio ) <sup>b</sup>	Coefficient <sup>a</sup> ( t-ratio ) <sup>b</sup>
CONSTANT	10.528 (1.565)	10214.7*** (7.987)
URATE	-1.2284*** (2.623)	-200.593*** (3.512)
URATESQ	0.0413* (1.689)	8.8697*** (3.258)
FED	-0.0835 (0.981)	24.5545* (1.725)
ASSET	0.0014** (1.996)	0.6509*** (5.329)
HOSP	-1.5279** (2.418)	-258.496** (2.059)
INFMR	0.0085 (1.306)	0.0242 (0.021)
PDIS	0.0498 (1.040)	-5.6229 (0.563)
LOCAL	0.3659* (1.767)	-30.8385 (0.961)
NOHIGH	0.0882* (1.784)	-44.0664*** (5.008)



Table 3 (continued)

Dependent Variable:	LABOR	INCOME
Estimation Method:	OLS (1)	OLS (2)
Independent Variable	Coefficient <sup>a</sup> ( t-ratio ) <sup>b</sup>	Coefficient <sup>a</sup> ( t-ratio ) <sup>b</sup>
BLACK	-0.0220 (1.108)	1.8314 (0.420)
MALE	-0.3745*** (3.579)	-69.2375*** (3.951)
YOUNG	0.1796*** (2.858)	26.0012** (2.166)
N	100	100
R <sup>2</sup>	0.5233	0.8162

a. \* denotes significance at the .10 level, \*\* at the .05 level, \*\*\* at the .01 level.

b. The t-ratios are based on White-corrected standard errors (White 1980).

## APPENDIX

### NORTH CAROLINA COUNTY VARIABLES

#### Sources

The data are drawn from four basic sources: the Area Resource File, the Bureau of Economic Analysis, the Bureau of the Census, and North Carolina's State Center for Health Statistics. INFMR was obtained from the Area Resource File. ASSET can be calculated using data from U.S. Department of Commerce, Bureau of Economic Analysis (1982). DISRATE and HOSP can be calculated using data from State Center for Health Statistics (1982a, 1982b, and 1985). The remaining variables are created from 1980 Census data. NOHIGH and INCOME are calculated using Census data provided by the Institute for Research in Social Science of Chapel Hill, North Carolina. BLACK can be calculated from data in U.S. Department of Commerce, Bureau of the Census (1982). The remaining Census variables can be found in U.S. Department of Commerce, Bureau of the Census (1983b). Unless otherwise specified, the Census variables reflect conditions at the time of the Census (April 1980).

#### Variable Descriptions

**ASSET** - The Bureau of Economic Analysis reports total income from rents, dividends, and interest by county for 1980. ASSET is equal to total income from these sources divided by the number of individuals over twenty-four years of age (as reported by the Census).

**BLACK** - Percentage of the 65 or older population that is black.

**DISRATE** - All non-Federal short-term general hospitals in North Carolina are required to provide information on utilization when they apply for license renewal each year. (The absence of information on Federal hospitals is not a serious problem because relatively few hospital stays occur in Federal hospitals. For North Carolina, only about 5 percent of the short-term general hospital admissions in 1981 occurred in Federal hospitals (American Hospital Association 1982).) Each non-Federal short-term general hospital must report to the state the number of discharges over a specified 12-month period and must provide the geographic distribution of its patients during 4 specified months of the year. The 12-month period runs from October 1, 1980 to September 30, 1981 and the four specified months are January, April, July, and October of 1981. All information is age specific. Essentially, for every hospital, the state allocates the hospital's yearly discharge figures to North Carolina counties and other states based on the geographic distribution information. For example, if over the four specified months, 20 percent of the 65 or older patients of Duke University Hospital were from Durham County, North Carolina, then the state assumes 20 percent of the yearly discharges in this age group from Duke University Hospital pertain to residents of Durham County. By only requiring four months of geographic distribution information, the state hoped to limit the reporting burdens of the

hospitals. To generate the number of age specific discharges for the residents of a given county, the state sums the discharges that pertain to that county over all non-Federal short-term general hospitals in the state. These estimates of 65 or older discharges by county of residence are published in Hospital Patient Origin Report, 1981 Data (State Center for Health Statistics 1982a). I will refer to these estimates as DISCHARGES. Since some residents of North Carolina travel out of state to receive hospital care they will not be reflected in the licensure data. For every county, however, the state estimates the percentage of hospital patients that travel out of state to receive care. These estimates are based on unpublished studies using Blue-Cross, Medicaid, and Medicare data. The state publishes these estimates for counties in which more than 5 percent of the patients received care out of state. The estimates were originally based on 1974 and 1977 data and were updated in 1983. I use the 1983 estimates to adjust DISCHARGES. For example, if 10 percent of a county's hospital patients receive care in another state, DISCHARGES is divided by 0.90. The out of state migration estimates are published in Hospital Patient Origin Report, 1984 Data (State Center for Health Statistics 1985). DISRATE is formed by multiplying DISCHARGES by 1000 and dividing by the number of elderly at the time of the Census.

FED - Percentage of the employed civilian population that is employed by the Federal Government.

HOSP - Value of 1 if a non-Federal short-term general hospital is located in the county, 0 otherwise.

INCOME - The income statistics of the Census pertain to the year 1979. There are two groups of elderly - unrelated individuals and individuals in families (institutionalized individuals are not included in the income statistics). Unrelated individuals report individual income whereas families report total family income. The Census provides county-level data on the number of individuals and families that have income within a specified range. For unrelated individuals 65 or older, the ranges, in dollars, are as follows: 0-999, 1000-1999, 2000-2999, 3000-3999, 4000-4999, 5000-5999, 6000-6999, 7000-7999, 8000-8999, 9000-9999, 10000-11999, 12000-14999, 15000-24999, 25000-49999, and 50000+. It is assumed that the mid-point of each range is the income of each unrelated individual that falls in that range (those in the 50000+ group are treated as having 50000). For each county, an average is taken to get the average income of unrelated individuals (AVGURI). The individuals in families present more of a problem because family income, by definition, is not age specific (family members can be of different ages). The Census does keep data on family income when the householder is 65 or older. A householder is the individual in the family in whose name the dwelling is owned or rented. If there is no such individual, a member of the family is arbitrarily defined to be the householder. For families in which the householder is 65 or older, the Census provides data on the number of families that have income within specified ranges. The ranges, in dollars, are as follows: 0-2499, 2500-4999, 5000-7499, 7500-9999, 10000-12499, 12500-14999, 15000-17499, 17500-19999, 20000-22499, 22500-24999, 25000-27499, 27500-29999, 30000-34999, 35000-39999, 40000-49999, 50000-74999, and 75000+. Family income is calculated by coding income ranges to the mid-point and assigning families in a given range the mid-point value (those in the

75000+ group are treated as having 75000). For each county, an average is taken to form AVGFAM. AVGFAM is divided by 2.4 (the statewide average family size for families where the householder is 65 or older) to form AVGFAMPC. INCOME is a weighted average of AVGURI and AVGFAMPC (the weights being the fraction of the county's elderly noninstitutionalized population that lives alone or only with nonrelatives and the fraction of the county's elderly noninstitutionalized population that lives with family members).

INFMR - The infant mortality rate over the period 1976 to 1980. Expressed in infant deaths per 10,000 births.

LABOR - Percentage of the 65 or older population that is in the labor force during the reference week of the Census survey (generally, the last week in March 1980).

LOCAL - Percentage of the employed civilian population that is employed by a local government.

MALE - Percentage of the 65 or older population that is male.

NOHIGH - Percentage of the 65 or older population that did not complete high school.

PDIS - Percentage of the noninstitutional elderly that report a health condition that has lasted at least six months that would make it difficult or impossible to use public transportation such as trains, buses, and cabs.

URATE - Civilian unemployment rate.

URATESQ - The square of URATE.

YOUNG - Percentage of the 65 or older population that is between the ages of 65 and 74.

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