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Geographic Accessibility to Hospitals in the United States: Rurality and Insurance Coverage

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Abstract: This paper uses census block groups in the contiguous 48 U.S. states and approximates the average speed traveled on various types of roadways to identify the "quickest" hospital for each block group, the one that can be reached in the least time along the road network. Results are summarized using these estimated travel times and both straight line and road network distances for rural and urban areas for comparison. The U.S. Bureau of Labor Statistics' SAHIE estimates of health insurance coverage at the County level are then used to construct estimates of insurance coverage at the block group level. These are used to examine whether there are differences in geographic access to hospitals for those with and without insurance coverage.

1. Introduction

There are many dimensions along which "accessibility" to health care can be defined, both spatial (distance, geography, and transportation-related) and nonspatial (social class, income, gender, etc.) (Wang and Luo, 2005). This paper constructs a detailed measure for spatial or geographic accessibility for the 48 contiguous U.S. states and the District of Columbia, measuring accessibility to the "General Medical and Surgical Hospital" that can be reached in the shortest time by automobile. U.S. Census block groups are the assumed locations of the population, and distances and approximate travel times along the road network are measured to the "quickest" hospital—the one that can be reached in the least time.

While this approach to approximating travel times is imperfect, it is a step forward in the measurement of a proxy for the travel cost of accessing certain types of health care. As will be discussed in the literature review, previous studies have either looked at small geographic areas (a city, county, or single state) or have used crude proxy measures of accessibility such as providers per capita or straight line distances. While a truly realistic accounting of the time that it takes to reach a destination would have to account for stochastic factors such as traffic patterns and the weather, the approach in this paper of using a standard table of average speeds varying by roadway type should give us an approximation of an expected travel time that people might face under ideal conditions.

This method allows for a comprehensive description of geographic accessibility at a fine geographic level for the contiguous U.S. Several commonly used measures in the literature are compared and contrasted, such as how straight line distances relate to road network distances and how measuring distance gives a different impression of accessibility than does measuring time. Differences in accessibility between rural and urban areas are also calculated.

Lastly, this paper presents an estimation of how geographic accessibility is related to health insurance coverage, an important nonspatial healthcare accessibility factor in the U.S. Data at the finest resolution available on health insurance (the county level) are used to create a predictive model which produces estimates at the much finer block group level. While these estimates are likely to be individually "noisy," they should produce an overall pattern that allows a general comparison of geographical accessibility between the insured and the uninsured in the U.S.

The work in this paper provides a first look at the distribution of accessibility to General Medical and Surgical Hospitals in the lower 48 states and Washington, D.C. using a fine geographic level and driving times along actual road networks. As will be demonstrated in the literature review, the time it takes to get to the hospital is directly related to many different health outcomes. An understanding of the underlying distribution of this measure of accessibility and how this measure compares to others common in the literature are essential elements when discussing health policy.

The next section provides a brief review of previous research on accessibility with a particular emphasis on accessibility to medical care. Section 3 describes the data and the methodology used for the measurement of accessibility. Section 4 describes the results of the accessibility measures. Section 5 describes the data and methodology for constructing estimates of insurance coverage, and the results are presented in Section 6. The last section presents a summary, conclusions, and suggestions for future work.

2. Literature review on accessibility

There are many studies that measure accessibility to health care using a variety of methods and defining "access" in many ways. For example, Newhouse et al. (1982) measured accessibility as the number of specialists per capita in counties. Rosenthal et al. (2005) examined customer and physicians' locations, modeling accessibility as the number of physicians per capita and looking at the average straight line distance between patients and physicians at the zip code level for a selection of states.

Looking at data at the finer block group level, Love and Lindquist (1995) assessed customer and hospital locations for the State of Illinois. They measured distances "as the crow flies" (straight lines between the origin and destination). Love and Lindquist then adjusted these straight line distances using Martin and Williams' (1992) findings that road-network distances are about 20-25% longer than the straight-line distances. This is somewhat lower than Burkey's (2011) findings in four southern U.S. States, in which the mean road network distances varied between 26 and 32% longer than straight line distances in these states.

Hare and Barcus (2007) used road network distances in Kentucky as proxies for the time traveled. The authors' main result is the correlation between areas of low accessibility of hospitals and (rural) areas of poverty. Despite the low degree of accessibility in these poor areas, they tend to have some of the highest utilization rates of hospitals for some diseases, particularly heart-related conditions. The authors cited a potential lack of preventive care and environmental characteristics associated with low income regions.

Even in urban areas the correlation between accessibility and preventive care is important. Currie and Reagan (2003) found that among inner-city children each additional mile to the closest hospital (which is the primary source of medical care for many in this cohort) corresponds to a 3% decrease in the probability that a child has had a recent medical checkup. Goodman et al. (1997) found similar results. In particular, they determined that patient–hospital distance is inversely correlated to the likelihood that they will seek care in discretionary services. Nattinger et al. (2001) found that longer patient–hospital distances correlated with lower use of follow-up radiation treatment after a lumpectomy for breast cancer. Using a quasi-experimental method, Buchmueller et al. (2006) used hospital closures to examine the effects on patient outcomes of changing accessibility. They find that patient–hospital distances positively correlate with deaths from heart attacks and accidental injuries.

An additional way to quantify accessibility that will be discussed in this paper is the proportion of people living within 30 minutes of the quickest hospital. Research (e.g., Newgard et al., 2010) has given credence to a "golden hour" in trauma cases, showing that arrival at a trauma center within 60 minutes of an accident occurring greatly increases survival rates. However, this 60 minutes typically includes three phases: notification, response, and transportation (Carr et al., 2009), and 30 minutes may be considered a reasonable cutoff for the transportation phase when discussing emergency care. A 30 minute threshold has also been used in several studies involving both emergency and non-emergency care (e.g., Bosanac, Parkinson, and Hall, 1976; Forrest and Starfield, 1998; Frezza and Mezghebe, 1999; Burkey, Bhadury, and Eiselt, 2012).

3. Measurement of accessibility and population characteristics

Earlier studies cannot be faulted for using fairly simple approximations for geographic accessibility—the computing power required to compute millions of routes[1] is just now becoming practical. By taking an additional step forward in the measurement process, this paper will shed some light on an important barrier to healthcare for many. This paper focuses on accessibility to hospitals, specifically "General Medical and Surgical Hospitals". According to the American Hospital Association (AHA)'s, a "General Medical and Surgical" hospital is any facility that provides diagnostic and therapeutic services for a variety of conditions, provides x-ray services, has a clinical laboratory, and has a staffed operating room (AHA, 2006). The locations of these 4,772 hospitals are taken from the 2001 AHA database. This year was chosen in order to match up closely with year 2000 Census data, which is the last year that small area data for demographic characteristics are available at the neighborhood (block group) level. More recent demographic data is only available at the county or MSA level, units too large to use for a detailed analysis of accessibility. From the Census Bureau's SF3 file, all of the block groups from the 48 contiguous U.S. states and D.C. with nonzero populations were extracted, giving a total of 206,254 block groups with an average population of 1,354 each.

Because geographic accessibility is such an important factor in determining health outcomes, four related accessibility measures will be computed. Taking population counts and population-weighted block group centroids from the 2000 U.S. Census, the travel time to the hospital that takes the minimum driving time to access along the road network is computed. For the sake of brevity, these will be called the "quickest" hospitals. These travel times and distances are calculated using Microsoft MapPoint and a third-party add-in[2], where speeds of 65 mph on interstate highways, 60 mph on limited access highways, 50 mph on major roads, 35 mph on minor roads, and 20 mph on city streets are assumed.[3] Of course, these speeds are approximations and will vary by place and time of day. In order to compare results to those from other studies, straight-line distances and road network distances from the centroid of each block group to these same quickest hospitals are also calculated. Lastly, the percentage of households that spend more than 30 minutes getting to the quickest hospital is computed.

4. Accessibility results and comparisons

For the entire sample, the average time between where people live and the quickest available hospital is 11.32 minutes.[4] Figure 1 shows the variation in the average time by state. The average road network distance travelled is 6.26 miles, which becomes 4.63 miles if measured as a straight line approximation as used in many papers. Therefore, in the current application road network distances are approximately 35.2% longer than the straight line distance for the average person. This is significantly higher than Martin and Williams' (1992) finding that road-network distances are about 20-25% longer than the straight-line distances and Burkey's (2011) finding of 26-32% for several southern U.S. states. This may be due to the high proportion of people living in metropolitan areas that will face so-called "Manhattan" (right angle path) distances, in addition to some who will face natural barriers such as rivers and mountains.

The results can be broken down into more detail in order to discover how accessibility differs for various groups. Figure 2 presents a smoothed histogram for the overall distribution of time to the quickest hospital in the U.S. The graph is truncated at 60 minutes for better viewing, though the maximum value in the data is 313 minutes.[5] Thus, there are 433,372 people (out of approximately 279 million) not represented by

[1] Technically, if one wants to find the quickest of 5,000 hospitals for each of 200,000 block groups, one would need to compute 1.0 billion routes. Our software uses some heuristics to avoid calculating some obvious non-optimal routes, but the process takes a very fast PC several weeks to complete.

[2] MPMileCharter by Winwaed Software. http://www.winwaed.com/.

[3] An additional, though uncommon, travel mode is by ferry. MapPoint usually provides a reasonable approximation of ferry times in these cases. However, in our data checking, we found 66 routes (out of the 206,254) where the ferry distance and time were apparently not included in the calculations along with the road portions. For these 66 routes we replaced the road network distance with 1.25 times the straight line distance and approximated the travel time assuming an average speed of 15 mph over all sections of the trip. While this is a bit *ad hoc*, it affects only 82,056 people in the data, or .029% of the population under study.

[4] All reported averages are populated-weighted means.

[5] The four highest values are quite interesting areas. The two highest values are block groups on Point Roberts, which is a small area of land in Washington State. While not an island, it is cut off from the continental U.S., being the tip of a peninsula in British Columbia below the 49th parallel. The next two highest values (at 286 and 235 minutes) are block groups on the Outer Banks of North Carolina (Ocracoke and Cape Hatteras), where people would normally have a long ferry ride in order to go to the hospital but use helicopters in emergencies.

this histogram who are estimated to travel more than one hour to reach the quickest hospital, amounting to 0.155% of the population. A total of 2.87% of the population live more than 30 minutes from the quickest facility.

It is well known that accessibility to hospitals will be worse for rural residents than for urban dwellers. We use the U.S. Census bureau's definition of rural and urban blocks, which classifies as "urban" all territory, population, and housing units located within an urbanized area (UA) or an urban cluster (UC). It delineates UA and UC boundaries to encompass densely settled territory, which consists of core census block groups or blocks that have a population density of at least 1,000 people per square mile and surrounding census blocks that have an overall density of at least 500 people per square mile (Census 2000 Urban and Rural Classification, n.d.).

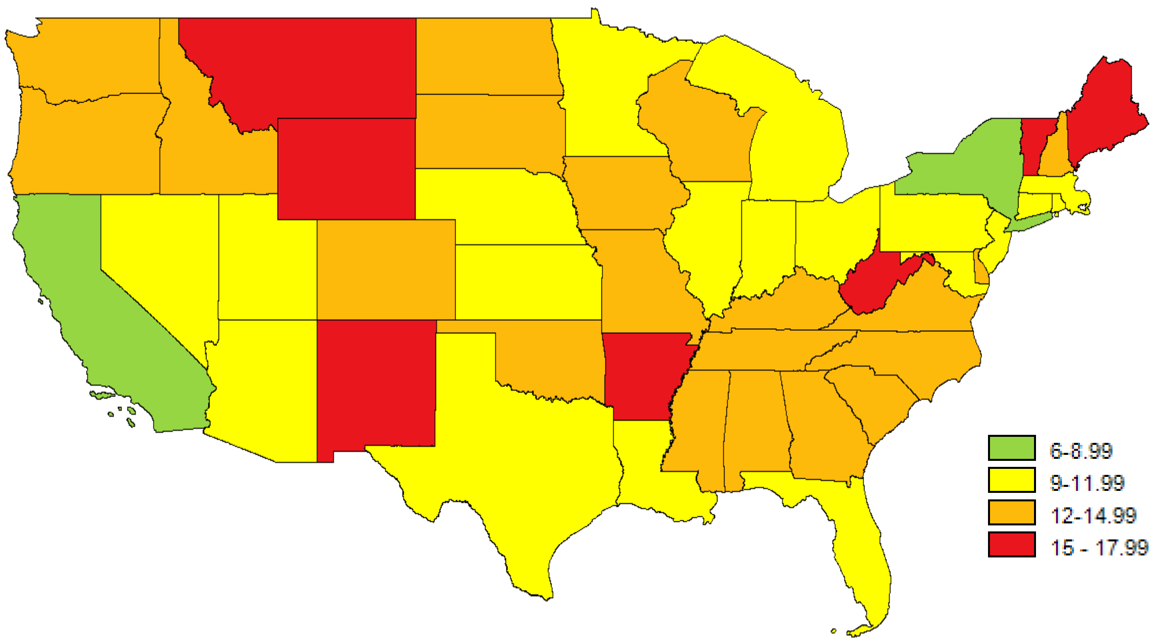

Figure 1. Average minutes to quickest hospital by state.

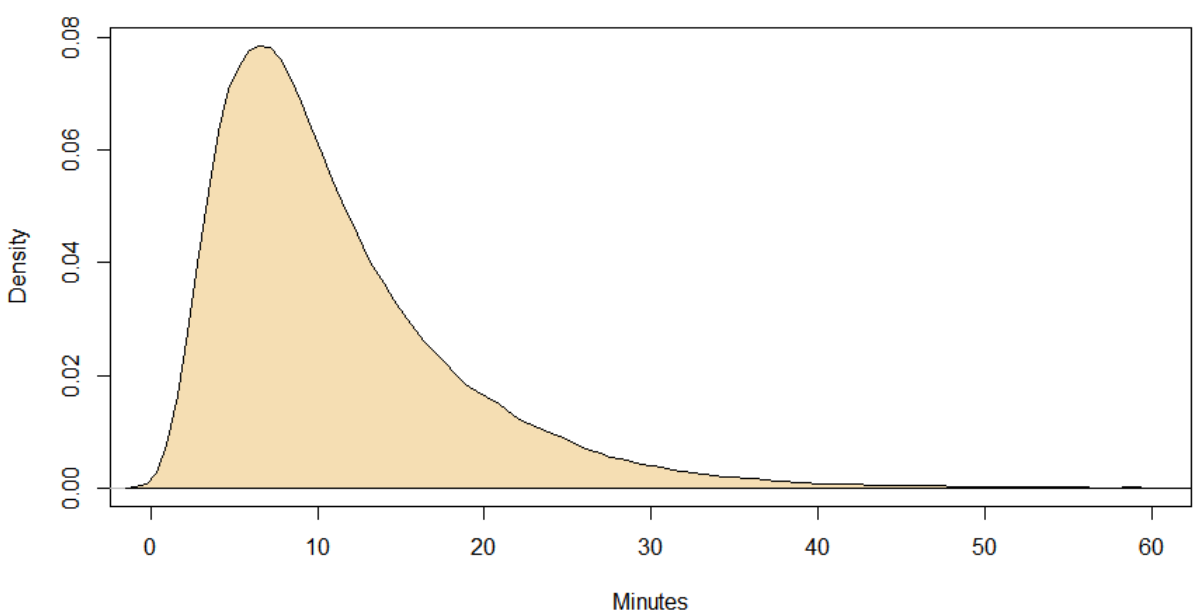

Figure 2. Accessibility distribution to the quickest hospital (truncated at 60 minutes).

Using this definition, the Census SF3 files for the 48 contiguous states and D.C. report that 78.97% of the population live in an Urban Block. Table 1 summarizes the various accessibility measures for the rural and urban population for comparison, and Figure 3 displays smoothed histograms for both time and distance accessibility measures for rural and urban dwellers. One interesting note is that while the average distance for the rural population is 2.9 times as large as that for the urban population, the estimated time it takes is only 2.2 times the urban value. While this difference is still large, using distance alone might be seen to overstate the accessibility differences between urban and rural residents. This overstatement is slightly worse when using straight line distances, as the rural mean is 3.0 times the urban mean in this case.

Table 1. Summary statistics, urban vs. rural.

	Mean Time	Mean Distance	Mean Straight Line Distance	Network/Line Ratio	% Over 30 Minutes
Urban	9.01	4.46	3.26	1.368	0.45%
Rural	19.99	13.03	9.78	1.332	11.94%
All	11.32	6.26	4.63	1.352	2.87%

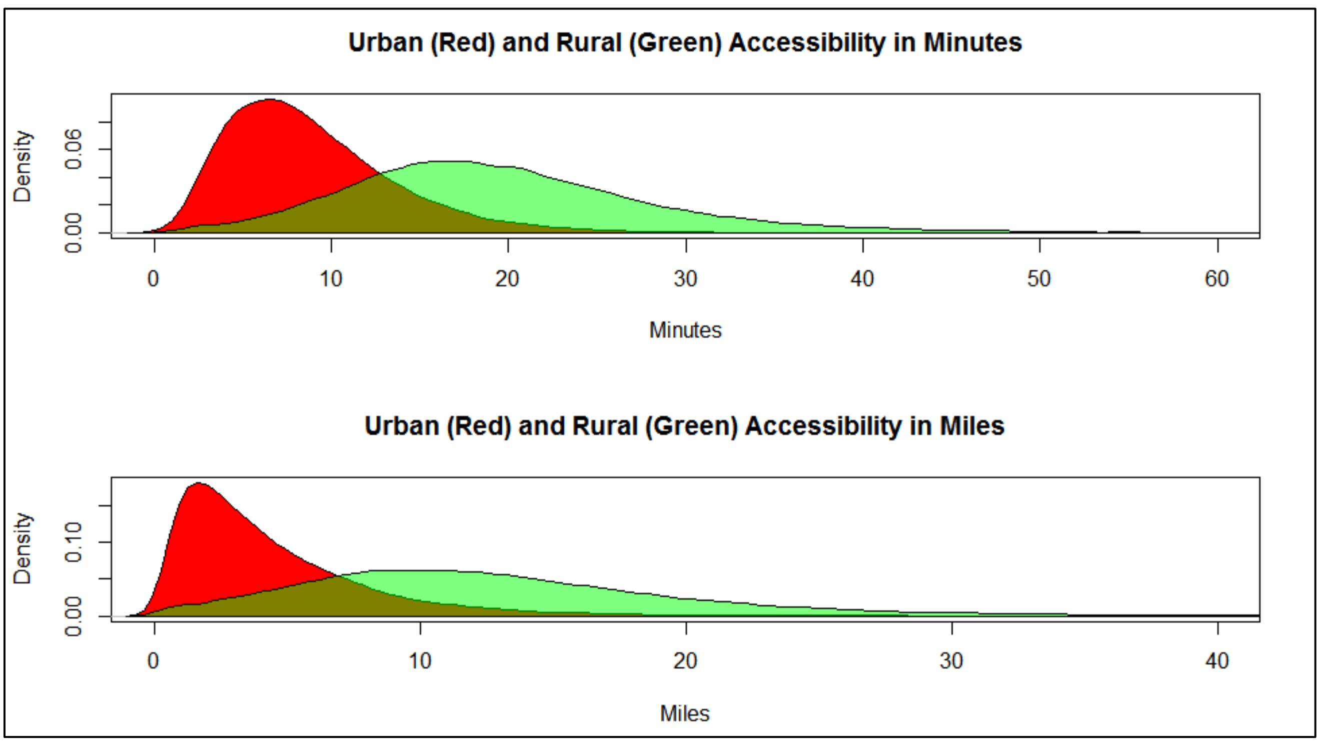

Figure 3. Comparison of Urban and Rural Accessibility.

5. Small area insurance estimates

While it would be useful to investigate the relationship between insurance coverage and accessibility to hospitals, accurate data on a small scale are not readily available. The smallest geographic area for which health insurance coverage estimates are available is the county level, found in the Small Area Health Insurance Estimates (SAHIE) created by the U.S. Census Bureau. Using publicly available data, a predictive model is constructed in an attempt to replicate as closely as is feasible the model used by the

BLS to generate SAHIE's estimates. Note that the purpose of this predictive model is neither to test any hypotheses nor to calculate any effect sizes; therefore, discussions of coefficient estimates or statistical significance are not germane.[6] After finding a model with a good fit, this model is used to generate estimates of insurance coverage at the Census Block Group level, since SAHIE does not provide sub-county estimates. The model is built based on data similar to that used in the SAHIE model (see Fisher and Turner (2003) for model details) and SAHIE estimates for the year 2000. This analysis is performed for the year 2000 out of necessity, because it is the latest year for which demographic data at the Census Block Group data exist in the U.S.[7] Additionally, looking at the data in this early time period before the 2010 Affordable Care Act (ACA) allows a look at insurance coverage and hospital location well before both the ACA and the several state initiatives for greatly increasing health care coverage (e.g., Massachusetts in 2006 (KFF, 2012)). Even after these changes and the implementation of the ACA, the correlation between SAHIE estimates for 2000 and 2013 is fairly high at 0.78.

The aggregated dataset consists of 3,139 counties after removal of some counties for which SAHIE did not provide insurance coverage estimates. A list of variables used by SAHIE and in the replication are given in Table 2. In the replication, variables were constructed from the available census data in Summary File 3 that matched the SAHIE variables closely. This data is extrapolated from the so-called "census long form" that was sent to approximately 1 in 6 households in 2000. In the replication of the SAHIE model some modifications were necessary, because the BLS used some data that is not publicly available when constructing their estimates, as described below.

Table 2. Variables used by SAHIE and in the replication.

<table>
<tr><td>SAHIE</td><td>SAHIE REPLICATION</td></tr>
<tr><td>log of the proportion insured in each county</td><td>log proportion insured in each county</td></tr>
<tr><td>log proportion who are 65 or more years old from demographic population estimates</td><td>log proportion of population 65 years and older</td></tr>
<tr><td>log of the proportion of people who are American Indian or Alaska Native from demographic population estimates</td><td>log proportion of population not Hispanic, Indian and Alaska Native alone</td></tr>
<tr><td>log of the proportion of people of Hispanic origin from demographic population estimates</td><td>log proportion of population Hispanic</td></tr>
<tr><td>indicator for the West Census region</td><td>State dummy variable</td></tr>
<tr><td>product of the indicator variable for the South Census region and the log proportion Hispanic</td><td>State dummy variable*log proportion Hispanic</td></tr>
<tr><td>log of the proportion of people with family Income to Poverty Ratios (IPRs) between 200% and 300%</td><td>log proportion of population with ratio of income in 1999 to poverty level of 1.5 to 2.0, and prop. income 2.00 and over</td></tr>
<tr><td>log proportions of persons under age 18 who are participants in the Medicaid program</td><td rowspan="3">log proportion of households receiving public assistance</td></tr>
<tr><td>log proportions of persons age 35-64 years who are participants in the Medicaid program</td></tr>
<tr><td>log proportion of the population who are receiving Supplemental Nutrition Assistance Program (SNAP) formerly known as the Food Stamp program</td></tr>
<tr><td>mean of the log IPR, as estimated from tax returns</td><td>Mean of log IPR using simplifying assumptions and Census data</td></tr>
<tr><td>variance of the log IPR, as estimated from tax returns</td><td>Variance of log IPR using simplifying assumptions and Census data</td></tr>
</table>

[6] However, we provide details on the estimation results in the Appendix for those who are interested.

[7] Also note that questions on health insurance coverage were added to the American Community Survey (ACS) in 2008, so earlier estimates using this data are not possible for model building or cross-validation.

5.1. Variables used in constructing the predictive model

In the predictive model, the dependent variable is the county-level SAHIE estimate. Note that the SAHIE model and the constructed model are both log-log models, though in the description of variables below the adjective "log" is eschewed to avoid repetition.[8] Just as with the SAHIE model, the proportion of the population that is over 65 is included (because all of these people are eligible for Medicare insurance), as are the proportion that are Hispanic and proportion that are American Indian or Alaska Native.

The SAHIE model used a dummy variable for the West Census Region and an interaction term for the product of a dummy variable for the Southern region times the proportion Hispanic. The replication includes dummies for state fixed effects and also includes interaction effects with proportion Hispanic in order to allow for a better fit and compensate for some of the data that is not publicly available.

SAHIE's model included as a variable the proportion of people living in households earning between 200-300% of the poverty threshold income, which in 2000 was $8,350 for a one person household plus $2,900 for each additional person in the household.[9] This variable was used because most people earning below 200% of the poverty level will be eligible for Medicaid, the health insurance assistance program for the poor in the U.S. SAHIE uses the proportion in the 200-300% range as a proxy for the "working poor", who might make too much to be eligible for Medicaid but not be in jobs that provide health insurance as a benefit or be able to afford to buy health insurance in the marketplace. While the Census data does provide some data on the number of people living in poverty and for certain percentages of the poverty level income (e.g., people in households making 100-124% of the poverty threshold, 125-149% of the threshold, etc.), the highest percentage given in the publicly available data is 200%. In order to capture some of the variation in income near the range considered in the SAHIE model, the replication model includes the percentage of people living in households earning in the range of 150-200% of the poverty threshold. The replication model also includes the proportion of people in households earning over 200% of the poverty threshold.

The SAHIE model includes the proportion of people who receive Medicaid (broken in to age rages for children and adults) as well as the proportion receiving funds from the Supplemental Nutrition Assistance Program (SNAP). Specific welfare programs are not broken down into such fine categories in the Census data, so the replication model includes the proportion of households receiving any kind of public assistance income as a proxy.

The final two variables used by SAHIE involve the Income to Poverty Ratios (IPRs) for households in a county. That is, they take the household income and divide it by the poverty threshold income for that size of household. They estimate the mean and the variance of the log of this ratio within each county, using both as predictor variables in their model. In order to construct IPRs, the Bureau of Labor Statistics accessed tax return data in order to estimate these ratios for each household, making the assumption that tax returns and households match up closely. Since this data is not publicly available, for the replication model a similar measure using Census data and a few necessary simplifying assumptions was constructed. The assumptions are kept as simple as possible, merely trying to construct a measure that will be correlated with the variables used in the SAHIE model. For each county, the average household size was calculated, and it is assumed that all households in the county are this size.[10] Then, the poverty threshold for a household of this average size is calculated using the formula for the year 2000. This generates a rough estimate of the mean poverty threshold for the mean household.

Using the tallies of the numbers of households in various income groups, a vector of IPRs is calculated. The Census data breaks households into categories as shown in Table 3. Making the assumption that households are uniformly distributed within each income bracket, and assuming that in the "$200,000 or more" bracket all make the average income in this bracket, crude estimates of the mean and variance of the IPR in each county can be created. While more elaborate assumptions could be used to (possibly) make more accurate estimates, the construction was kept simple since the goal is to make a predictive model rather than to make policy-oriented interpretations or test hypotheses.

[8] In order to avoid the zero problem with logs, 0.001 was added to the proportion variables where this would have caused an issue.
[9] See, e.g., https://aspe.hhs.gov/2000-hhs-poverty-guidelines.
[10] We are forced to make this assumption because, even though the Census data provide distributions of household size, there is no relationship given between household size and income.

Table 3. Census household income brackets.

Household income in 1999 less than $10,000
Household income in 1999 $10,000 to $14,999
Household income in 1999 $15,000 to $19,999
Household income in 1999 $20,000 to $24,999
Household income in 1999 $25,000 to $29,999
Household income in 1999 $30,000 to $34,999
Household income in 1999 $35,000 to $39,999
Household income in 1999 $40,000 to $44,999
Household income in 1999 $45,000 to $49,999
Household income in 1999 $50,000 to $59,999
Household income in 1999 $60,000 to $74,999
Household income in 1999 $75,000 to $99,999
Household income in 1999 $100,000 to $124,999
Household income in 1999 $125,000 to $149,999
Household income in 1999 $150,000 to $199,999
Household income in 1999 $200,000 or more

The empirical PDF for IPR is made up of 15 uniform segments and a mass point at the mean of the county's household income in the highest category. Since it is assumed that the same number of people are in each household, the PDF can be made with respect to households instead of individuals. Designating n_i as the number of households in each income bracket, N the total number of households in each block group, and a_i and b_i the upper and lower limits of each bracket, the PDF is:

$$f(x) = \frac{n_i}{N(b_i - a_i)} \text{ for } i{=}1..16,\ f(\mu_{17}) = \frac{n_i}{N} \text{ for } i{=}17, \quad (1)$$

where μ_{17} is the mean income in the highest group.

5.2. Results of creating the predictive model

Using the variables in Table 2 did a fairly good job of replicating the SAHIE results. Using the same log-log functional form as the SAHIE model produces an R^2 of 0.9041. Figure 4 provides a scatterplot illustrating the closeness of the fit between the SAHIE and the OLS replication model. While there are some outliers, and it is not recommended to use this technique to generate meaningful predictions for an individual small area, it is reasonable to use this model as a descriptive tool to explore overall relationships between insurance coverage and hospital accessibility. The estimated model is used to generate block-group level estimates, and these are matched with the times and distances to the quickest hospital discussed previously.

When creating the estimates at the block group level, Washington, D.C., is omitted because SAHIE did not provide estimates for this region in the data. When generating the block group predicted values with the county model, there were 34 block groups without valid household data that were removed, leaving 205,793 block groups.[11] There were 56 block groups with a predicted value of greater than 1.0, with a maximum of 1.22. These out-of-bounds values were reset to 1.0, the logical maximum for the proportion insured.

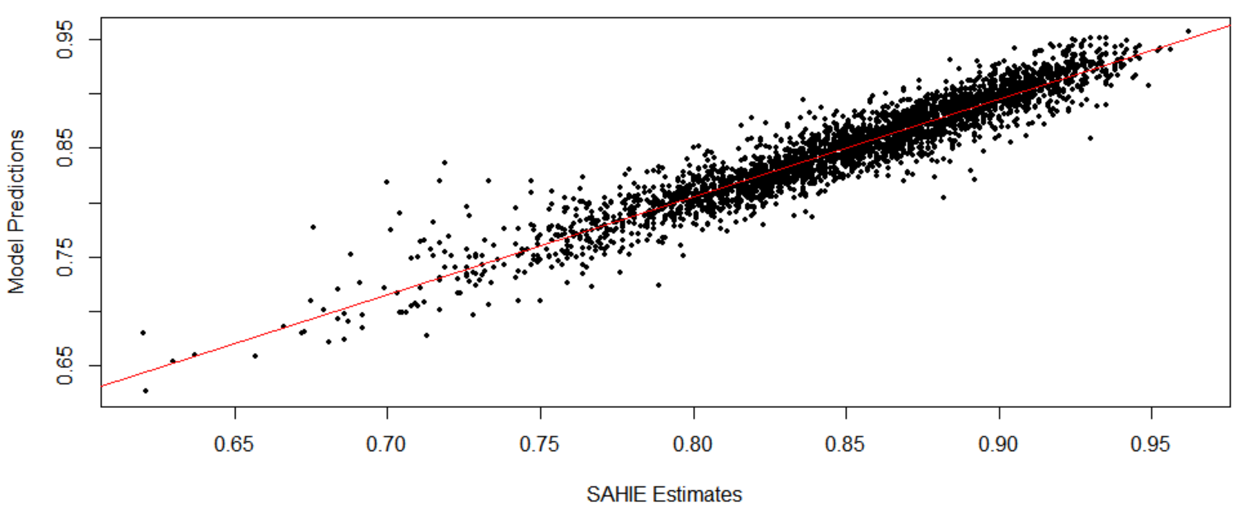

Figure 4. County model: SAHIE (actual) vs. predicted values for OLS model for proportion insured.

[11] A typical example is block group 060552009001 near Napa California, which contains a park and golf course. The Census records 1,102 people in the block group but records only one "household". There don't appear to be any housing units in this area, so perhaps this represents homeless persons estimated to live in the park and surrounding area. An article in the Napa Valley Register appears to confirm this (Courtney, 2008).

6. Insurance coverage and accessibility

The predictions generated in the previous section are used to explore the relationship between insurance coverage and hospital accessibility. Theoretically, hospitals should desire to locate close to paying customers. However, patients covered by public insurance programs (Medicare and Medicaid) may provide little or negative profitability, which can be a burden to for-profit hospitals (Evans, 2015). Additionally, hospitals are unlikely to move, and the demographics around a hospital are likely to change over the decades. Therefore, no *a priori* expectations are formed about the relationship between insurance coverage rates and accessibility.

Table 4 displays some comparisons regarding accessibility to the quickest hospital and insurance coverage for all people and for rural and urban block groups considered separately. The first column is repeated from Table 1 for ease of comparison. It appears that the uninsured have slightly better accessibility to hospitals than the insured (almost a minute closer, on average) assuming that the mode of transportation is by personal car. This may not be the case for many low income, uninsured people who rely on public transport. This lower number for the uninsured is driven by those in urban areas. Those people that are uninsured in rural areas appear to have the worst of both worlds: they appear to have lower geographic accessibility even when compared to the rural insured. The rural uninsured appear to have a longer journey by almost one minute compared to their insured counterparts. This compounded barrier to healthcare accessibility should be of concern for those interested in rural health and development.

Table 4: Insurance coverage and accessibility in minutes

	Mean Time Overall	Mean Time Insured	Mean Time Uninsured
Urban	9.01	9.14	8.29
Rural	19.99	19.88	20.75
All	11.32	11.46	10.54

7. Summary and conclusions

This paper has explored the geographic accessibility to hospitals using estimates of travel time along the road network. This was done for the 48 contiguous states and Washington, D.C., using assumptions of various speeds traveled along different road types. This allowed the production of a big picture overview of accessibility using very fine-level data at the Census Block Group level. The analysis in this paper allowed highlighting of the differences between using straight line distances, road network distances, and estimated travel times along road networks for analyzing accessibility. It was found that disparities in accessibility may be overstated when using straight line distances and road network distances compared to what is seen using travel times. If economists and epidemiologists are interested in using geographical access as a proxy for a cost variable in obtaining health care, then travel times might arguably be a more appropriate measure of this barrier than either network or straight line distances. It is hoped that researchers will gravitate toward more realistic measures over time.

Publicly available data were then used to attempt a replication of the BLS' Small Area Health Insurance Estimates at the county level, achieving fairly good results. After using this model to predict insurance coverage rates at the Block Group level, it was shown that there are only small differences in accessibility for insured versus uninsured people overall, with the uninsured having slightly better geographic access. More concerning was that for those in rural areas, the uninsured face compounding difficulties in accessing healthcare. In addition to their lack of insurance, these rural residents face worse geographic access to care than the rural insured. This seems to add another layer of concern for the provision of healthcare in rural areas.

Monitoring changes in accessibility for more recent data may become a challenge unless more demographic data at a fine geographical level become available. With the loss of the "long form" in the U.S., many kinds of research are now restricted. However, researchers can hope that some small area data on health insurance coverage may become available as the ACA matures.

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Appendix: SAHIE Replication Predictive Model Results

Variable	Estimate	Std. Error	t value	p value
Intercept	-0.04401	0.018394	-2.393	0.016781
log(Pop IPR 150to 199%)	0.003391	0.002516	1.348	0.177827
log(Pop IPR 200 +%)	0.299732	0.006843	43.8	0.000000
log(Public Assistance)	0.003356	0.001174	2.859	0.004282
log(Hispanic)	-0.01261	0.003695	-3.412	0.000653
log(Pop Indian/Alaska Native)	-0.00308	0.000468	-6.578	0.000000
log(Pop 65+)	-0.00278	0.001668	-1.664	0.096217
Mean log IPR	-0.03818	0.005315	-7.183	0.000000
Variance log IPR	-0.00618	0.003076	-2.01	0.044534
State FE				
State*Proportion Hispanic FE				

Residual standard error: 0.01897 on 3031 degrees of freedom

Multiple R-squared: 0.9041, Adjusted R-squared: 0.9008

F-statistic: 269.7 on 106 and 3031 DF, p-value: < 2.2e-16