Effects of Neighborhood Characteristics on Length of Inpatient Stay: Findings from the U.S. National Data

Huairan Ye, Sungkyu Lee, and Hyun Kim

Using a nationally representative U.S. sample, this study examined the extent to which neighborhood characteristics affected length of inpatient stay (LOS) in the United States. Data were obtained from the 2012 Area Health Resource Files. A total of 3,148 U.S. counties were included in the study. Generalized linear models and the geographically weighted regression model were used to examine the extent to which neighborhood characteristics affected LOS and its spatial variation. Exploratory spatial data analysis was also conducted to examine the geographic patterns in LOS. Hospital bed capacity was found to be the strongest predictor of LOS. Counties with a lower poverty rate, a lower uninsured rate, a higher proportion of female residents, a higher proportion of residents living in urban areas, and more diverse racial groups had a longer LOS. Significant spatial clustering pattern of LOS was also found. Findings suggest that social work professionals should be aware of spatial disparity in health care resources and develop ways of providing equitable health care for vulnerable populations in socioeconomically disadvantaged neighborhoods.

KEY WORDS: *health care resources; health care use; length of inpatient stay; neighborhood characteristics; spatial disparity*

According to the U.S. national data, the average length of inpatient stay (LOS) declined from 5.7 to 4.6 days between 1993 and 2005 (Healthcare Cost and Utilization Project, 2011). Shortening length of hospital stay is one of the main strategies applied by managers and hospital administrators to cope with the increasing financial pressures, as hospitalization is the most expensive form of health care (Gandsas, Parekh, Bleech, & Tong, 2007). The United States is facing an increasing health care demand and a great shortage of physicians (Association of American Medical Colleges, 2012). In this context, despite the ongoing debate on the relationship between LOS and health care expenditures, many health care professionals believe that reducing LOS frees up capacity to increase admissions, increase revenue, and improve health care quality (L. A. Martin, Neumann, Mountford, Bisognano, & Nolan, 2009).

Previous studies on LOS have mainly focused on individual and hospital characteristics. S. Martin and Smith (1996) identified several important determinants of variations in LOS, such as access to hospitals, waiting time for elective surgery, poverty status, and availability of informal care. Epstein et al. (1988)

found that patients with lower socioeconomic status (SES) had longer hospital stays when the variables of age, gender, and the severity of illness were adjusted. However, another study by Ellison and Bauchner (2007) argued that SES had no effect on LOS among children with vaso-occlusive crises caused by sickle cell disease. Remarkably, Gifford and Foster (2008) postulated that LOS is better explained by hospital characteristics than individual characteristic, and several studies also supported that hospital type is greatly associated with variations in LOS (Burns & Wholey, 1991; Cohen & Casimir, 1989; Lee, Rothbard, & Noll, 2012).

Considering disparities in hospitalization from a geographic perspective, Ashton and colleagues (1999) confirmed that significant geographic variation existed in LOS among veterans. Nguyen-Huynh and Johnston (2005) also found regional variation in LOS among Asian and Pacific Islander patients with stroke. Using the Pennsylvania Medicaid claims data, Lee and colleagues (2012) found that people with serious mental illness (SMI) stayed longer at hospitals in counties where a larger percentage of the state's mental health budget was allocated and a smaller percentage of the budget was used for residential purposes.

However, notice that these studies are limited by the use of a specific health condition (such as a stroke or SMI), a specific hospital type (for example, U.S. Department of Veterans Affairs [VA] hospitals), and a specific location (for example, Pennsylvania), resulting in a lack of evidence to draw a general conclusion. Our study investigates the relationship between neighborhood characteristics and LOS using a nationally representative U.S. sample. By adopting a geographical perspective, our study contributes to the literature on hospital utilization with an emphasis on the development and allocation of health care resources within different neighborhoods.

THEORETICAL FRAMEWORK

In light of the ecological perspective, our study specifically focused on the effects of neighborhood characteristics on LOS. The core assumption of the perspective is that humans are dependent on their environments. To reveal the dependency, the ecological theory emphasizes the interaction between individuals and their environments, such as family, work, and community as well as cultural and political environments at large (Chung, 2012).

Previous research has shown the importance of the ecological perspective in understanding the effect of environment on health. For example, a recent study by Chung (2012) highlighted the reciprocal interactions of biological, psychological, social, and cultural variables on suicide attempts among Chinese immigrants in New York City. By applying the ecological system approach, Sanders, Fitzgerald, and Bratteli (2008) also identified barriers to mental health services for older adults in rural areas where resources are relatively limited (for example, lack of knowledgeable health care providers, funding cutbacks, and limited access to services).

According to Kwag, Jang, Rhew, and Chiriboga (2011), the ecological perspective considers factors in both physical and social environment. In particular, physical environment factors, recognized as geographic characteristics, such as the availability and proximity of health facilities, have drawn increasing attention. For example, Andersen et al. (2002) found a positive correlation between the number of federally qualified health centers available and the likelihood of having a usual source of care. Arcury et al. (2005) also found that a shorter distance between patients and physicians increased the frequency of regular family physical exams. Buchmueller, Jacobson, and Wold (2006) suggested that increasing distance

from hospital resulted in higher death rates from heart attacks and unintentional injuries.

Social characteristics of neighborhoods (such as SES or proportion of racial and ethnic groups) have also been proven to be significant predictors of an individual's health status. For example, Black and Macinko (2008) demonstrated that indicators of neighborhood socioeconomic composition have a significant impact on the risk of obesity. Another study by Dai (2010) found that a higher risk of late-stage diagnosis of breast cancer was greatly associated with living in areas with greater black segregation. It has been documented that socioeconomically disadvantaged neighborhoods tend to have relatively poor access to health care resources (Cummins, Curtis, Diez-Roux, & Macintyre, 2007). A recent study by Kwag et al. (2011) found that neighborhood characteristics, such as proportion of individuals living below poverty, proportion of individuals 65 years of age and older, and proportion of racial or ethnic minorities in the neighborhood, significantly affected physical and mental health of Korean American older adults. Due to the residential segregation in the United States, lack of access to health-promoting resources is also associated with racial disparity in health outcomes (Mennis, Stahler, & Baron, 2012).

Despite the abundance of research on the influence of neighborhood characteristics on the individual's health or access to health care, little is known about how neighborhood characteristics affect LOS in the United States. Thus, our study addresses the following research question: To what extent do neighborhood characteristics influence LOS in the United States? To answer this question, we explored (a) the geographic pattern of LOS using global Moran's I and local indicators of spatial autocorrelation (LISA) statistics; (b) significant neighborhood characteristics associated with LOS using generalized linear models (GLMs); and (c) possible spatial variations at county level using a geographically weighted regression (GWR) model.

METHOD

Data Source and Sample

Data were obtained from the 2012 Area Health Resource Files (AHRF), which comprise data collected from more than 50 sources, including the American Hospital Association (AHA) annual survey of hospitals. The data set contains more than 6,000 variables associated with health care access and utilization

at the county level (U.S. Department of Health and Human Services [HHS], 2014). The sample for the current study consisted of 3,148 counties across the United States. Given that the AHRF provide county-level data only, no individual-level data were used in the current study. Based on the use of aggregated secondary data, which were also obtained from publicly available sources, the University of Tennessee institutional review board has exempted the study from review.

Study Variables

Dependent Variable. All hospital utilization data in the AHRF were extracted from the AHA annual survey of hospitals. Because the county is the unit of analysis in the current study, an aggregated LOS per county was used as the dependent variable. According to the AHA survey instructions (AHA, 2015), LOS refers to the number of adult and pediatric days of care rendered during the entire reporting period. Those days included both medical and psychiatric short-term and long-term inpatient hospitalizations regardless of the type of hospital (whether general, nongeneral, community, or VA), with an exception of newborns.

Explanatory Variables. Explanatory variables were based on Andersen's behavioral model of health services utilization (Aday & Andersen, 1974; Andersen, 1968, 1995), which has been broadly used in previous studies on health care access (Babitsch, Gohl, & von Lengerke, 2012). The Andersen model specifies the role of predisposing (for example, age, gender, race), enabling (for example, income, poverty, employment, insurance status), and need (for example, perceived health status, medical diagnosis) factors in examining access and use of health care services. Although these variables have been used extensively to explain health care use, neighborhood characteristics (for example, population factors, health care resources in the community) may also play an important role in determining how long an individual stays in an inpatient setting (Lee et al., 2012).

Two sets of explanatory variables were constructed to represent neighborhood characteristics under two categories: (1) aggregated sociodemographic characteristics and (2) health care resources. Aggregated sociodemographic characteristics included a set of eight variables: (1) the proportion of residents 65 years of age and older, (2) the proportion of female residents, (3) the proportion of white residents, (4)

the proportion of residents living in urban areas, (5) the proportion of residents living below the poverty level, (6) the proportion of residents who were unemployed, (7) the proportion of residents who had no insurance, and (8) the total number of the population. In the AHRF data, *urban* was defined as all territory, population, and housing units located within urbanized areas, which consist of densely developed territory that contains 50,000 or more people, and urban clusters, which consist of densely settled territory that has at least 2,500 people but fewer than 50,000 people (HHS, 2013). Health care resource variables included the number of hospitals and inpatient service unit beds. In the AHRF data, facilities with six or more inpatient beds, cribs, or pediatric bassinets were considered as hospitals.

Data Analysis

Exploratory Spatial Data Analysis. Global Moran's I and LISA statistics were applied to explore the geographic pattern of LOS by assessing the similarity of LOS among neighboring counties. Specifically, the global Moran's I statistics were used to examine whether there is spatial autocorrelation in LOS within the study area, and the extent of spatial autocorrelation was determined using the local Moran's I statistic, which is known as LISA (Anselin, 1995). By comparing similarities and differences among counties, LISA generates four categories of spatial clusters: high-high, low-low, low-high, and high-low. In the context of our study, a high-high LOS cluster is one in which counties and their surrounding counties all have high values of LOS. Conversely, a low-low cluster is one in which counties and their surrounding counties all contain low values of LOS. A low-high cluster is one in which counties with low values of LOS are surrounded by counties with high values of LOS; a high-low cluster is one in which counties with high values of LOS are surrounded by counties with low values of LOS. Statistical significance of the clusters was evaluated by a Monte Carlo test, which estimates the likelihood of the clusters arising out of randomness (Anselin, 1995; Hope, 1968). To identify neighborhoods, we applied a Queen's case spatial weight (Getis & Aldstadt, 2004; Stetzer, 1982). The spatial weight counts spatial units sharing the same edges and nodes as neighbors.

Statistical Analysis. To examine the extent to which neighborhood characteristics affected LOS, we conducted GLMs with a log link, which account

for positive skewness in LOS (Manninga & Mullahy, 2001). GLMs generate global coefficients and assume that the relationships are constant across the study area. To capture the possible spatial variation in the relationship between LOS and covariates among counties, we also applied a GWR, which represents detailed local variations, as the fitted coefficient values of a global model (for example, GLM) fail to do so (Brunsdon, Fotheringham, & Charlton, 1996; Fotheringham, Brunsdon, & Charlton, 2003).

The formula for GWR can be written as

$$\gamma_i = \beta_{i0}(u_i, v_i) + \sum_{k=1}^p \beta_{ik}(u_i, v_i)x_{ik} + \epsilon_i, \quad \forall i$$

where $\beta_{i0}(u_i, v_i)$ is the intercept parameter at spatial unit (that is, county) i , $\beta_{ik}(u_i, v_i)$ is the local regression coefficient for the k th independent variable at i , and (u_i, v_i) is the coordinate of the i th point in the study area (Fotheringham et al., 2003).

RESULTS

Table 1 shows the aggregated neighborhood characteristics of 3,148 counties in the United States. The average LOS was 75,185.4 days, but the standard deviation was 6,078.9, indicating the large variation in LOS among counties. The mean proportion of residents who lived below the poverty level was 17.2%; the mean proportion of white residents was approximately 82.9%. The mean proportion of older people (65 and older) was 16.2%, and the mean proportion of the uninsured was 18.5%. The average number of hospitals was 1.91 ($SD = 4.14$), and the

mean number of hospital beds was 285.4 ($SD = 1,002.73$).

Figure 1 shows the geographic variation in LOS in the United States. For clear comparison, our study used nine regions according to the U.S. Census Regions. The LOS was the highest in the West Pacific, South Atlantic, and Northeast coastal regions, especially within or around California, New York, and Florida (for example, in Los Angeles, New York, and in Cook, Harris, and Maricopa counties).

The value of global Moran's I was 0.1685 with a corresponding z -score of 16.6931 ($p < .001$), indicating that there is a positive spatial autocorrelation in the LOS at county level. In Figure 2, a LISA cluster map shows four categories of spatial clusters: high–high, low–low, low–high, and high–low. No significant low–low clusters were identified at county level. High–high clusters were mainly located in the West Pacific, Northeast, and South Atlantic regions. Very few high–high clusters were scattered in the West Mountain, West South Central, East North Central, and East South Central regions. No high–high clusters were identified in the West North Central region. Noticeably, high–low clusters were mainly scattered in the Midwest and South, and very few low–high clusters were identified near the high–high clusters.

To further examine the factors that contribute to this spatial pattern of LOS, two GLMs were constructed (see Table 2). First, to examine the gross effect of bed capacity—an indicator of neighborhood health care resources on the LOS—Model 1 included only the number of beds without control-

Table 1: Aggregated Neighborhood Characteristics (N = 3,148)				
Variable	%	M	SD	Range
Dependent variable				
Length of inpatient stay (days)		75,185.4	206,078.9	0–6,502,662
Sociodemographic characteristics				
Total population		92,610	316,349	90–3,880,244
Population density per square miles		234.2	1,724	0–35,369.2
White	82.89			2.70–99.20
Female	50.01			28.73–56.84
Age 65 and older	16.16			3.72–45.54
Urban	41.28			0.00–100.00
Uninsured	18.54			3.60–41.40
Living in poverty	17.24			2.90–49.90
Health care resources variables				
Total hospitals		1.91	4.14	0–48.00
Hospital beds		285.4	1,002.735	0–9,804.0

Figure 1: Length of Inpatient Stay across the United States

Figure 2: Results of Local Indicators of Spatial Autocorrelation Statistics

Notes: HH = high-high; HL = high-low; LH = low-high; LL = low-low.

ling for covariates. The result indicates that a higher bed capacity increased LOS ($b = 0.002, p < .001$). Second, Model 2 included both the bed capacity and other neighborhood socioeconomic characteristics. After controlling for covariates, the variable of bed capacity remained as a significant predictor

of LOS ($b = 0.001, p < .001$), implying that hospital capacity is a significant determinant for LOS. All other covariates were found to be associated with LOS. For example, LOS was longer in counties with a lower poverty rate, a lower uninsured rate, and a higher proportion of female residents. LOS was also

longer in counties with a higher proportion of residents living in urban areas. Moreover, counties with more diverse racial groups and a younger population had a longer LOS.

Because the bed capacity is proven to be the major determinant of LOS, we constructed a GWR model using LOS as the dependent variable and number of hospitals beds as the explanatory variable. The GWR model has an adjusted r^2 of 0.99, suggesting that the

model is a good fit to capture the spatial variation of LOS. The mean of hospital beds coefficients was 249.925 with a standard deviation of 9.020 (range = 240.200–274.410). In GWR model, we confirmed significant spatial variation in the relationship between LOS and hospital bed capacity by establishing more accurate local coefficients.

Figure 3 represents the visualization of the spatial variation in the relationship between LOS and hospital bed capacity. The Northeast region has the strongest positive correlation between the LOS and bed capacity ($262.6 < b < 274.4$); the Midwest and South regions have the smallest positive correlation ($240.2 < b < 243.5$). In other words, the effect of bed capacity on LOS was greater in the Northeast region than in the Midwest and South regions.

DISCUSSION

Our study confirmed the spatial clustering pattern of LOS and identified its associated neighborhood factors. Hospital bed capacity as an indicator of health care resources was found to be the major predictor of LOS. Particularly, our findings suggest that people living in urban areas tend to have better access to health care resources than their counterparts living in rural areas. Consistent with the findings of previous studies (Kwag et al., 2011; S. Martin & Smith, 1996), our study also highlights the importance of

Table 2: Predictors of the Length of Inpatient Stay: Results of Generalized Linear Models

Variable	Model 1 <i>b</i>	Model 2 <i>b</i>
Hospital beds	0.002***	0.001***
Poverty (%)		0.016**
Total population		−0.002**
Population density per square miles		−5.970E−7**
White (%)		−0.003*
Female (%)		5.969***
Age 65 and up (%)		−1.731**
Urban (%)		0.020***
Uninsured (%)		−0.061***
Akaike information criterion	57,574.860	56,777.399

Note: A variable of number of hospital was excluded from Model 2 due to its high correlation with hospital bed capacity ($b = 0.95, p < .001$).
* $p < .05$. ** $p < .01$. *** $p < .001$.

neighborhood's economic status (that is, the relationship between poverty and LOS), implying that residents in socioeconomically disadvantaged neighborhoods are likely to experience lack of health care resources, which in turn limits health care access (Macintyre, Ellaway, & Cummins, 2002). The spatial distributions of health care resources and population in need do not match in a desirable level across the country (Guagliardo, 2004; Ye & Kim, 2014), and the shortage of health care supply is especially severe in rural areas and impoverished urban communities (Campbell et al., 2000; Monnet et al., 2008; Ye & Kim, 2014). Consequently, living in disadvantaged neighborhoods reduces the possibility of having a usual source of care and receiving recommended preventive services (Kirby & Kaneda, 2005). Noticeably, our data show that 615 counties out of 3,184 do not have any facilities with six or more inpatient beds. Considering the importance of developing community health care resources for both inpatients and outpatients, health care policymakers should be aware of this spatial disparity and develop ways of providing equitable health care for vulnerable populations in socioeconomically disadvantaged neighborhoods.

Furthermore, given that many health care providers tend to refuse Medicaid patients due to its lower reimbursement rate than that of private insurance (Dayaratna, 2012), health care policymakers should consider reforming Medicaid so that the poor have equal access to needed and quality health services. Likewise, those without insurance may be limited to have shorter length of hospital stay due to their financial burden from out-of-pocket health expenditures. Thus, the provision of affordable health insurance would be helpful for those who need to stay longer at the hospital for the necessary health services. The passage of the *Patient Protection and Affordable Care Act (ACA) of 2010* (P.L. 111-148) in the United States has increased health care access for vulnerable populations, such as individuals with mental illness and substance use disorders (Donohue, Garfield, & Lave, 2010), women (Johnson, 2010), and low-income families (Decker, Kostova, Kenney, & Long, 2013). However, the ACA still does not address lack of insurance for recently arrived documented immigrants (less than five years of residence in the United States) and undocumented immigrants (González Block, Vargas Bustamante, de la Sierra, & Martínez Cardoso, 2014). Considering that delayed treatment may require costly care later in the disease

process, policymakers should consider providing limited and selected health care services, instead of excluding all benefits of the ACA coverage, for this vulnerable population. Alternatively, developing community resources, which can be substituted for hospitalization, would help this vulnerable population. For example, medical homes would be a good option, especially for the neighborhoods in which there is a great shortage of health care resources, such as primary physicians. The Commonwealth Fund 2006 Health Care Quality Survey indicated that when people have a medical home, their access to needed care, receipt of routine preventive screening, and management of chronic conditions improves greatly (Beal & Fund, 2007). Thus, expanding medical homes for patients, particularly those who are living in the neighborhoods with a lack of primary health care resources, may improve overall health care accessibility. Considering that community health centers and other public clinics are less likely to provide medical homes for the uninsured (Beal & Fund, 2007), policymakers should consider expanding medical homes for this vulnerable population.

The proportion of white population turned out to have a negative effect on LOS. In other words, racial minority populations tend to have longer stays than their white counterparts. A study by Thompson, Neighbors, Munday, and Trierweiler (2003) found that white patients are more likely to receive a referral to aftercare, which decreases the risk of readmission. Other studies also indicated that racial minority groups are more likely to have less access to quality aftercare, suffer from long-term functional outcomes after traumatic injury, and have a higher chance of readmission and longer inpatient stays (Ball & Elixhauser, 1996; Bolden & Wicks, 2005; Kwag et al., 2011; Shafi et al., 2007; Thompson et al., 2003). Considering the potential risks of longer stays without proper referrals among racial or ethnic minority groups, health care professionals should develop a comprehensive and systematic referral system in the context of culturally competent health care to reduce racial disparity in health care access and service utilization.

Several limitations should be noted. First, individual characteristics, such as severity of health condition, were not considered in the study, because the literature supports little effect of individual characteristics on LOS (Gifford & Foster, 2008). Further studies are recommended to use a hierarchical methodology, which accounts for individual, facility, and neighborhood characteristics. Second, the current

study used the county as the unit of analysis in the examination of the relationship between neighborhood characteristic and length of stay. Because different boundaries or sizes of neighborhoods create modified areal unit problem (Openshaw, 1983), the study is limited in its generalizability. Third, this study is a cross-sectional study. Thus, it is limited to known temporal order of study variables. For instance, we cannot know whether the greater bed capacity allows patients to stay longer or whether longer lengths of stay need a greater bed capacity. Therefore, to investigate this causality, further studies are recommended to replicate this study with a longitudinal design. Finally, our study findings are limited in terms of the lack of additional explanatory variables. Particularly, due to data unavailability, our current study could not control for specific diseases or illnesses (need factors proposed by the Andersen model) as covariates. To better understand comprehensive factors associated with LOS, further studies should also examine the role of need factors in health care utilization.

Nevertheless, as the first empirical study to examine the effects of neighborhood characteristics on length of stay using a nationally representative U.S. sample, our findings contribute to the literature by exploring spatial clustering pattern of LOS, identifying significant neighborhood characteristics associated with LOS, and providing implications for health care policy and practice. Social work professionals should be aware of spatial disparity in health care resources and understand the effects of neighborhood characteristics on LOS to provide continued quality health care in collaboration with community partners. **SWR**

REFERENCES

- Aday, L. A., & Andersen, R. M. (1974). A framework for the study of access to medical care. *Health Services Research, 9*, 208–220.
- American Hospital Association. (2015). *AHA annual survey database: Survey instrument*. Retrieved from <http://www.ahadataviewer.com/Global/survey20instruments/201320AHA20Annual20Survey%20Questionnaire.pdf>
- Andersen, R. M. (1968). *A behavioral model of families' use of health services*. Chicago: Center for Health Administration Studies.
- Andersen, R. M. (1995). Revisiting the behavioral model & access to medical care: Does it matter? *Journal of Health and Social Behavior, 36*, 1–10.
- Andersen, R. M., Yu, H., Wyn, R., Davidson, P. L., Brown, E. R., & Teleki, S. (2002). Access to medical care for low-income persons: How do communities make a difference? *Medical Care Research and Review, 59*, 384–411.
- Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis, 27*(2), 93–115.
- Arcury, T. A., Gesler, W. M., Preisser, J. S., Sherman, J., Spencer, J., & Perin, J. (2005). The effects of geography and spatial behavior on health care utilization among the residents of a rural region. *Health Services Research, 40*(1), 135–156.
- Ashton, C. M., Petersen, N. J., Soucheck, J., Menke, T. J., Yu, H., Pietz, K., et al. (1999). Geographic variations in utilization rates in Veterans Affairs hospitals and clinics. *New England Journal of Medicine, 340*, 32–39.
- Association of American Medical Colleges. (2012, September). *AAMC physician workforce policy recommendations*. Retrieved from <https://www.aamc.org/download/304026/data/2012aamcworkforcepolicyrecommendations.pdf>
- Babitsch, B., Gohl, D., & von Lengerke, T. (2012). Re-visiting Andersen's behavioral model of health services use: A systematic review of studies from 1998–2011. *GMS Psycho-Social-Medicine, 9*, Doc11. doi:10.3205/psm000089
- Ball, J. K., & Elixhauser, A. (1996). Treatment differences between blacks and whites with colorectal cancer. *Medical Care, 34*, 970–984.
- Beal, A. C., & Fund, C. (2007). *Closing the divide: How medical homes promote equity in health care*. New York: Commonwealth Fund.
- Black, J. L., & Macinko, J. (2008). Neighborhoods and obesity. *Nutrition Reviews, 66*, 2–20.
- Bolden, L., & Wicks, M. N. (2005). Length of stay, admission types, psychiatric diagnoses, and the implications of stigma in African Americans in the nationwide inpatient sample. *Issues in Mental Health Nursing, 26*, 1043–1059.
- Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis, 28*(4), 281–298.
- Buchmueller, T. C., Jacobson, M., & Wold, C. (2006). How far to the hospital?: The effect of hospital closures on access to care. *Journal of Health Economics, 25*, 740–761.
- Burns, L. R., & Wholey, D. R. (1991). The effects of patient, hospital, and physician characteristics on length of stay and mortality. *Medical Care, 29*, 251–271.
- Campbell, N., Elliott, A., Sharp, L., Ritchie, L., Cassidy, J., & Little, J. (2000). Rural factors and survival from cancer: Analysis of Scottish cancer registrations. *British Journal of Cancer, 82*, 1863–1866.
- Chung, I. (2012). Sociocultural study of immigrant suicide-attempters: An ecological perspective. *Journal of Social Work, 12*, 614–629. doi:10.1177/1468017310394240
- Cohen, C. I., & Casimir, G. J. (1989). Factors associated with increased hospital stay by elderly psychiatric patients. *Psychiatric Services, 40*, 741–743.
- Cummins, S., Curtis, S., Diez-Roux, A. V., & Macintyre, S. (2007). Understanding and representing 'place' in health research: A relational approach. *Social Science & Medicine, 65*, 1825–1838.
- Dai, D. (2010). Black residential segregation, disparities in spatial access to health care facilities, and late-stage breast cancer diagnosis in metropolitan Detroit. *Health & Place, 16*, 1038–1052.
- Dayaratna, K. D. (2012). *Studies show: Medicaid patients have worse access and outcomes than the privately insured*. Retrieved from <http://www.heritage.org/research/reports/2012/11/studies-show-medicaid-patients-have-worse-access-and-outcomes-than-the-privately-insured>
- Decker, S. L., Kostova, D., Kenney, G. M., & Long, S. K. (2013). Health status, risk factors, and medical conditions among persons enrolled in Medicaid vs

- uninsured low-income adults potentially eligible for Medicaid under the Affordable Care Act. *JAMA*, 309, 2579–2586. doi:10.1001/jama.2013.7106
- Donohue, J. M., Garfield, R. L., & Lave, J. R. (2010). *The impact of expanded health insurance coverage on individuals with mental illnesses and substance use disorders* [White paper]. Washington, DC: U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation.
- Ellison, A. M., & Bauchner, H. (2007). Socioeconomic status and length of hospital stay in children with vaso-occlusive crises of sickle cell disease. *Journal of the National Medical Association*, 99(3), 192–196.
- Epstein, A. M., Stern, R. S., Tognetti, J., Begg, C. B., Hartley, R. M., Cumella, E. Jr., & Ayanian, J. Z. (1988). The association of patients' socioeconomic characteristics with the length of hospital stay and hospital charges within diagnosis-related groups. *New England Journal of Medicine*, 318, 1579–1585.
- Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2003). *Geographically weighted regression: The analysis of spatially varying relationships*. Chichester, West Sussex, England: John Wiley & Sons.
- Gandsas, A., Parekh, M., Bleech, M. M., & Tong, D. A. (2007). Robotic telescreening: Profit analysis in reducing length of stay after laparoscopic gastric bypass. *Journal of the American College of Surgeons*, 205(1), 72–77. doi:10.1016/j.jamcollsurg.2007.01.070
- Getis, A., & Aldstadt, J. (2004). Constructing the spatial weights matrix using a local statistic. *Geographical Analysis*, 36(2), 90–104. doi:10.1111/j.1538-4632.2004.tb01127.x
- Gifford, E., & Foster, E. M. (2008). Provider-level effects on psychiatric inpatient length of stay for youth with mental health and substance abuse disorders. *Medical Care*, 46, 240–246.
- González Block, M., Vargas Bustamante, A., de la Sierra, L., & Martínez Cardoso, A. (2014). Redressing the limitations of the Affordable Care Act for Mexican immigrants through bi-national health insurance: A willingness to pay study in Los Angeles. *Journal of Immigrant and Minority Health*, 16(2), 179–188. doi:10.1007/s10903-012-9712-5
- Guagliardo, M. F. (2004). Spatial accessibility of primary care: Concepts, methods and challenges. *International Journal of Health Geographics*, 3(1), 3. doi:10.1186/1476-072X-3-3
- Healthcare Cost and Utilization Project. (2011). *HCUP facts and figures: Statistics on hospital-based care in the United States, 2005*. Retrieved from http://www.hcup-us.ahrq.gov/reports/factsandfigures/facts_figures_2005.jsp#ex1_2
- Hope, A. C. (1968). A simplified Monte Carlo significance test procedure. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 30, 582–598.
- Johnson, K. A. (2010). Women's health and health reform: Implications of the Patient Protection and Affordable Care Act. *Current Opinion in Obstetrics and Gynecology*, 22, 492–497. doi:10.1097/GCO.0b013e3283404e31
- Kirby, J. B., & Kaneda, T. (2005). Neighborhood socioeconomic disadvantage and access to health care. *Journal of Health and Social Behavior*, 46(1), 15–31.
- Kwag, K. H., Jang, Y., Rhew, S. H., & Chiriboga, D. A. (2011). Neighborhood effects on physical and mental health: A study of Korean American older adults. *Asian American Journal of Psychology*, 2(2), 91–100. Retrieved from <http://proxy.lib.utk.edu:90/login?url=http://search.proquest.com/docview/864787457?accountid=14766>
- Lee, S., Rothbard, A. B., & Noll, E. (2012). Length of inpatient stay of persons with serious mental illness: Effects of hospital and regional characteristics. *Psychiatric Services*, 63, 889–895.
- Macintyre, S., Ellaway, A., & Cummins, S. (2002). Place effects on health: How can we conceptualise, operationalise and measure them? *Social Science & Medicine*, 55(1), 125–139.
- Manninga, W. G., & Mullahy, J. (2001). Estimating log models: To transform or not to transform? *Journal of Health Economics*, 20, 461–494.
- Martin, L. A., Neumann, C. W., Mountford, J., Bisognano, M., & Nolan, T. W. (2009). *Increasing efficiency and enhancing value in health care: Ways to achieve savings in operating costs per year* [IHI Innovation Series White Paper]. Cambridge, MA: Institute for Healthcare Improvement. Retrieved from <http://cdn2.hubspot.net/hub/276565/file-410068373-pdf/docs/856157170.pdf>
- Martin, S., & Smith, P. (1996). Explaining variations in inpatient length of stay in the National Health Service. *Journal of Health Economics*, 15, 279–304.
- Mennis, J., Stahler, G. J., & Baron, D. A. (2012). Geographic barriers to community-based psychiatric treatment for drug-dependent patients. *Annals of the Association of American Geographers*, 102, 1093–1103.
- Monnet, E., Ramée, C., Minello, A., Jooste, V., Carel, D., & Di Martino, V. (2008). Socioeconomic context, distance to primary care and detection of hepatitis C: A French population-based study. *Social Science & Medicine*, 66, 1046–1056.
- Nguyen-Huynh, M. N., & Johnston, S. C. (2005). Regional variation in hospitalization for stroke among Asians/Pacific Islanders in the United States: A nationwide retrospective cohort study. *BMC Neurology*, 5(21), 1–7.
- Openshaw, S. (1983). *The modifiable areal unit problem* (Vol. 38). Norwich, UK: Geo Books.
- Patient Protection and Affordable Care Act, P.L. 111-148, 124 Stat. 119 (March 23, 2010).
- Sanders, G. F., Fitzgerald, M. A., & Bratteli, M. (2008). Mental health services for older adults in rural areas: An ecological systems approach. *Journal of Applied Gerontology*, 27, 252–266. doi:10.1177/0733464807311646
- Shafi, S., de la Plata, C. M., Diaz-Arrastia, R., Shipman, K., Carlile, M., Frankel, H., et al. (2007). Racial disparities in long-term functional outcome after traumatic brain injury. *Journal of Trauma Injury, Infection, and Critical Care*, 63, 1263–1270.
- Stetzer, F. (1982). Specifying weights in spatial forecasting models: The results of some experiments. *Environment and Planning*, 14, 571–584.
- Thompson, E. E., Neighbors, H. W., Munday, C., & Trierweiler, S. (2003). Length of stay, referral to aftercare, and rehospitalization among psychiatric inpatients. *Psychiatric Services*, 54, 1271–1276.
- U.S. Department of Health and Human Services. (2013). *User documentation for the Area Health Resource File (AHRF) 2012–2013 release*. Retrieved from <http://ahrh.hrsa.gov/index.htm>
- U.S. Department of Health and Human Services. (2014). *Area Health Resources Files: National, State and County Health Resources Information Database*. Retrieved from <http://ahrh.hrsa.gov/index.htm>
- Ye, H., & Kim, H. (2014). Measuring spatial health disparity using a network-based accessibility index method in a GIS environment: A case study of Hillsborough County, Florida. *International Journal of Geospatial and Environmental Research*, 1(1), Article 2.

Huairan Ye, MS, is a doctoral student, Department of Geography, College of Arts and Sciences, University of Tennessee, Knoxville. **Sungkyu Lee, PhD**, is assistant professor, School of Social Welfare, Soongsil University, Seoul, South Korea. **Hyun Kim, PhD**, is assistant professor, Department of Geography, College of Arts and Sciences, University of Tennessee, Knoxville. Address correspondence to Sungkyu Lee, School of Social Welfare, Soongsil University, 369 Sangdo-Ro, Dong-gu, Seoul, 156-743, South Korea; e-mail: slee90@ssu.ac.kr.

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Returning Home

Reintegration after Prison or Jail

STEPHEN J. BAHR

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