Neighborhood Effects on the Nursing Home Admissions among Older Patients in the State of Nevada, USA: Multilevel Analysis of Administrative and Census Data

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Abstract

Nursing home admission risk profile is useful for reducing costly long-term care service use through environmental and public health efforts. However, in this respect, relatively newer data and impacts of living environment have not been extensively analyzed. This study analyzed the 2010 hospital administrative data from the Center for Health Information Analysis for Nevada (n = 82,492) and the 2010 U.S. Census data for ZIP code areas among older hospital patients age 65 and older in Nevada, USA. Results from multilevel logistic regressions validated the known risk factors including age, gender, race, marital status and health after adjusting for the neighborhood disadvantages. Also, living in more disadvantaged neighborhood was associated with the higher risk of nursing home admissions among older patients. Findings suggested the needs for further public health research on the living environment and risk of nursing home admissions, and the possible community-level interventions for promote aging in place.

Keywords: long-term care; public health; neighborhood; aging;

Introduction

Development of the nursing home admission (NHA) risk profile is useful for projecting future demand of nursing home care, informing intervention programs, and designing education programs for the public --- ultimately for advocating possible policy changes to help older adults stay in communities in later life (Gaugler, Duval, Anderson, & Kane, 2007; Jette, Branch, Sleeper, Feldman, & Sullivan, 1992; Kane & Matthias, 1984). The American population has been and continuing to age. Americans age 50 and older have greater than a 50% chance of using nursing home care service at least once during their life time (Hurd, Michaud, & Rohwedder, 2014). Clearly, nursing homes play an important role in the eldercare service, and also increasingly function as a post-acute care and rehabilitation facility (Howell, Silberberg, Quinn, & Lucas, 2007).

However, the cost of long-term care for older adults in general, and for nursing home in particular, has been widely recognized. Additionally, the majority of older adults hope to stay in the community (AARP, 2011). Finally, the needs of long-term care including nursing home care will most likely grow in accordance with population aging (Centers for Medicare & Medicaid Services, 2013). Reduction of preventable NHA not only economically benefits the nation but also enhance older adults' preference for living in community (i.e., aging in place) (AARP, 2011; Lawton, 1982).

Organizing framework – Andersen's behavioral model of health services use

This study was guided by the behavioral model, which conceptualizes the determinants of health care service utilization (Andersen, 1995). The model depicts theoretically relevant determinants of health care use ---sequentially organized into (1) predisposing (e.g., demographic characteristics), (2) enabling (e.g., socioeconomic status) and (3) need (e.g., health, disability) factors (Andersen & Newman, 2005). The behavioral model has been adopted by a number of researchers not only for health care utilization, but also on multiple health outcomes (e.g., heart disease, self-rated health, limitation in daily activities) (Ani et al., 2008; Babitsch, Gohl, & von Lengerke, 2012). Although the original model was developed in the 1960s, social contextual determinants have been explicitly incorporated into revised models mainly as results of increasing evidence about such influential higher level factors (i.e., contextual characteristics) on individual-level determinants of health care use (Andersen & Davidson, 2007). That is, addressing multi-level determinants is a key to advance health care utilization research as well as relevant health outcomes research.

In fact, the influential work by Lawton (1983) --- the environmental press theory --- explicitly supports such idea of the relationship between neighborhood environment and NHA through adaptation of living environment and individual capacity (e.g., health, disability) over the life course (Buys et al., 2013). In the current study, the model was operationalized to examine the multi-level determinates of the NHA among older patients. Specifically, this study investigates the neighborhood effects (discussed in the later sections) on the nursing home admission of older patients.

Risk factors of nursing home admissions (NHA)

Previous studies identified risk factors of NHA (Miller & Weissert, 2000). With regards to the predisposing factors, the risk factors include older age, female gender, and white (race) (Coughlin, McBride, & Liu, 1990; Greene & Ondrich, 1990; Jette et al., 1992; Kahn et al., 1994; Kane & Matthias, 1984; Kane, Matthias, & Sampson, 1983; Rudberg, Sager, & Zhang, 1996; Russell, Cutrona, de la Mora, & Wallace, 1997; Weissert & Scanlon, 1985). The predisposing factors are generally inherent to individuals and not easily modifiable. With regard to the enabling factors, no house ownership, lower income, lower educational attainment and being unable to drive are associated with greater likelihood of NHA (Coughlin et al., 1990; Greene & Ondrich, 1990; Russell et al., 1997).

The enabling factors can be considered mediators of predisposing factors as well as predictors of need factors. Previous studies also identified several social network related enabling factors including living alone, not being married, not having family/informal caregivers (e.g., sibling, daughter) and lack of social contact (Coughlin et al., 1990; Freedman, 1996; Greene & Ondrich, 1990; Russell et al., 1997; Weissert & Scanlon, 1985). These social factors most likely reflect the network of possible informal caregivers. Also, greater resources (e.g., financial resource) are widely known to result in better health and to prevent excessive medical care service use (e.g., Marmot & Wilkinson, 2001).

With regards to the need factors, overall physical and mental health status, disabilities (e.g., limitations with Activity of Daily Living), injuries (e.g., injurious falls) and chronic conditions (e.g., heart disease, dementia) increase the chance of NHA (Coughlin et al., 1990; Gaugler et al., 2007; Greene & Ondrich, 1990; Jette, Tennstedt, & Crawford, 1995; Miller & Weissert, 2000). Importantly, some evidence suggests that severity as well as number of comorbidity (e.g., multiple diagnosed conditions) are associated with the greater risk of NHAs (Miller & Weissert, 2000; N.

P. Roos, Roos, Mossey, & Havens, 1988). Additionally, other need factors such as history of nursing home use (Coughlin et al., 1990; Gaugler et al., 2007; Kane et al., 1983) and length of stay at hospitals (Rudberg et al., 1996) are reported to be the risk factors of NHA. The need factors are the most proximate predictors of health behaviors and relevant outcomes (e.g., health care service use) (Andersen, 1995; Andersen & Davidson, 2007).

There are two unexplored areas in the previous studies. First, the majority of NHA risk profiles are based on relatively older data from 1970s, 1980s and 1990s. The U.S. experienced the rapid change in the demographic composition in the last decades, use of newer data for investigating the risk factors would not only ensure the validity of previous studies but also could identify emerging trends in recent years. Second, almost all known risk factors are identified at the individual-level and therefore, significantly less is known about the higher-level risk factors such as living environment or quality of residential areas. Often, the concept of neighborhood effect is used to express unobserved influence from conditions of living environment on individuals' behaviors and resource access (Diez Roux & Mair, 2010; Ellen, Mijanovich, & Dillman, 2001). Better understanding about the neighborhood effect beyond individual characteristics and behaviors is critical for improving health of communities and ultimately, of nations .

Indeed, individuals' behaviors (e.g., dietary choices) and resource/service access (e.g., transportation, preventive care service) could be significantly affected by the neighborhood where they live in (Diez Roux & Mair, 2010). As stated earlier, the recent revision of the behavioral model explicitly includes the contextual characteristics (i.e., neighborhood effects) in relation to individual characteristics (Andersen, 1995; Andersen & Davidson, 2007). Yet, such neighborhood effects have not been extensively investigated in the context of NHA among older patients.

Brief overview of the neighborhood and health

In their review, Diex-Roux and Mair (2010) argue that living in socioeconomically disadvantaged neighborhoods results in poorer health of community members even after accounting for individual characteristics. In other words, continuous exposure to the deprived neighborhoods is a higher level risk factor of health and disabilities beyond the individual-level factors (Ellen et al., 2001; Pruchno, Wilson-Genderson, & Cartwright, 2012). Previous studies suggested three possible linkages between neighborhood and health outcomes. First, the physical characteristics of neighborhoods such as air and water quality may directly influence residents' health (Committee of the Environmental and Occupational Health Assembly of the American Thoracic Society, 1996). Second, resource availability and its distribution could create health inequality across neighborhoods. For instance, the public safety-related municipal services (e.g., sanitation, police, fire) are critical to the health of communities (General Accounting Office, 1983). Additionally, neighborhood health resource availability including public transportation, healthy food outlets (Larson, Story, & Nelson, 2009) and places for physical activities (Saelens & Handy, 2008) are powerful determinants of healthful behaviors.

Third, neighborhood social environment, often expressed as social norms and social cohesion, are related to health outcomes, particularly to mental health through stress.

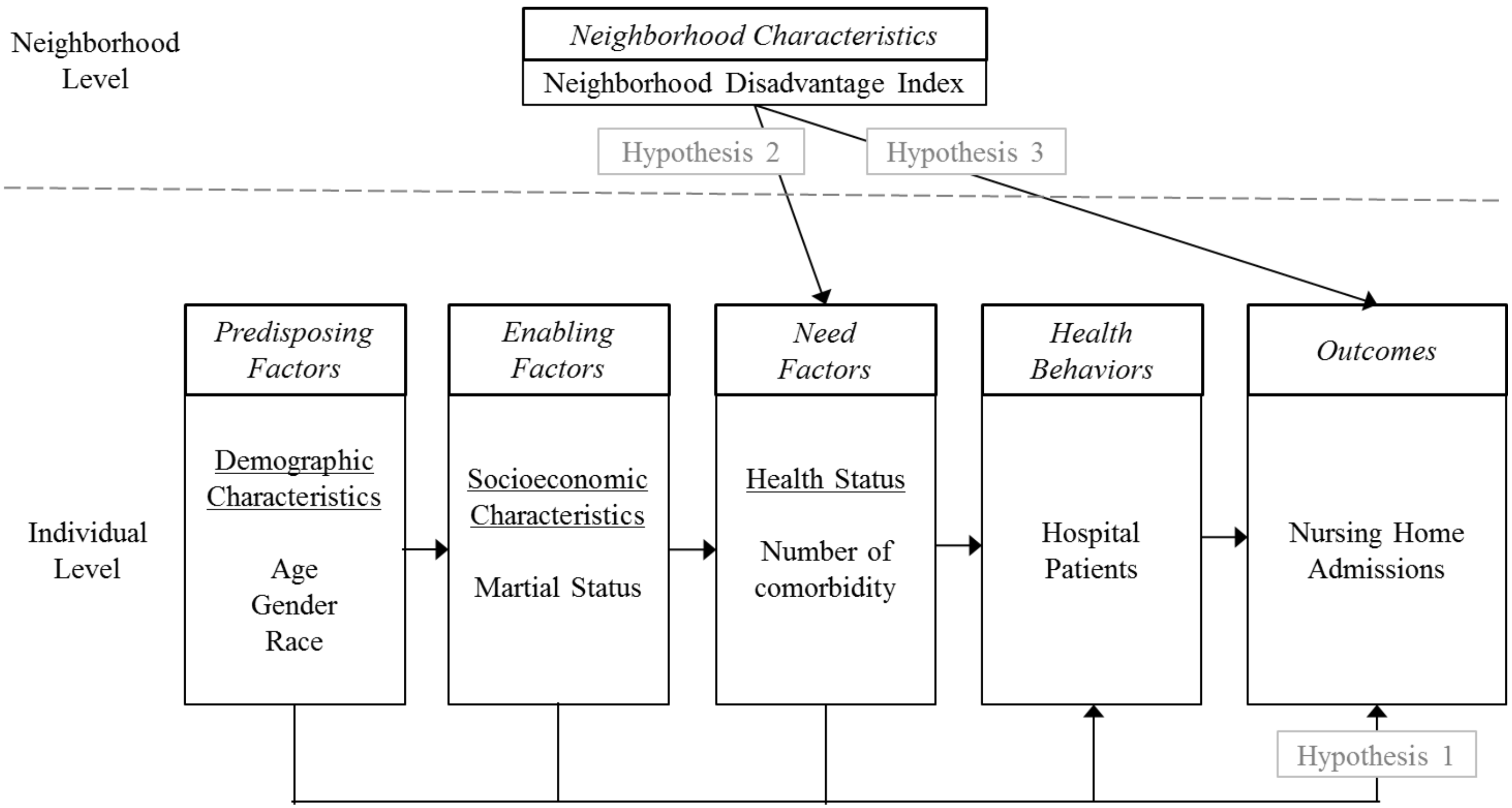
Also, several kinds of neighborhood disorders reflected in the crime rate and social isolation are linked to depression and depressive symptoms (Aneshensel & Sucoff, 1996; Yen, Yelin, Katz, Eisner, & Blanc, 2006). Importantly, the aforementioned neighborhood effects most likely interact with each other and determine residents' resource accessibility, health behaviors and stress level (Diez Roux & Mair, 2010).

Objectives of the current study

The most powerful predictors of NHA are the need factors such as health problems and disabilities, which are more prevalent in later life (e.g., Jette et al., 1995). Also, older adults are more susceptible to the negative neighborhood effects on health outcomes due to their age-related decline of physical (e.g., mobility) and mental capacity, social network and resilience (Yen, Michael, & Perdue, 2009). Moreover, exposure to the neighborhood effects is arguably greater in the older population as older adults spend more time in their communities (Lawton, 1977; Pruchno et al., 2012). Taken together, the existing evidence suggests that the neighborhood conditions affect one's health and disability, which are associated with the use of long-term care services (i.e., nursing home), particularly among vulnerable populations like older adults. There is a need to empirically investigate the neighborhood effects in the context of NHA among older adults.

This study aims to develop an initial multi-level risk profile of NHAs among older adults in light of the behavioral model (Andersen, 1995). Specifically, this study aims to identify the individual-level risk factors after adjusting for the neighborhood characteristics, and to examine the neighborhood effects on health outcomes and NHAs among older patients. This study focuses on older patients because hospital is a logical starting point for older adults who have acute and/or chronic conditions, and therefore have the higher risk of NHA (Kane et al., 1983). An overview of the study is depicted in the operationalized behavioral model (Figure 1). It is hypothesized that the known individual-level risk factors predict NHAs after accounting for the neighborhood characteristics among older adults (hypothesis 1). Also, it is hypothesized that the neighborhood characteristics (discussed in the methods section) are associated with health outcomes (hypothesis 2) and the likelihood of NHA (hypothesis 3).

Figure 1: Operationalized Behavioral Model and Hypotheses Tested



Data and Methods

Data

The patient-level data were State Inpatient Data (SID) of Nevada obtained from the Center for Health Information Analysis (CHIA) for Nevada upon the verification of confidentiality agreement and approval from the ethics committee. CHIA data include basic demographic information and detailed diagnosis, treatment, billing and discharge information. The most recent data (2010) at the time of this study were employed. According to the Department of Health and Human Services Nevada Division of Public and Behavioral Health online database, there were 44 general hospitals listed (Nevada Division of Public and Behavioral Health, 2015). Also, the Nevada Hospital Association database returned 54 hospitals including general and specialized facilities, as well as one federal hospital (Nevada Hospital Association, 2015). The 2010 CHIA data include 51 hospitals and therefore, the vast majority of general hospitals in the State of Nevada were covered. For the neighborhood level data, the 2010 U.S. Census ZIP code area summary demographic profile and the American community survey 2007-2011 five-year estimate file for the census tracts were obtained from The U.S. Census Bureau website (U.S. Census Bureau, 2015). After excluding the out-of-state patients, those who were younger than 65 years old, nursing home residents and those with missing discharge information, there were 82,492 older patients.

Measures

Patient-level measures. The outcome measure in this study was the discharge status to a nursing homes. Based on the 63 types of discharge status information, the discharge to nursing home was recorded (1) and discharge to all other locations such as home, other hospitals, hospice care facility and rehabilitation hospitals were recorded (0). The patients' age was recorded in years. The gender variable was coded (1) for women and (0) for men. The four dichotomous variables for racial/ethnic groups were created for whites, blacks, Hispanics and other race. White was used as a reference group. The dichotomous variable indicating (1) married and (0) not married (e.g., divorced, never married) was created. Finally, a number of comorbidity measures were created for capturing the patients' health status. The International Classification of Diseases 9th edition with clinical modification (ICD-9-CM) information (see Centers for Disease Control and Prevention, 2011 for the detailed description) was classified using the Comorbidity Software, Version 3.7 (Elixhauser, Steiner, Harris, & Coffey, 1998; Healthcare Cost and Utilization Project (HCUP), 2015). A comorbidity index was computed and used as a summary measure of one's health status and disease burden. The ICD-9-CM-based comorbidity indices have been extensively used in medical and epidemiological research and proven to be the useful indicators/predictors of health status/disease burden. (Schneeweiss et al., 2001). However, given the design of this study, most of existing specific comorbidity indices (e.g., targeting patients with stroke or mental disorder) may not be appropriate for the general older populations (Elixhauser et al., 1998; Goldstein, Samsa, Matchar, & Horner, 2004). As the concept of geriatric syndrome depicts, coexistence of multiple conditions and/or physical impairments is a critical marker of health status among older adults (Flacker, 2003). As such, this study employed comorbidity as a health indicator for older patients. The individual-level measures were classified into the predisposing (i.e., age, gender, race), enabling (i.e., marital status) and need (i.e., the comorbidity index) factors for the interpretation of results (Andersen, 1995).

Neighborhood-level measures. The objective neighborhood disadvantage index was created based on four measures including the prevalence of poverty, mother-only households, house ownership and college educated residents in the neighborhood (Ross & Mirowsky, 2001). In this study, the percentages of home owners and college educated residents were subtracted from the sum of the percentages of poverty and female-headed households with children for each ZIP code area. One unit (one percent) increase in the neighborhood disadvantage index is equivalent to one percent increase in all four measures on average. Ross and Mirowsky (2001) assert that the objective neighborhood disadvantage index based on these four measures reflects both theoretically and empirically sound neighborhood quality indicators, and composes a reliable measure (Cronbach's alpha = 0.61). Comparable indices are employed in previous studies and found to be significantly associated with health-related outcomes (Kirby & Kaneda, 2005; L. L. Roos, Magoon, Gupta, Chateau, & Veugelers, 2004).

The total number of owner occupied households, and female-headed households with children age 18 and younger were obtained from the U.S. Census ZIP code area level data file, and the percentages were calculated based on the total number of households (U.S. Census Bureau, 2015). As the poverty and educational attainment data were not available at the ZIP code level, data were obtained from the American Community Survey (ACS) 2007-2011 five year estimates file at the Census block group level (U.S. Census Bureau, 2015). The ACS data were imported into the ArcGIS version 10 (ESRI, 2011) and spatial join (i.e., aggregate data from a set of Census block group areas within or adjacent to a ZIP code area) technique was used to estimate the total number of households in poverty and the total number of residents with college or higher degrees (ESRI, 2011). The percentages were calculated based on the total number of households due to the different population size in each census tract. Finally, the objective neighborhood disadvantage index was merged to the patient data using the ZIP codes.

ZIP code area as a neighborhood.
In this study, ZIP code areas were considered neighborhoods. The definition of neighborhood has not been established. As such, appropriate use of the term, neighborhood, may be significantly influenced by outcome measures, purpose of study, data availability, etc. (Diez Roux, 2008). Zip code area was chosen for three reasons including: to ensure the comparability to key previous neighborhood effect studies with ZIP code as unit of analysis (e.g., Kahn et al., 1994; Ross & Mirowsky, 2001; Wen & Christakis, 2005); to protect patients' privacy with a large enough ZIP code area population (Cromley & McLafferty, 2012), and to utilize routinely collected hospital administrative data with ZIP code information. Result of this study will be comparable not only to previous work but also to hospital administrative data with ZIP code area information.

Analytic Strategies
Given the purpose of this study and hierarchical data structure (i.e., older hospital patients nested in the unique ZIP code areas), a generalized multilevel regression model with logit link function

was employed. In view of the general guidelines (Heck & Thomas, 2015; Raudenbush & Bryk, 2002) and the purposes of this study, the model construction was sequentially executed in five steps: (1) unconditional random intercept model (a.k.a., null model); (2) conditional random intercept model; (3) means-as-outcomes model; (4) partially conditional (only with the number of comorbidity) mixed effect model (i.e., random intercept and random slope model); and (5) fully conditional mixed effect model in this study (Heck & Thomas, 2015; Raudenbush & Bryk, 2002). All hypotheses were tested in the step (5) yet other steps were to ensure the appropriate model construction and non-spurious relationships specified in hypotheses. All models were estimated using Mplus version 7 (L. K. Muthén & Muthén, 1998 - 2012).

In the step (1), the log odds of NHA was expressed as the following:

$$\ln\left(\frac{p}{1-p}\right) = \beta_{0j} + \varepsilon_{ij} \text{ (Equation 1.0)}$$

Where β_{0j} is the baseline log odds (p = the proportion of patients admitted to nursing home) for the j th ZIP code area, and ε_{ij} is the error term for individual i in j th ZIP code area. The between ZIP code area differences are modeled as:

$$\beta_{0j} = \gamma_{00} + u_{0j} \text{ (Equation 1.1)}$$

Here, the intercept (β_{0j}) is modeled as a function of the grand mean (γ_{00}) of ZIP code areas and the random effects (i.e., u = between-ZIP code area difference; ε = between-individual difference). Therefore, the unconditional random intercept model was:

$$\ln\left(\frac{p}{1-p}\right) = \gamma_{00} + u_{0j} + \varepsilon_{ij} \text{ (Equation 1.2)}$$

Based on the estimated parameters in Equation 1.2, the ZIP code area dependency was assessed using the intra-class correlation (ICC) coefficient (ρ), and the design effect (*deff*) (B. O. Muthén & Satorra, 1995). The ICC is the ratio of the between-group variance over the sum of between-group and between-individual variances. The design effect is a function of the mean number of samples in groups (i.e., the mean number of patients in ZIP code areas in this study) and ICC. The design effect greater than 2 suggests the between-ZIP code area dependency and therefore, use of multilevel models (Maas & Hox, 2005; B. O. Muthén & Satorra, 1995). The design effect was 6.60 (ICC = 0.02; the mean number of patients in ZIP code areas = 330.25). Thus, use of multilevel model was appropriate to test the hypotheses in this study.

In the step (2), the individual level predictors were added to the model in the step (1). This fully conditional random intercept model was:

$$\ln\left(\frac{p}{1-p}\right) = \gamma_{00} + u_{0j} + \beta_1 x_1 + \cdots + \beta_k x_k + \varepsilon_{ij} \text{ (Equation 1.3)}$$

Building on Equation 1.2, k individual-level predictors were incorporated into the model and each regression coefficient was estimated. In the step (3), using the means-as-outcomes model, the log odds of NHA was predicted by the ZIP-code level predictor (i.e., neighborhood disadvantage index).

$$Individual\ level\colon \ln\left(\frac{p}{1-p}\right) = \beta_{0j} + \varepsilon_{ij}$$
(Equation 1.4)

$$ZIP\ code\ area\ level\colon \beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j} \text{ (Equation 1.5)}$$

Here, the individual-level random intercept was predicted by the fixed ZIP code level intercept (γ_{00}) and the ZIP code level predictor -- neighborhood disadvantage index (W for *j* th ZIP code area). In step (4), the key individual-level predictor (need factor) – the number of comorbidities was added and its slope was a function of the neighborhood disadvantage index (i.e., partially conditional mixed effects model).

$Individual\ level$: $\ln\left(\frac{p}{1-p}\right) = \beta_{0j} + \beta_{1j}x_{ij} + \varepsilon_{ij}$ (Equation 1.6)

$ZIP\ code\ area\ level$: $\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j}$ (Equation 1.7)

$\beta_{1j} = \gamma_{10} + \gamma_{11}W_j + u_{1j}$ (Equation 1.8)

Given the neighborhood effect on health of residents, the random slope (β_{1j}) of the number of comorbidities (x_{ij}) for individuals (i) in *j* th ZIP code area was predicted by the neighborhood disadvantage index (W_j). Finally, in the step (5), all individual-level predictors were added to the models in the step (4). However, the preliminary analysis (step 4) showed that the random slope (γ_{11}) was not statistically significant, and therefore, was not included in the final model.

$$Final\ model: \ln\left(\frac{p}{1-p}\right) = \gamma_{00} + \gamma_{01}W_j + u_{0j} + \beta_1 x_i + \cdots + \beta_k x_k + \varepsilon_{ij} \text{ (Equation 1.9)}$$

The Equation 1.9 or final multilevel model is a fully conditional individual-level model adjusted for the ZIP-code level area dependency (i.e., random intercept) explained by the neighborhood disadvantage index (W_j).

In all steps, the recommended sample size (i.e., the number of groups over 100) was met as the number of valid ZIP code areas with at least one NHA were 154 and the average number of patients by ZIP code areas was over 330 (Maas & Hox, 2005). Also, the key variable including age, number of comorbidities and neighborhood disadvantage index were grand-mean centered (Raudenbush & Bryk, 2002). As such, when all variables have values of zero, the model can be interpreted for the white men with the mean age and mean number of comorbidities in the ZIP code area with the mean neighborhood disadvantage index. All models were estimated using the robust maximum likelihood (MLR function in Mplus). The model fit was evaluated using the deviance statistics and Akaike Information Criteria (AIC) (Heck & Thomas, 2015).

Table 1: Descriptive Summary of the Individual-level and ZIP Code Area-level Variables

Variables	Mean (Standard Deviation) or Percentage
Outcome Variable	
Admission to nursing homes	14.55%
Individual Level	
Predisposing factors	
Age (Years)	76.41 (7.54)
Gender (Women)	53.67%
Race	
White	77.94%
Black	7.13%
Hispanic	5.64%
Others	9.29%
Enabling factor	
Marital status (Married)	47.37%
Need factors	
Number of comorbidities	3.04 (1.84)
ZIP code level	
Neighborhood disadvantage index (-200 : 200 = Least : most disadvantaged)	-15.72 (7.00)

Note: N (patients) = 82,492; N (valid ZIP code area) = 241; Only in-state non-institutionalized patients 65 years and older with the discharge information were included.

Results

Table 1 shows the characteristics of older patients in this study. The total number of uninstitutionalized older patients with valid discharge information was 82,492 in this study. Approximately 15% of them were discharged to nursing homes. The mean age of respondents was 76.4 years old and about half of them were women. The majority of older patients (78%) were white. As expected in older adults, the relatively lower percentage (47%) of married individuals was observed. The mean number of comorbidities was 3 in this study. Finally, the mean neighborhood disadvantage score was -15.7, which indicates that typical ZIP code areas in Nevada were slightly "advantaged."

A series of multilevel logistic regressions were estimated. Odds ratios and other relevant statistics are reported in Table 2. In the step 1, the statistically significant intercept variable indicated the between-ZIP code areas variability and therefore, the need of multilevel model. In step 2, one key variable -- the number of comorbidities ($p < 0.001$) was significantly associated with NHA even after adjusting for all individual-level variables and between-ZIP code area variability. In step 3, the neighborhood disadvantage index was a significant predictor ($p < 0.01$) of NHA. The step 2 and step 3 were to ensure the role of key variables important to the hypotheses in this study. In step 4, the random slope of number of comorbidities was examined with the neighborhood disadvantage index. Results showed that the random slope coefficient was not significant (p > 0.05), and therefore, was not included in the final model. This non-significant finding suggests that the neighborhood disadvantage was associated with NHA but it was not through health or the number of comorbidities.

In the final model (i.e., step 5), the NHA was regressed on all individual-level predictors while adjusted for the between-ZIP code area variability and the neighborhood disadvantage index. All individual-level predictors except other race (vs. white) were significantly associated with NHA. Interestingly, Blacks and Hispanics had approximately 21% (p < 0.001) and 41% (p < 0.001) lower odds of NHA than whites adjusting for the covariates. As expected, older age, gender (women), racial minority (i.e., Black and Hispanics), being single (i.e., not married), and having greater number of comorbidities were the risk factors of NHAs (all at least $p < 0.05$). Of those, the number of comorbidities seemed to be critical as an additional comorbidity increased the odds of NHA by 24%.

At the ZIP code area level, the significant threshold ($p < 0.001$) indicated that there is appreciable between-area variability in the likelihood of NHA. Importantly, one unit increase in the neighborhood disadvantage index increased the odds of NHA by 0.3%. Although the effect appears to be small, the range of neighborhood disadvantage index is to 200 from -200. For example, the difference between the most and least disadvantaged Zip code areas was about 35 in the index. This could be translated into the 11% higher odds of NHA for the older residents in the most disadvantaged neighborhood compared to those in the least disadvantaged, holding all other variables constant. As a side note, the negative threshold (-6.835) reflects the log odds when all variables had the value of 0, or for patients with the mean age and mean number of comorbidities in the ZIP code areas with the mean disadvantage index.

Table 2: Estimated Odds Ratios and Relevant Statistics from Multilevel Logistic Regressions on the Discharge to Nursing Homes

	Step 1 Intercept-only model	Step 2 Fully conditional random intercept model	Step 3 Means-as-outcomes model	Step 4 Partially conditional mixed effects model	Step 5 Fully conditional random intercept model with the neighborhood disadvantage index
		Odds ratio (SE)	Odds ratio (SE)	Odds ratio (SE)	Odds ratio (SE)
Individual Level					
Intercept (variance)	0.124 ***			0.24 (0.01)***	
Predisposing factors					
Age (Years)		1.061 (0.01)***			1.061 (0.01)***
Gender (Women)		1.047 (0.03)			1.058 (0.03)*
Race					
White		Reference			
Black		0.791 (0.06)***			0.798 (0.06)***
Hispanic		0.594 (0.07)***			0.600 (0.07)***
Others		1.004 (0.04)			1.002 (0.04)
Enabling factor					
Marital status (Married)		0.597 (0.03)***			0.599 (0.03)***
Need factors					
Number of comorbidities		1.239 (0.01)***			1.241 (0.01)***
Random slope (γ_{11}) (number of comorbidities)				0.001 (0.01)	
ZIP code level					
Thresholds (mean)	0.145***	6.228 (0.17)***	1.794 (0.03)***	2.501 (0.04)***	6.835 (0.17)***
Residual variance	0.002***	0.094 (0.02)***	0.114 (0.012)***	0.104 (0.02***	0.083 (0.01)***
Neighborhood disadvantage index			1.004 (0.01)***	1.004 (0.01)**	1.003 (0.01)**
Deviance	60204.98	61239.80	64283.19	62618.10	59713.35
AIC	60210.99	61257.90	64289.19	62630.10	59733.35
Degrees of freedom	3	9	3	6	10

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Discussion

Guided by the behavioral model (Andersen, 1995; Andersen & Davidson, 2007), this study analyzed the routinely collected hospital administrative data and U.S. Census data to investigate the multilevel risk factors of NHA among older patients in the State of Nevada, U.S.A. Results of multilevel logistic regressions showed that older age, gender (women), being single and having greater number of comorbidities were identified as the risk factors even after adjusting for the between-neighborhoods (i.e., ZIP code areas) variability and their disadvantage index. At the same time, older black and Hispanic patients had significantly lower chance of being discharged to nursing homes compared to white patients. Finally, living in the neighborhoods with higher disadvantage index was associated with the greater chance of NHA among older patients. Collectively, the findings supported the hypotheses 1 (i.e., individual risk factors adjusting for the neighborhood characteristics) and 3 (i.e., effects of the neighborhood disadvantaged on NHA). However, the hypothesis 2 (i.e., the neighborhood disadvantage on the need factor – health) was not supported.

Referring to the operationalized behavioral model (Figure 1), age, gender and race were classified as the predisposing factors. Findings regarding the predisposing factors were consistent with previous studies (Greene & Ondrich, 1990; Jette et al., 1992; Kane & Matthias, 1984; Kane et al., 1983; Russell et al., 1997). However, the between neighborhood variability as well as the neighborhood disadvantage were taken into account. Older age is generally an indicator of declining health and increasing disabilities, and therefore, is related to the growing need of long-term care services such as nursing homes. By the same token, one possible explanation about being women as a risk factor may be the differential longevity since women live longer than men on average. Due to the fact that more women survive into older ages than men, the chance of NHA is presumably greater.

Findings regarding race and ethnicity were consistent with previous studies (Coughlin et al., 1990; Greene & Ondrich, 1990). Although exact mechanism about why non-white populations have lower chances of NHA, Green and Ondrich (1990) argues that race and ethnicity may be a summary indicator of educational attainment, income and availability of informal care network. As such, some racial and ethnic minorities like blacks and Hispanics may utilize informal care (i.e., family care) to older kin more often than whites, and delay use of long-term care services. Green and Ondrich (1990) also indicated that blacks and Hispanics may have different brief systems in long-term care service use for their older family members. However, further studies are needed to clarify reasons for racial and ethnic differences in the NHA among older patients.

With respect to the enabling factor, marital status (being married) was identified as the protective factor of NHA. In this context, Freedman (1996) explains that family members could be direct informal caregiver, instrumentally assist older kin to obtain community-based care services, and provide beneficial emotional support to stay in community. Also, given the married individuals are generally healthier than unmarried, marital status-related health benefit may lower the need of formal long-term care services (see Carr & Springer, 2010 for the recent review). It should be noted that the hospital administrative data did not have common enabling factors such as income and educational attainment. Marital status might have reflected other common enabling factors which were not available in this study. Yet, paying greater attention to and/or providing information about community-based care services to unmarried older patients and/or those living alone in hospital settings would be beneficial to promote aging in place.

In this study, comorbidities was employed as a need factor. Consistent with previous studies, health status captured by the number of comorbidities was a significant predictor of NHA among older patients (Miller & Weissert, 2000; N. P. Roos et al., 1988). As managing one chronic disease is already challenging, multiple chronic conditions imply tremendous burden to patients (Vogeli et al., 2007). Given the multilevel design of this study, detailed investigation on individual effect of numerous diagnoses/conditions was beyond the scope of this study. Yet, future research should examine the known risk factors such as dementia and heart disease in the multilevel analysis (Coughlin et al., 1990; Miller & Weissert, 2000).

In addition to the between-ZIP code area variability in the likelihood of NHAs among older patients, the neighborhood disadvantage index was identified as the risk factor in this study. Previous studies also found relatively simple geographic factors (e.g., location of hospitals, rural vs. urban areas) as the predictors of NHAs (Kahn et al., 1994; Rudberg et al., 1996). Although evidence is still premature and mixed (e.g., Buys et al., 2013), Rudberg et al. (1996) discuss the neighborhood characteristics such as the availability of beds in local nursing homes and community-based long-term care services, and neighborhood level socioeconomic status (e.g., financial resource) as possible explanations of geographic variability in NHAs.

In light of the operationalized behavioral model derived from the work by Andersen and Davidson (2007), this study hypothesized that the neighborhood disadvantage is associated with the need factor – health, which is an important predictor of NHA. Indeed, previous studies have generated convincing evidence of the neighborhood effects on health outcomes (Diez Roux & Mair, 2010). Nonetheless, the findings did not support this hypothesis. This study analyzed the data from older patients and therefore, their characteristics and response to living environments may be different from the data in previous studies (Lawton, 1983). In addition, whereas the neighborhood disadvantage index has been used in several seminal studies, the comparability to other neighborhood quality indicators is still not established (Diez Roux & Mair, 2010). Future research needs to take a closer look at these common challenges.

The neighborhood disadvantage index was a significant predictor of NHA among older patients although the health indicator (i.e., the number of comorbidities) did not explain the possible mechanism in this study. Importantly, the neighborhood disadvantage index is not a comprehensive measure but it is an attempt to capture a kind of neighborhood effects. At the same time, the random intercept most likely captured at least some remaining unknown neighborhood effects that were not explicitly reflected in the disadvantage index in the multilevel models. It is possible that other long-term care-related factors such as housing quality/safety, home care service availability and social network in community might have impacted the chance of NHA in this study. It should be noted that the strength of neighborhood disadvantage index is to capture one type of average neighborhood quality and achieve parsimonious multilevel models (Ross & Mirowsky, 2001). Future research may further examine individual neighborhood quality indicators although possible complex interactions between them would be a challenge to overcome.

Several preliminary public health policy implications can be derived from this study. To begin with, given older patients' residential areas have impacts on the likelihood of NHA, healthcare professional may incorporate such assessment into the regular inquiries. Also, the known risk and protective factors of NHA in the healthcare settings are still valid even after adjusting for the between-neighborhood variability (Miller & Weissert, 2000). Results of this study also supported possible policy level intervention for older adults in the disadvantaged neighborhoods for reducing unnecessary NHAs. Creating the neighborhood disadvantage profile with available data such as the U.S. Census data can be done in any states based on this study. In this respect, although systematic community-level intervention programs are yet to be developed, some approaches such as home visit of healthcare professionals and community-based housing quality (e.g., safety) assessment (Krieger & Higgins, 2002) are worth considering. Finally, policy-level resource allocation for reviewing existing hospital administrative data and adding important information (e.g., family structure, educational attainment, income) to future data collection are potentially beneficial.

Limitations

Several limitations in this study should be noted. Information regarding the length of nursing home stay was not available in this study. Yet, any type (e.g., post-acute care short-term rehabilitation, long-term stay) of NHA usually costs more than home and community-based care, and therefore, the risk profile of NHA is useful. Future study should examine whether risk profiles are comparable between types of NHAs. Also, as discussed in the literature, the definition of neighborhood (i.e., ZIP code area) and measurement of neighborhood characteristics (i.e., neighborhood disadvantage index) employed in this study are only comparable to the previous studies with the same or similar designs. Indeed, any research with neighborhood information must make a number of difficult methodological decisions. Moreover, while use of administrative data is one of the strengths in this study, possible omitted variable bias cannot be ruled out. Patients' socioeconomic status (e.g., educational attainment, income, wealth), family structure, housing quality and local long-term care service availability might have added valuable information to the statistical models. Although the hospital administrative data have some advantages (e.g., routinely collected; population data), available information is limited as not designed for social scientific inquiry. Additionally, there might have been differing local policies related to provision of health and long-term care services even within the state. Finally, this study focused only on the State of Nevada with cross-sectional data. Although the older patients in this study are representative of the state, generalizability of the findings require additional studies in other states and longitudinal data.

Contributions

Despite some limitations, this study made several important contributions. First, this study analyzed the recent data for developing the risk profile of NHAs among older patients as the majority of previous studies used relatively old data. Second, this study provided a multilevel risk profile of NHAs in the hospital settings. The insights regarding the between-neighborhood variability and neighborhood disadvantage in the risk of NHA add to the literature. Third, this study could be the basis for future research investigating more specific neighborhood effects. Fourth, this study covered an underutilized approach of a combinations of publically available community data (e.g., U.S. Census) and existing hospital administrative data for identifying both individual-level and neighborhood-level risk factors. Last but not least, the multilevel risk profile development suggested in this study can be easily replicated in other states or areas.

Conclusion

Guided by the behavioral model (Andersen & Davidson, 2007), this study developed a multilevel risk profile of NHA among older patients in the State of Nevada, USA. Results validated the known risk factors including age, gender, race, marital status and health (i.e., number of comorbidities) even after adjusting for the between-neighborhoods variability. Additionally, the neighborhood disadvantage was identified as the neighborhood-level risk factor of NHA above and beyond the individual characteristics among older patients. Patients' neighborhood quality is an important area to explore in the context of long-term care as well as public health research, practice and policy to reduce preventable NHA. Hospital is a logical place to start such initiative (Kane et al., 1983). Further research is needed to validate the findings from this study and to contribute to the aging in place not only for older adults but also for the public in terms of quality of life and long-term care financing in aging American society (Lawton, 1982).

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