

ORIGINAL RESEARCH

# Sociodemographic Determinants of Acute Myocardial Infarction Hospitalization Risks in Florida

Evah Wangui Odoi, PhD; Nicholas Nagle, PhD; Russell Zaretski, PhD; Melissa Jordan, MS, MPH; Chris DuClos, MS, GISP, CPM; Kristina W. Kintziger, PhD

**BACKGROUND:** Identifying social determinants of myocardial infarction (MI) hospitalizations is crucial for reducing/eliminating health disparities. Therefore, our objectives were to identify sociodemographic determinants of MI hospitalization risks and to assess if the impacts of these determinants vary by geographic location in Florida.

**METHODS AND RESULTS:** This is a retrospective ecologic study at the county level. We obtained data for principal and secondary MI hospitalizations for Florida residents for the 2005–2014 period and calculated age- and sex-adjusted MI hospitalization risks. We used a multivariable negative binomial model to identify sociodemographic determinants of MI hospitalization risks and a geographically weighted negative binomial model to assess if the strength of associations vary by location. There were 645 935 MI hospitalizations (median age, 72 years; 58.1%, men; 73.9%, white). Age- and sex-adjusted risks ranged from 18.49 to 69.48 cases/10 000 persons, and they were significantly higher in counties with low education levels (risk ratio [RR]=1.033,  $P<0.0001$ ) and high divorce rate (RR, 0.995;  $P=0.018$ ). However, they were significantly lower in counties with high proportions of rural (RR, 0.996;  $P<0.0001$ ), black (RR, 1.026;  $P=0.032$ ), and uninsured populations (RR, 0.983;  $P=0.040$ ). Associations of MI hospitalization risks with education level and uninsured rate varied geographically ( $P$  for non-stationarity test=0.001 and 0.043, respectively), with strongest associations in southern Florida (RR for <high school education, 1.036–1.041; RR for uninsured rate, 0.971–0.976).

**CONCLUSIONS:** Black race, divorce, rural residence, low education level, and lack of health insurance were significant determinants of MI hospitalization risks, but associations with the latter 2 were stronger in southern Florida. Thus, interventions for addressing MI hospitalization risks need to prioritize these populations and allocate resources based on empirical evidence from global and local models for maximum efficiency and effectiveness.

**Key Words:** geographically weighted regression ■ myocardial infarction hospitalization risks ■ socioeconomic determinants of health

Cardiovascular disease (CVD) is the leading cause of morbidity in the United States.<sup>1</sup> Acute myocardial infarction (MI), or heart attack, contributes significantly to this burden, particularly in southeastern United States,<sup>2,3</sup> such as Florida, where 6.0% and 12.2% of the state's adult and older adult (>65 years old) populations, respectively, reported a history of acute MI in 2018.<sup>4,5</sup> By comparison, 4.6% of the US adult population reported a history of acute MI in 2018.<sup>1,4</sup>

Improvements in prevention and treatment efforts for MI have resulted in substantial reductions in the overall burden of MI hospitalizations among various population groups across the United States.<sup>6–10</sup> In Florida, age-adjusted MI hospitalization risks decreased by 20.4% between 2005 and 2014.<sup>11</sup> However, these declines may overstate the success of preventive and control efforts, because the analyses did not consider cases where MI was coded as

Correspondence to: Evah Wangui Odoi, PhD, Comparative and Experimental Medicine, College of Veterinary Medicine, The University of Tennessee, 2407 River Drive, Knoxville, TN 37996. E-mail: ewangui@utk.edu

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## CLINICAL PERSPECTIVE

### What Is New?

- This study identified sociodemographic determinants of myocardial infarction (MI) hospitalization risks for different locales in Florida, regardless of whether MI is the principal or secondary cause for hospitalization.
- MI hospitalization risks were positively associated with low education levels and high divorce rates but negatively associated with high proportions of rural, black, and uninsured populations.
- Associations of MI hospitalization risks with rural residence, black race, and divorce were constant across Florida, but associations with low education level and uninsured rate were strongest in southern Florida.

### What Are the Clinical Implications?

- Interventions for addressing MI hospitalization risks need to consider social context, specifically targeting counties with low high school graduation and high divorce rates, and high proportions of rural, black and uninsured populations to reduce health disparities and achieve lasting improvements in population health.
- “One size fits all” strategies would not be suitable for addressing MI hospitalization risks in Florida.
- Study findings are also instructive for the rest of the United States, because Florida’s current demographic structure portends future changes projected for the US population.

## Nonstandard Abbreviations and Acronyms

<b>AICc</b>	bias-corrected Akaike Information Criteria
<b>GWNB</b>	geographically weighted negative binomial
<b>MAD</b>	mean absolute deviance
<b>MAPE</b>	mean absolute percentage error
<b>NB</b>	negative binomial
<b>SES</b>	socioeconomic status
<b>SDoH</b>	socioeconomic determinants of health

secondary discharge diagnosis.<sup>12</sup> It is useful to know the extent of morbidity attributable to MI, regardless of whether it is the primary or secondary cause for hospitalization.

Mounting evidence from ecologic studies indicate that the prevalence of area-level socioeconomic

determinants of health (SDoH) can affect the types of exposures and/or access to health care that one experiences and hence the risk of MI in a given population.<sup>13,14</sup> According to Bookse et al,<sup>15</sup> SDoH are responsible for shaping 40% of the health of a population, and they also strongly influence health behaviors, the second greatest contributor to health and longevity. Therefore, SDoH are fundamental drivers of persistent health disparities and are the underlying causes of geographic disparities in MI prevention and treatment.<sup>2</sup> Accordingly, it has been suggested that identifying and dealing with SDoH offers the greatest opportunities for reducing morbidity, deaths, and disability from MI and other CVD and achieving lasting improvements in population health at the lowest cost.<sup>13</sup>

There is no single comprehensive surveillance system for MI morbidity in the United States.<sup>7</sup> However, because MI is a severe health event requiring catheterization within 90 minutes of first medical contact to prevent adverse health outcomes,<sup>16</sup> MI hospitalization risks may serve as a proxy for MI morbidity. Therefore, identifying specific SDoH predictors of MI hospitalizations may provide clues regarding distal causes of MI and aid in the development of evidence-based strategies for MI prevention, leading to reduced health disparities and improved population health.

Studies of associations of health events and SDoH factors are traditionally performed using spatial global models that implicitly assume constant effects of explanatory variables across the study area. As such, they estimate a single coefficient for each explanatory variable averaged over the entire study area. However, a number of studies have shown that the influence of SDoH factors on the risks of cardiovascular health outcomes<sup>17–19</sup> vary by geographic location. Therefore, it is highly unlikely that associations between MI hospitalization risks and SDoH factors would be realistically reflected by global models. Rather, due to substantial local variations in the sociodemographic characteristics of the population in Florida, it is more plausible for the influence of SDoH factors to vary geographically, with some factors being more important determinants of MI hospitalization risks at certain locations but less important at other locations.<sup>20</sup> Accordingly, identifying the most important determinants of MI hospitalization risks for different geographic areas may aid in the development of location-specific strategies for MI prevention, which is critical for efficient allocation of scarce resources. Therefore, the objectives of this study were to identify sociodemographic determinants of the disparities in MI hospitalization risks and to assess if the effects of these determinants vary by geographic location in Florida.

## METHODS

All the analytic methods used to conduct the research have been described in detail for purposes of reproducing the results or replicating the procedure. However, due to the sensitive nature of the MI hospitalization data analyzed for this study, we are unable to make the data available publicly. The data belong to a third party (Florida Agency for Health Care Administration). The authors were able to access the data through a formal data use agreement with this agency. Requests to access the data set from qualified researchers trained in human subject confidentiality protocols may be sent to the Florida Agency for Health Care Administration by contacting the Public Records Office at PublicRecordsReq@ahca.myflorida.com.

This study was approved by the University of Tennessee, Knoxville (Approval # UTK IRB-17-03601-XP) and Florida Department of Health (Protocol # 170032UTN) Institutional Review Boards as expedited review. We used secondary data for MI hospitalizations; hence, no human participants were recruited and a waiver for consent to participate was granted.

### Study Design and Population

This was a retrospective ecological study using Florida MI hospitalization data for the period January 1, 2005, to December 31, 2014. The study population included all Florida resident in-patient hospitalizations admitted with any MI discharge diagnoses (ie, principal or a secondary code 410 according to the *International Classification of Diseases, Ninth Revision, Clinical Modification [ICD-9-CM]*), but it did not include Veterans Affairs, Indian Health Services, prison populations, or state-owned facilities.

### Data Sources and Preparation

#### Hospital Discharge Data

Individual-level MI hospitalization data, collected by the Florida Agency for Health Care Administration, were obtained from the Florida Department of Health. We extracted the following variables: admission date, primary diagnosis and up to 30 secondary diagnoses to enable extraction of cases with a secondary MI diagnosis, patient age, sex, race/ethnicity, and ZIP code and county of residence. We used the county as the geographic unit of analysis.

The MI data for each county and for Florida were aggregated by sex, age (ie, 0–34, 35–44, 45–54, 55–64, and ≥65 years) and race/ethnicity (ie, non-Hispanic white, Hispanic Latino, non-Hispanic black Other races) for each year and for the entire 10-year study period. These data were used as numerator

data for calculating sex-, age-, and race/ethnicity-specific MI hospitalization risks and for age and sex adjustment of risks. To assess seasonal trends, state-level data were also aggregated by season and year.

#### Population Data

We downloaded state- and county-level annual population estimates for Florida from the Florida Department of Health,<sup>21</sup> and stratified the data into sex, age, and race/ethnicity categories similar to those for the MI hospitalization data. We used state-level data as denominator data for calculating attribute-specific MI hospitalization risks for Florida for the entire study period. We used county-level estimates as denominator data for calculating age- and sex-adjusted MI hospitalization risks, using the 2010 decennial data for the United States<sup>22</sup> as the standard population.

#### Cartographic Boundary Files

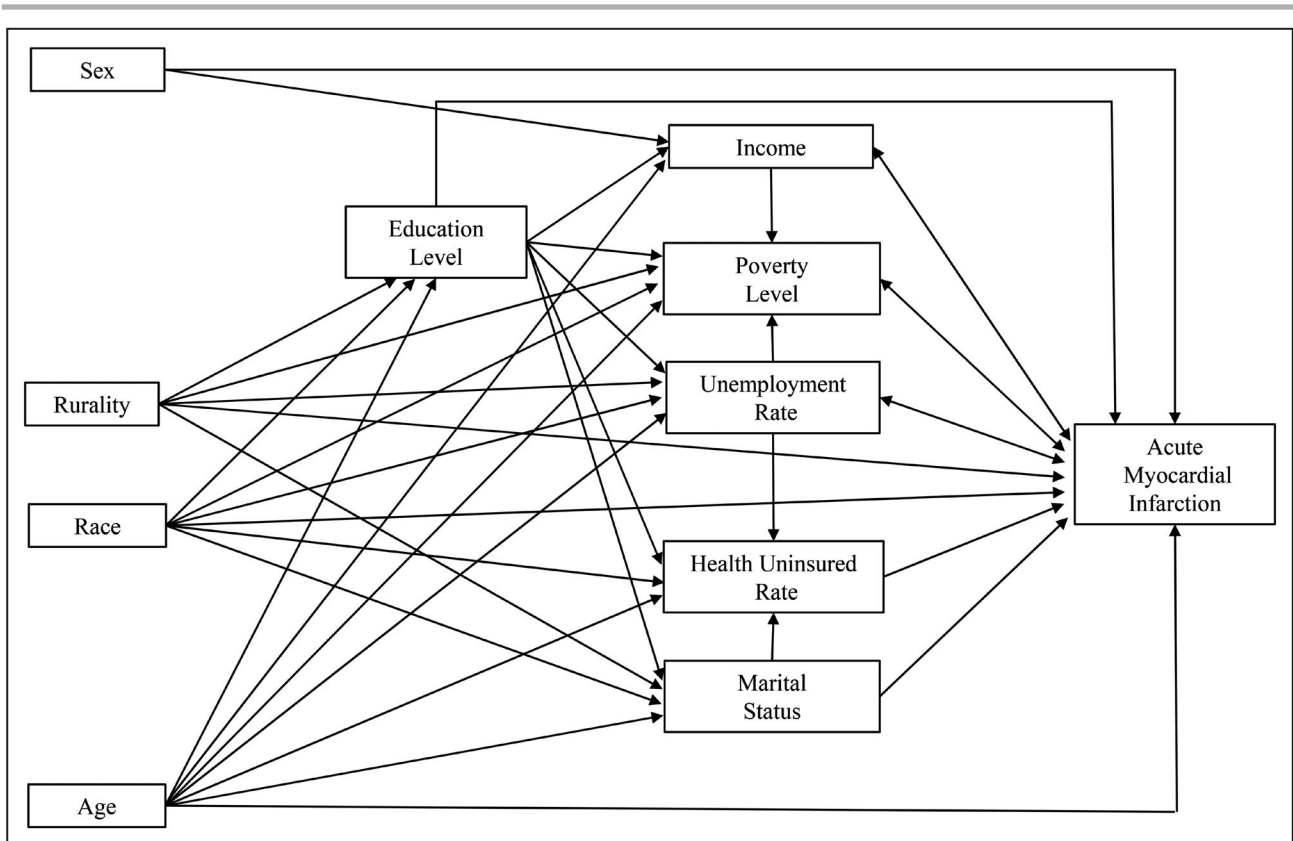
We downloaded county-level cartographic boundary shape files for 2010 from the US Census Bureau website.<sup>23</sup> These were used as base maps for all cartographic displays.

#### Socioeconomic and Demographic Data

Five-year (2008–2012) American Community Survey estimates for several sociodemographic variables related to race/ethnicity, marital status, place of residence, education level, health insurance, employment, and economic status of the population in each county were also pulled from the US Census Bureau via the American FactFinder website.<sup>24</sup>

#### Conceptual Model Used to Guide Selection of Potential Determinants of MI

We built a conceptual causal web model (Figure 1) to guide the selection of potential SDoH study variables. The variables of interest were selected based on hypothesized associations with MI hospitalization risks and they included proportion of population with less than high school education; proportion of population living below poverty level; median income; proportion of population living in owner-occupied housing; unemployment rate for population aged ≥16 years old; proportion of uninsured population; proportion of population classified as rural/urban; proportion of population aged ≥65 years and older; proportion of population classified as white, black or Hispanic; proportion of widowed, married, divorced, separated, and never married populations, and proportion male population.



**Figure 1.** Causal web model used to guide selection of sociodemographic determinants of myocardial infarction hospitalization risks.

**Statistical Analysis**

**Summary Statistics**

We computed the percentage of MI hospitalizations by age (0–34, 35–44, 45–54, 55–64, and ≥65 years), sex (male and female) and race/ethnicity (white, Hispanic, and black), as well as factor-specific MI hospitalization risks for the different demographic groups. We also computed summary statistics including median or mean, minimum, and maximum values for all SDoH variables. All descriptive statistics were done in SAS version 9.4 (SAS Institute Inc., Cary, NC).

MI hospitalization risks were age and sex adjusted to the 2010 US census standard population<sup>25</sup> to allow for valid comparisons of risks across different counties and years. We used the 2010 US census population for risk adjustment. This is because although the 2000 US population is recommended for age-adjustment of age-dependent health events,<sup>25</sup> the 2010 US population represent the most recent actual age compositions of the US population, and it also falls within the range of our data collection. Moreover, because the risk of MI increases with age, using a standard population with a lower proportion of older ages could yield lower age-adjusted risks.<sup>26</sup> Thus, 2010 US census population may provide us with

more realistic and more current risk estimates. Finally, we computed seasonal MI hospitalization risks by defining seasons: winter (December 1 to February 28/29), spring (March 1 to May 31), summer (June 1 to August 31), and fall (September 1 to November 30).

**Model Building Process to Identify Sociodemographic Determinants of MI Hospitalizations Risks**

Spearman’s rank pairwise correlations were used to screen highly correlated ( $r \geq 0.7$ ) SDoH variables to avoid multicollinearity issues. We chose a cutoff correlation coefficient of 0.7 or higher based on a study by Fotheringham and Oshan<sup>27</sup> showing geographically weighted regression to be highly robust to moderate levels of collinearity between explanatory variables. Only 1 variable of a pair of highly correlated variables was retained for subsequent analysis. The choice of variable for retention was based on statistical and biological considerations.

Uncorrelated variables were then investigated for potential associations with MI hospitalization risks in 2 steps. First, the relationship between MI risks and all potential predictors of interest was assessed by fitting univariable ordinary Poisson regression

models to the data using the generalized linear model procedure, PROC GENMOD in SAS version 9.4 (SAS Institute Inc.). The dependent variable was the expected MI hospitalization count in each county based on age and sex adjustment, and the offset was the natural log of the 2005–2014 period county population estimates from the Florida Department of Health. In the second step of the modeling, variables that had potentially significant associations with MI hospitalizations based on a liberal  $P$  value of 0.15 in the univariable model were included for assessment in a multivariable Poisson regression model. The multivariable model was built using a manual backward elimination approach, specifying a 5% significance level. Overdispersion of the final model was assessed using the ratio of deviance to degrees of freedom of the final model. Ratios  $>1$  imply significant overdispersion. The value of the overdispersion parameter was 95.93 indicating overdispersion.

Because the Poisson regression model had significant overdispersion, a negative binomial (NB) model was fit to the data, using PROC GENMOD. As with the Poisson regression model, the dependent variable was the expected MI hospitalization count obtained from the direct age and sex standardization of risks in each county, and the offset was the natural log of the 2005–2014 period population for each county. Significant SDoH variables from the multivariable Poisson model were entered into a full global NB model, and manual backward elimination was used to select significant ( $P < 0.05$ ) determinants, using the likelihood ratio test to assess variable significance. Confounders were identified by assessing the change of parameter estimates of variables in the model with and without the suspected confounder. Variables whose removal resulted in a change of at least 20% in the parameter estimates of any significant variable in the model were considered as important confounders and were retained in the model. All biologically plausible 2-way interaction terms between significant variables in the final model were explored, and significant ones retained. Biological plausibility was assessed based on consistency of the relationships with the current body of knowledge regarding etiology and mechanism of MI.

We assessed multicollinearity in the final model through the variance inflation factor and tolerance using PROC REG and the natural log of age- and sex-adjusted MI hospitalization risks as the dependent variable. Variance inflation factor  $>10$  and tolerance values  $<0.1$  indicate presence of multicollinearity. Goodness-of-fit for the final NB model was assessed using the deviance and Pearson  $\chi^2$  goodness-of-fit tests. Standardized Pearson's residuals and Cook's distance were used to assess for presence of outliers and influential points, respectively. Standardized Pearson residuals were assessed for spatial autocorrelation using

Global Moran's  $I$  in Geoda,<sup>28</sup> specifying first order queen spatial weights. The conceptual model for potential sociodemographic determinants of MI hospitalizations was revised based on the results of the global NB model.

### **Geographically Weighted Negative Binomial Regression**

Global models, such as the multivariable NB regression model, estimate a single coefficient averaged over all locations for each of the explanatory variables. As such, they have limited ability to take local variations into account. By contrast, the geographically weighted NB (GWNB) regression model<sup>29</sup> estimates as many regression coefficients as the number of geographic locations in the study area. Thus, it enables the investigator to assess whether relationships between the dependent and explanatory variable(s) vary with geographic location. Thus, we used the GWNB regression model proposed by Silva and Rodrigues<sup>29</sup> to assess if the strength of relationships between MI hospitalization risks and significant SDoH determinants varied by geographic location. This was implemented in SAS using a set of SAS/IML macros developed by Silva and Rodrigues.<sup>30</sup> Briefly, the procedure accounts for spatial dependency and overdispersion of residuals by fitting a GWNB regression model (i) with spatially varying regression coefficients ( $\beta$ 's) and a single global overdispersion parameter, ( $\alpha$ ), which is equivalent to the  $\alpha$  value in the nonspatial NB regression model. Here,

$$E(y_j) \sim \text{NB} \left[ t_j \exp \left( \sum_k \beta_k (\mu_j, v_j) x_{jk} \right), \alpha \right] \quad (i)$$

where  $y_j$  is the  $j$ -th dependent variable for  $j=1, \dots, n$ , NB represents negative binomial,  $t_j$  is an offset variable,  $\beta_k$  is the parameter related to the SDoH variable,  $x_k$ , for  $k=1, \dots, K$ ,  $(\mu_j, v_j)$  are the location coordinates of data points  $j$ , for  $j=1, \dots, n$ , and  $\alpha$  is the overdispersion parameter.

Similar to the global NB model, the dependent variable in the GWNB model was the age- and sex-adjusted MI hospitalization count,  $E(y_j)$ , with  $j$  indicating 1 of the 67 counties, and the log of 2005–2014 period Florida Department of Health population estimates for each county was used as the offset,  $t_j$ , as noted previously. The biquadratic kernel weighting function was used to determine the geographical weighting to estimate local coefficients; see Silva and Rodrigues.<sup>30</sup> A major concern when applying a biquadratic kernel weighting function is the choice of bandwidth. According to Fotheringham et al,<sup>31</sup> a small bandwidth would result in large standard errors for the coefficients and make spatial patterns difficult to detect. A large bandwidth, on the other hand, would yield oversmoothed local extremes and

lead to biased local estimates.<sup>32</sup> Because Florida comprises both densely populated urban counties and sparsely populated rural counties, the adaptive method, where the size of the bandwidth varies to adapt to the variations in the density of observations, was used to adjust for the differences in population density, shapes, and sizes of counties in the state. The optimum kernel bandwidth was determined by minimizing the bias-corrected Akaike Information Criteria (AICc). The AICc was also used to compare the performance of the global NB and GWNB regression models. Mean absolute deviance (MAD) and mean absolute percentage error (MAPE) were also used to compare the model fits. These were computed as:

$$MAD = \frac{1}{n} \sum_{i=1}^n |y_i^{obs} - y_i^{pred}|$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right|$$

where *n* is the number of counties in Florida, *y<sub>i</sub><sup>obs</sup>* and *y<sub>i</sub><sup>pred</sup>* are the observed and expected number of hospitalizations respectively, in each county. Lower AICc, MAD or MAPE values all indicate a better model fit.

As with the NB model, the Pearson standardized residuals for the GWNB were assessed for spatial autocorrelation using Global Moran's I in Geoda.<sup>28</sup> Non-stationarity of the coefficients for the GWNB model was assessed using the randomization non-stationarity test<sup>33</sup> based on 999 replications. This was also implemented in SAS v.9.4 using the macros developed by Silva and Rodrigues.<sup>30</sup> A family-wise error rate (family-wise critical *P*=0.0297) was used to correct for multiple testing.<sup>34</sup> The non-stationarity of the local regression coefficients for the GWNB was also assessed by comparing the interquartile range of the local regression coefficients with the standard error estimates of the global NB model. Any local regression coefficient whose interquartile range was larger than twice the standard error of the regression coefficient from the global NB model was considered non-stationary across the study area.<sup>20,31</sup>

### Spatial Patterns Identification

We used ArcGIS Version 10.6.1 (ESRI, Redlands, CA) to perform all geographic information system manipulations and to display the spatial distributions of MI hospitalization risks, SDoH factors, and regression coefficients for non-stationary SDoH variables. Jenk's optimization classification scheme was used to

determine break points for displaying MI hospitalization risks and SDoH factors as choropleth maps.

## RESULTS

### Descriptive Statistics

There was a total of 645 935 MI hospitalizations in Florida during the 10-year study period, of which 66.3% had a principal MI discharge diagnosis, with the rest being secondary diagnoses. Males accounted for a larger (58.1%) proportion of total MI hospitalizations than females (41.9%) (Table 1). The MI hospitalization risks for men (40.9 cases/10 000 persons) were significantly greater (*P*<0.0001) than those for women (28.2 cases per 10 000 persons). Among the different ethnic groups, Whites accounted for the largest (73.9%) proportion of MI-related hospitalizations followed by Hispanics (12.1%) and then blacks (9.5%) (Table 1). Whites had the highest MI hospitalization risks, followed by blacks and Hispanics, respectively. The median age of hospitalized patients was 72 years (interquartile range, 22 years), and 66.2% of hospitalizations occurred in individuals ≥65 years and older. The highest MI hospitalization risks (130.2 cases per 10 000 persons) was observed in the ≥65-year age group whereas the lowest (0.6 cases per 10 000 persons) was observed in the 0- to 34-year-old age group.

There were gradual declines in annual MI hospitalization risks (Figure 2), with risks for MI with any and principal discharge diagnoses declining by 15% and 20%, respectively. There was a distinct seasonal pattern, with highest

**Table 1. Myocardial Infarction Attribute-Specific Hospitalization Risks for Florida, 2005–2014**

Sociodemographic Characteristic	Percentage of Cases Total Number of Cases=645 935	Hospitalization Risk (Per 10 000 Persons)
Sex		
Male	58.1	40.9 (40.8–41.0)*
Female	41.9	28.2 (28.1–28.3)
Age group, y		
0–34	0.8	0.6 (0.6–0.7)
35–44	3.5	9.2 (9.1–9.2)
45–54	11.2	27.0 (26.8–27.2)
55–64	18.3	52.0 (51.7–52.3)
≥65	66.2	130.2 (129.9–130.6)
Race/ethnicity		
Non-Hispanic White	73.9	43.3 (43.3–43.5)
Hispanic Latino	12.1	18.9 (18.8–19.0)
Non-Hispanic Black	9.5	21.4 (21.3–21.6)
All other races	2.8	23.6 (23.2–23.9)

Cases with missing race/ethnicity was 10 645.

\*95% confidence limit of the mean.

risks occurring in winter and lowest risks occurring in summer throughout the 10-year study period. Winter, spring, summer, and fall accounted for 27.1%, 25.7%, 23.2%, and 24% of total MI hospitalizations, respectively.

Summary statistics for the 23 SDoH variables considered potential determinants of MI hospitalization risks are presented in Table 2, and the spatial distributions of MI hospitalization risks and selected SDoH factors are shown in Figure 3. Age- and sex-adjusted MI hospitalization risks (Figure 3) varied widely across Florida, ranging from 18.49 cases per 10 000 persons in Jackson County to 69.48 cases per 10 000 persons in Okeechobee County. The median MI hospitalization risk was 28.18 cases/10 000 persons. In general, high MI hospitalization risks were observed in counties in northern central, western, and southern central parts of Florida.

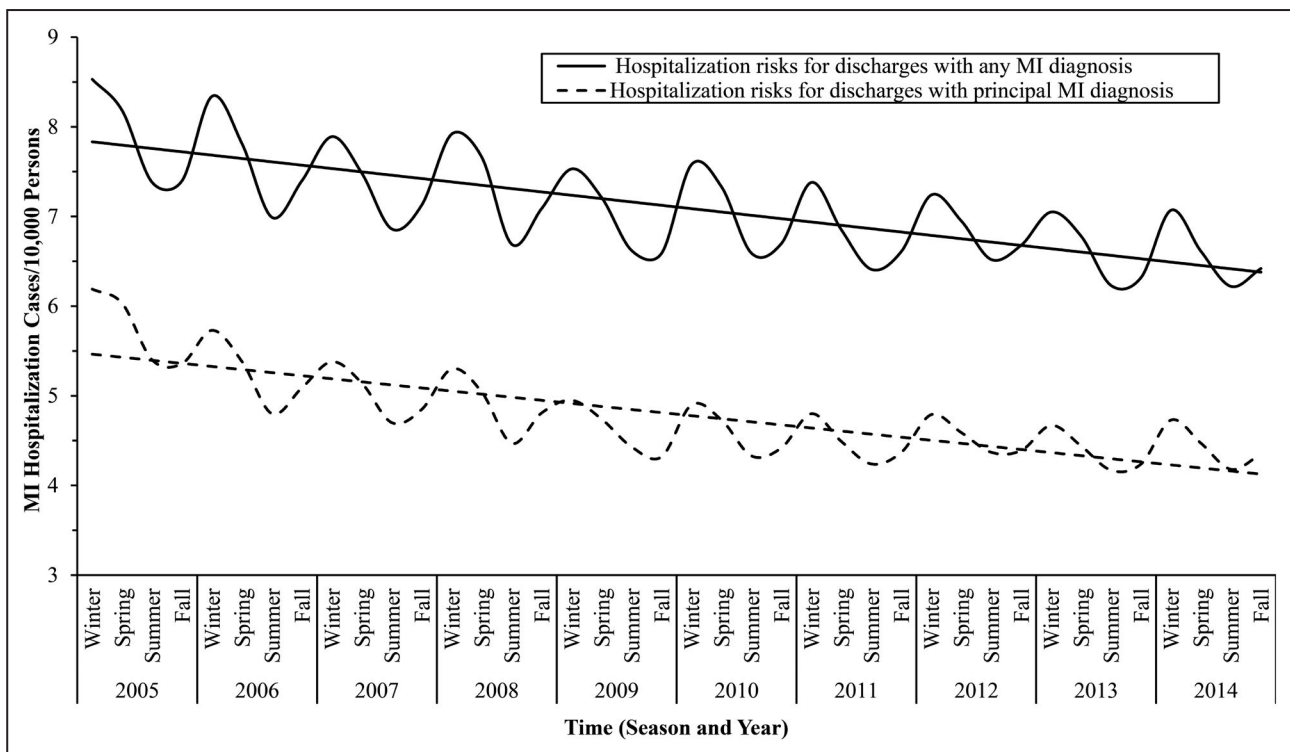
With respect to demographic factors, 50% of the counties had at least 16% of their population aged ≥65 years and older. The distributions of male and female residents across the state were relatively similar. Florida is predominantly white, with 50% of the counties having at least 74% of their population being white. However, a number of counties in the north and south have large proportions of minority populations (Figure 3). Most of the state’s population reside in urban counties, with 50% of the counties having at least 76% of their population classified as urban (Table 2). A large proportion of the

urban population reside in counties in southern Florida, whereas northern central and southern central Florida counties comprised mostly rural populations (Figure 3). The proportion of the population with less than high school education level varied widely across the state (7–37%) (Table 2), but it was highest in rural counties in the Panhandle, northern central and southern central Florida (Figure 3). On average 18% of the population in Florida counties live below the federal poverty level. The unemployment rates and proportion of the population without health insurance varied widely across the state, with some counties having up to 23% and 22% of their population being unemployed and lacking health insurance, respectively. These counties were predominantly located in southern Florida (Table 2, Figure 3).

Counties with a high prevalence of risk factors (Figure 3) also appeared to have high MI hospitalization risks, suggesting potential associations between MI hospitalization risks and SDoH factors.

### Spearman Rank Correlations and Simple Associations

Several SDoH variables had high ( $r \geq 0.70$ ) pairwise correlations. The proportion of the population with less than high school education level was highly correlated with several variables including all variables related to education attainment ( $r = -0.72$  to  $-0.86$ ), the



**Figure 2.** Temporal trends of age- and sex-adjusted myocardial infarction hospitalization risks with any or principal discharge diagnosis, Florida, 2005–2014.

**Table 2. Summary Statistics for Sociodemographic Assessed for Potential Associations With Myocardial Infarction Hospitalization Risks**

Category	Sociodemographic Characteristic*	Mean	SD	Median	Min	Max
Age	≥65 y	0.18	0.07	0.16	0.09	0.43
Sex	Male	0.51	0.04	0.49	0.48	0.65
Race/ethnicity	Black	0.14	0.09	0.11	0.03	0.55
	Hispanic	0.14	0.12	0.10	0.03	0.65
	White	0.70	0.15	0.74	0.16	0.90
Marital status	Divorced	0.13	0.02	0.13	0.07	0.21
	Separated	0.02	0.01	0.02	0.01	0.04
	Widowed	0.07	0.02	0.07	0.02	0.11
	Never married	0.28	0.06	0.28	0.15	0.47
Rural/urban status	Rural	0.38	0.32	0.24	0.00	1.00
	Urban	0.62	0.32	0.76	0.00	1.00
Education level	<High school education	0.17	0.07	0.15	0.07	0.37
	High school education	0.34	0.06	0.35	0.20	0.48
	Some college education	0.22	0.03	0.22	0.16	0.26
	Associate degree	0.08	0.02	0.08	0.16	0.26
	Bachelor degree	0.13	0.05	0.13	0.05	0.27
	Graduate degree	0.07	0.04	0.06	0.02	0.20
Economic status	Median income \$ (ln 10 000s)	4.39	0.74	4.38	3.25	6.43
	Living below poverty	0.18	0.05	0.17	0.10	0.30
	Owner-occupied housing units	0.73	0.07	0.75	0.55	0.90
Employment	Unemployment rate for ≥16 y old (unemployment rate)	0.12	0.03	0.12	0.07	0.23
Health insurance	Uninsured rate for ≤64 y old (health uninsured rate)	0.13	0.03	0.12	0.07	0.22

\*All variables but median income are expressed as proportions of county population.  
Data source: US Census Bureau, 2010 and American Community Survey (2005–2008).

proportion of population living below poverty ( $r=0.78$ ), and the median income ( $r=-0.81$ ). Other highly correlated variables included the proportion of widows and the proportion of population ≥65 years old ( $r=0.82$ ), proportion of male population and proportion of population living in rural areas ( $r=0.72$ ), the median house value and unemployment rate ( $r=-0.71$ ), proportions of never married and married populations ( $r=-0.91$ ), and the proportion of population living in rural and those living in urban areas ( $r=-1$ ). Only 12 of the 23 initial sociodemographic variables considered as potential determinants of MI hospitalization risks were uncorrelated and had potentially significant ( $P<0.15$ ) univariable associations with MI hospitalization risks (Table 3).

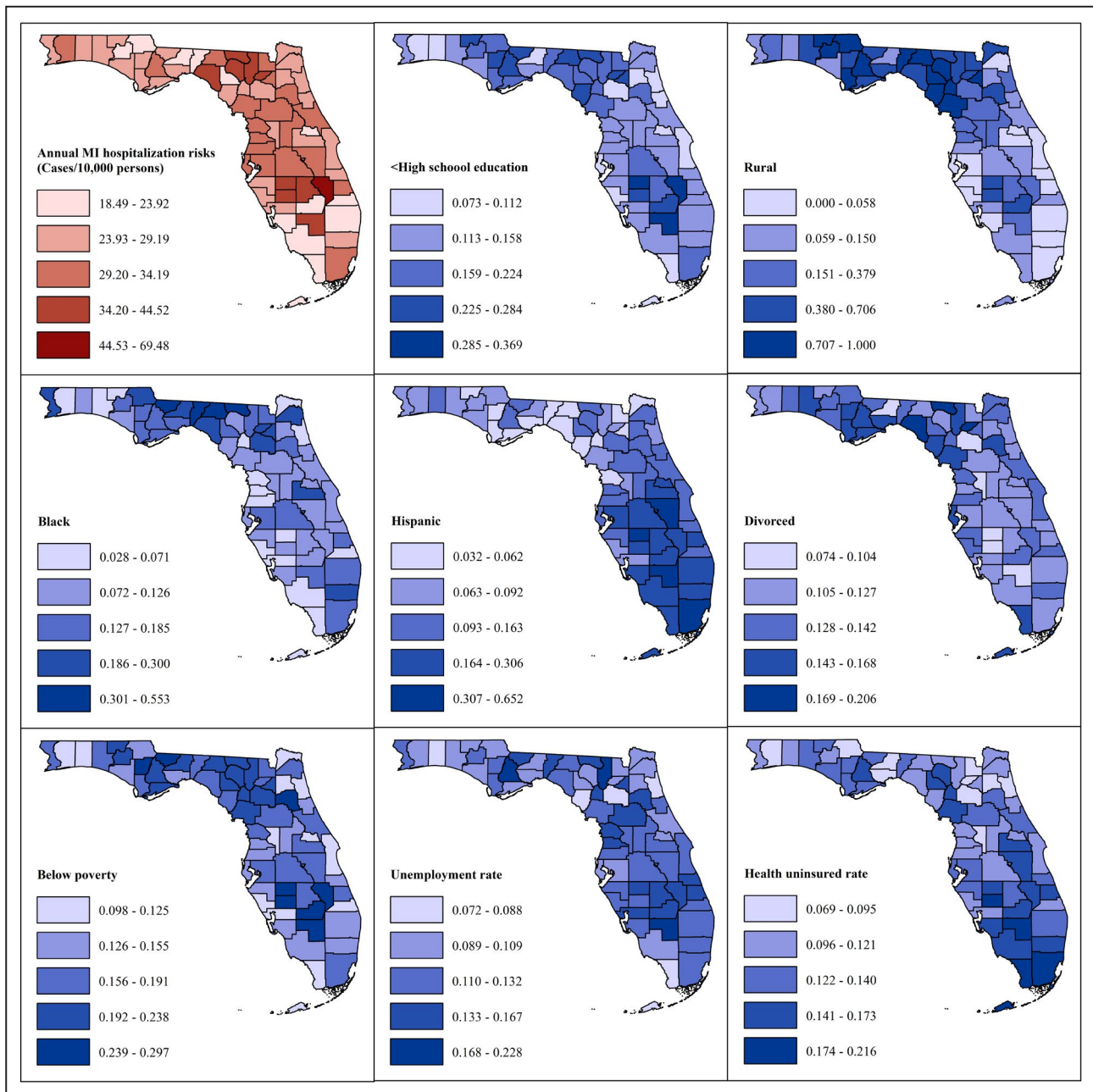
### Sociodemographic Determinants of MI Hospitalizations Risks Global Multivariable NB Regression Model

The coefficients for the final multivariable NB model for the estimated global relationship between MI hospitalization risks and significant SDoH variables are presented in Table 4. There were significant

positive associations between MI hospitalization risks and proportions of divorced residents (risk ratio [RR], 1.026;  $P<0.018$ ) and population with less than high school education (RR, 1.033;  $P<0.0001$ ). Surprisingly, counties with high proportions of rural and black populations tended to have significantly lower (RR=0.996,  $P<0.0001$  and RR=0.995,  $P=0.032$ , respectively) MI hospitalization risks than counties with low proportions of these. Counties with high proportions of the population lacking health insurance were marginally (RR=0.983,  $P<0.040$ ) associated with low MI hospitalization risks. Based on the results of the global NB model, the conceptual causal model for sociodemographic determinants of MI was revised to show only those variables that were significantly associated with MI hospitalization risks in Florida (Figure 4).

The tolerance values and the variance inflation factors for all the explanatory variables in the final NB model (Table 4) were above 0.1 and below 10, respectively, indicating lack of multicollinearity. The  $P$  values for both the Pearson and Deviance  $\chi^2$  goodness-of-fit tests were large (0.22572 and





**Figure 3.** Spatial distribution of myocardial infarction hospitalization risks and selected sociodemographic determinants in Florida, 2005–2014.

0.27616, respectively) indicating a good fit for the NB model.

**Local GWNB Model**

The results of assessment of stationarity of the coefficients of the GWNB model are shown in Table 5. There is evidence of non-stationarity of relationships between MI hospitalization risks and the proportions of population with less than high school education level and population with no health insurance

coverage ( $P=0.043$  and  $P=0.001$ , respectively). However, the coefficients for proportions of divorced, black, and rural populations were stationary ( $P>0.05$ ).

The interquartile ranges of the local coefficients for the proportions of the population with less than high school education level and population with no health insurance coverage were at least twice the standard error of the coefficients of the global NB model, but those for the proportions of divorced, black, and rural populations were not (Table 5). This provided corroborating statistical evidence to reject the null hypothesis

**Table 3. Univariable Associations of Uncorrelated Sociodemographic Determinants With Myocardial Infarction Hospitalization Risks in Florida**

Sociodemographic Characteristic*	Coefficient (CI) <sup>†</sup>	LRT P Value
Male	1.27 (1.08 to 1.46)	<0.0001
≥65 y	-0.23 (-0.27 to 0.18)	<0.0001
Black	-0.17 (-0.20 to 0.13)	<0.0001
Hispanic	0.17 (0.15 to 0.19)	<0.0001
Divorced	1.43 (1.22 to 1.63)	<0.0001
Separated	9.18 (8.67 to 9.68)	<0.0001
Rural	0.18 (0.16 to 0.19)	<0.0001
<High school education	1.64 (1.58 to 1.70)	<0.0001
Some college education	-0.96 (-1.05 to -0.86)	<0.0001
Owner-occupied housing	-0.14 (-0.17 to -0.10)	<0.0001
Unemployment rate	2.64 (2.47 to 2.81)	<0.0001
Health uninsured rate	0.76 (0.69 to 0.84)	<0.0001

Univariable results are for a model with Poisson error distribution. LRT indicates likelihood ratio test.

\*All variables except median income are expressed as proportions of county population.

<sup>†</sup>95% confidence limit of the coefficient estimate.

of stationarity of associations between MI hospitalization risks and its SDoH predictors across Florida. Thus, the associations between MI hospitalization risks and the proportions of population with less than high school education level and uninsured population varied based on location in Florida.

The spatial distribution of the local regression coefficients provides visual evidence for variability of the local relationships between MI hospitalization risks and proportions of population without high school diploma and uninsured population (Figure 5). Thus, associations of MI hospitalization risks with education level and lack of health insurance varied considerably across Florida, with a strong north-south gradient. Low education levels were significantly associated with high MI hospitalization risks throughout Florida (RR, 1.022–1.041; family-wise  $P=0.0000$  to  $P=0.0164$ ), but stronger associations were observed in southern Florida (RR, 1.036–1.041). On the

other hand, counties with high proportions of uninsured population tended to have low MI hospitalization risks, but this association was only significant in southern Florida (RR, 0.971–0.976, family-wise  $P=0.0101$  to  $P=0.0297$ ).

The AICc, MAD, and MAPE values used to compare the performances of global and local models are presented in Table 6. Moran’s I statistics indicating the extent of spatial autocorrelation of residuals are also presented in Table 6. According to Fotheringham et al,<sup>31</sup> the difference in AICc scores between any 2 models needs to be at least 3 units for the performance of any 2 models to be considered different. Based on this rule, the Poisson regression model had the worst fit, but the NB and GWNB models had similar fit. However, based on MAD and MAPE criteria, the spatial GWNB model outperformed the global Poisson and NB models. Moreover, minimal clustering of residuals for the GWNB model as indicated by the nonsignificant global Moran’s I statistic ( $I=-0.102$ ,  $P=0.116$ ), coupled with non-stationarity of coefficients for education level and lack of health insurance indicate that the GWNB model is more appropriate for modeling of these data than the global NB model.

## DISCUSSION

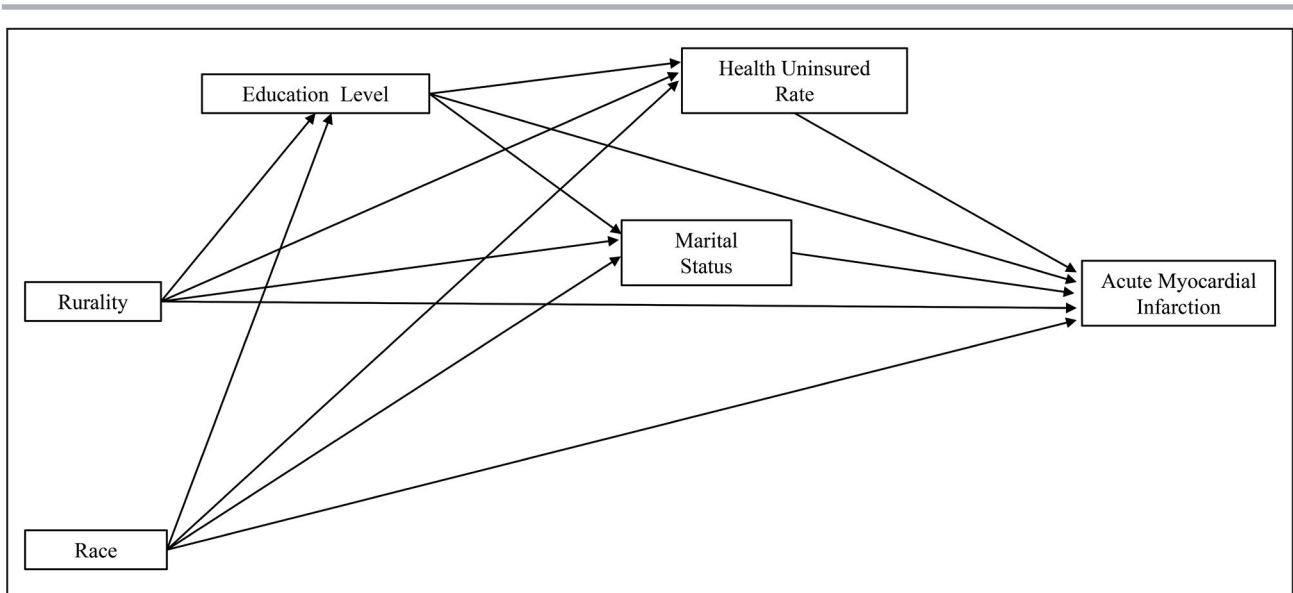
In this study, we identified the sociodemographic determinants of MI hospitalization risks among Florida residents from 2005 to 2014. We then assessed if model regression coefficients varied by geographic location to identify the most important determinants of MI hospitalization risks for different geographic areas in Florida. Because SDoH factors are responsible for shaping 40% of the health of a population,<sup>15</sup> study findings will aid in the development of evidence-based, location-specific strategies for reducing the high MI burden in Florida. Moreover, MI shares similar risk factors with other CVD such as stroke, hence, these health conditions tend occur together geographically. Thus, public efforts targeting MI risk factors would address the burdens of MI and stroke and several of their risk factors such as diabetes mellitus, high blood pressure. Additionally, because Florida’s current age structure

**Table 4. Final Negative Binomial Model Showing Significant Sociodemographic Determinants of Myocardial Infarction Hospitalization Risks in Florida**

Sociodemographic Characteristic	Coefficient (CI)*	LRT P Value	VIF	Tolerance
<High school education	3.23 (2.30 to 4.18)	<0.0001	2.559	0.391
Divorced	2.53 (0.44 to 4.64)	0.0181	1.176	0.850
Rural	-0.38 (-0.56 to -0.19)	0.0001	2.309	0.433
Health uninsured rate	-1.76 (-3.41 to -0.09)	0.0395	1.506	0.664
Black	-0.50 (-0.93 to -0.04)	0.0323	1.119	0.895
Intercept	-6.27 (-6.62 to -5.95)	<0.0001*	0	

Divide the regression coefficients by 100, then exponentiate the quotient to obtain the amount by which the risk ratio of myocardial infarction hospitalization changes due to a unit increase (ie, 1% increase) in any given sociodemographic variable. LRT, likelihood ratio test; and VIF, variance inflation factor.

\*Wald P value.



**Figure 4.** Conceptual causal model for sociodemographic determinants of myocardial infarction hospitalization risks in Florida based on the final global multivariable negative binomial model.

and racial/ethnic composition portend the changes projected for the US population by the year 2030,<sup>35</sup> Florida’s strategy to address the high MI burden will also be instructive for the rest of the United States.

We found that 66.3% of the MI hospitalizations had a principal MI discharge diagnosis, with the rest being coded as secondary MI. Thus, including only MI cases with a principal diagnosis in the analysis would have excluded a substantial burden of MI hospitalizations from the study. Sacks et al<sup>12</sup> also reported a similar proportion of principal MI hospitalizations in a study of fee-for-service Medicare population aged ≥65 years and older. Acute MI is a serious clinical condition requiring percutaneous coronary intervention in a specialized cardiac center within 90 minutes of disease onset to prevent adverse consequences on patient outcomes.<sup>16</sup> Therefore, hospitalization may be used as a proxy of morbidity, in which case the

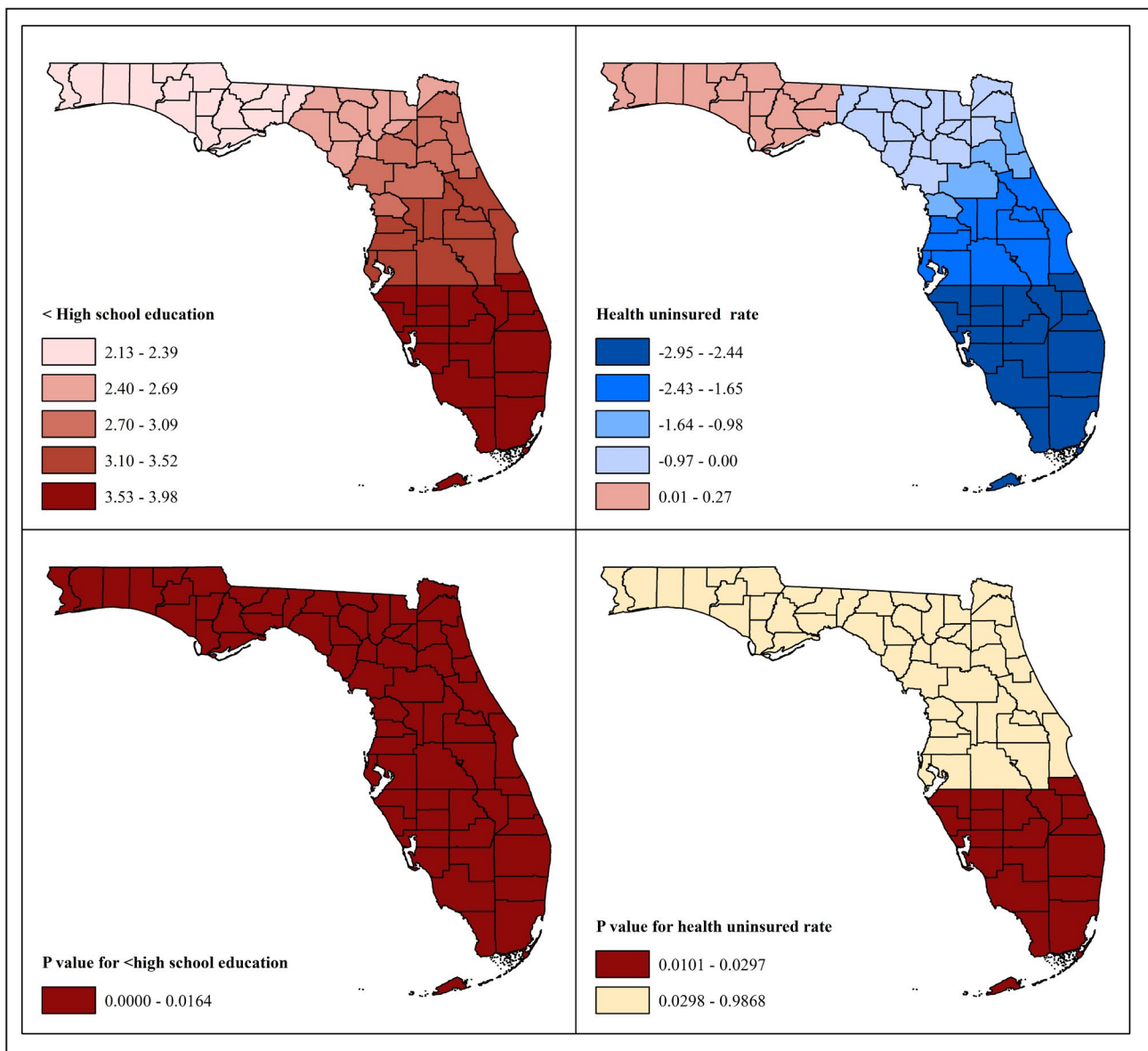
decline in MI hospitalization risks observed during the 10-year study period may represent declining MI risks in Florida over time. These secular decreases are consistent with decreases in the prevalence of CVD risk factors at the individual and community levels, primarily smoking,<sup>36</sup> exposure to secondhand smoke,<sup>37</sup> and physical inactivity.<sup>38</sup> Broad application of evidence-based primary prevention measures for coronary heart disease (CHD) with aspirin and statins<sup>39</sup> and improvements in air quality<sup>40</sup> may also have contributed to reduced MI morbidity risks. However, MI hospitalization is not necessarily equivalent to a morbidity measure,<sup>41</sup> particularly for populations with limited access to resources for appropriate cardiac care such as to percutaneous coronary intervention-capable hospitals and health insurance coverage. In this instance, MI hospitalization risks are a proxy of utilization rates for MI care, in which case

**Table 5.** Results of Assessment of Stationarity of Coefficients of Geographically Weighted Negative Binomial Model

Sociodemographic Characteristic	NB SE	NB SEx2	GWNB IQR	Is Regression Coefficient for GWNB Non-Stationary?	GWNB P Value*
<High school education	0.4735	0.947	1.178	Yes	0.043
Divorced	1.0556	2.1112	0.298	No	0.776
Rural	0.0934	0.1868	0.045	No	0.766
Health uninsured rate	0.8360	1.672	2.351	Yes	0.001
Black	0.2242	0.4484	0.092	No	0.559
Intercept	0.1697	0.3394	0.069	No	0.751

GWNB indicates geographically weighted negative binomial model fitted with a global overdispersion parameter ( $\alpha=0.0256$ ); IQR, interquartile range for the coefficients for the geographically weighted negative binomial model. An IQR of local regression coefficient  $>2 \times SE$  of global NB model is evidence for non-stationarity; NB, negative binomial regression model; and SE, standard error of the coefficients for the negative binomial regression model.

\*P value based on randomization test (m=999 replications).



**Figure 5.** Spatial distributions of non-stationary regression coefficients and associated family-wise *P* value.

declining MI hospitalization risks would be reflective of reduced rates of utilization for MI care.

The annual rate of decline in MI hospitalization risks with any discharge diagnoses reported in our study

(1.6% per year) is lower than the 2.45% annual rate reported for a Medicare population aged  $\geq 65$  years.<sup>12</sup> However, the annual rate of decline of MI hospitalization risks with a principal discharge diagnosis in

**Table 6.** Goodness-of-Fit and Moran’s I Statistics for Global Poisson, Global Negative Binomial, and Geographically Weighted Negative Binomial Regression Models

Model	Bandwidth	No. of Parameters	AICc*	MAD	MAPE (%)	Moran’s I (P Value†)
Poisson	...	10	5865.30	714.11	13.53	0.156 (0.023)
NB	...	6	1034.91	613.22	12.37	-0.113 (0.1)
GWNB	65	10.09	1032.00	580.88	11.37	-0.102 (0.116)

GWNB indicates geographically weighted negative binomial model fitted with a global overdispersion parameter ( $\alpha=0.0256$ ); MAD, mean absolute deviance; MAPE, mean absolute percentage error; and NB, negative binomial regression model.

\*Small sample bias-corrected Akaike’s Information Criteria.

†P value based on Monte Carlo simulations (rep=9999).

our study (2.27% per year) is close to rates reported in recent studies considering only acute MI hospitalizations with a principal MI diagnoses. For instance, age- and sex-adjusted incidence rates of acute MI hospitalization decreased by an average of 3.8% per year among US adults aged >25 years.<sup>6</sup> Yeh et al<sup>10</sup> found a 2.75% per year rate of decline, over a 10-year period, of incident MI hospitalizations in a community-based population with patients ≥30 years old. In contrast, Talbott et al<sup>7</sup> reported an overall 7.6% increase in principal MI hospitalization risks among Florida residents ≥35 years of age between 2000 and 2008. In general, our results, together with those of other studies, suggest that studies that consider only a section of the population or fail to account for both principal and secondary MI hospitalizations may underestimate the current MI burden.

### Seasonal Trends

MI hospitalization risks showed seasonal fluctuations, with highest risks during the winter months and lowest risks during the summer. Seasonality of MI hospitalizations with winter peaks and summer troughs have been observed in other studies. Spencer et al<sup>42</sup> observed a marked winter increase or summer decrease, or both, in the number of acute MI cases reported in a large, prospective US registry of acute MI cases, irrespective of geographic area, age or sex. Bhaskaran et al<sup>43</sup> reported elevated risks of MI morbidity at colder temperature in 8 out of 12 studies with data from the winter season.

The higher MI hospitalization risks we observed during winter than summer seasons may partly be attributable to the “snowbird” phenomenon, whereby elderly individuals, who experience more morbidity from MI, migrate from the Northern Hemisphere into Florida and into other sun-belt states in southeast and southwest United States during the winter, and migrate out during the summer.<sup>44</sup> This is corroborated by a nationwide study showing a predominance of inpatient admissions for non-ST-segment-elevation myocardial infarction during winter in warmer southern states but not in cooler northern states.<sup>45</sup> However, there is evidence that the seasonal migration of elderly individuals may not substantially contribute to the seasonal variations we observed. For instance, similar temporal patterns as those we observed have been reported for CHD deaths in Los Angeles County, California, where the “snowbird” phenomenon is not prevalent and temperatures tend to be mild throughout the year.<sup>44–46</sup> Moreover, higher MI hospital admission rates during winter compared with summer seasons have also been observed for younger (<70 years old) and older (≥70 years old) groups in both northern (snowbird source states) and southern (snowbird destination states) states.<sup>47</sup>

Other potential explanations for the seasonal patterns we observed include higher respiratory infections, such as influenza,<sup>44,48,49</sup> and increased cardiac workload caused by increased blood pressure and hemoconcentration and vascular thromboses during the winter season.<sup>50</sup>

### Spatial Distribution of MI Hospitalization Risks and its Sociodemographic Determinants

This study shows that MI hospitalization risks were high in counties with large proportions of population with less than high school education level and high divorce rates and low in counties with large proportions of rural, black and uninsured populations. However, only the effects of education attainment and uninsured rate varied with geographic location, with stronger impacts being observed in southern compared with northern counties.

#### Education Level

Our results showing higher MI hospitalization risks in counties with high proportions of population with less than high school education are consistent with previous area-level studies showing higher CVD risks in areas with low education attainment.<sup>51–54</sup> These results may be attributable to higher burdens of CVD risk factors such as hypertension,<sup>55</sup> diabetes mellitus,<sup>56</sup> and obesity,<sup>57</sup> and risky behaviors such as unhealthy southern dietary patterns,<sup>58</sup> cigarette smoking and alcohol consumption<sup>59</sup> and lower prevalence of protective healthy behaviors such as fruit/vegetable consumption,<sup>60,61</sup> nonsmoking,<sup>62</sup> and regular exercise<sup>63</sup> in counties with low education levels. This is not unexpected because health literacy has been shown to mediate the association between education level and health behaviors.<sup>64,65</sup> In fact, low education attainment may confer a cardiovascular risk that is equivalent to traditional risk factors.<sup>66,67</sup> Accordingly, counties with low education levels may have low health literacy levels, resulting in a large proportion of their population having limited ability to obtain, process, and understand basic health-related information needed to communicate, navigate health systems, and make decisions regarding lifestyle and personal health behaviors.<sup>68,69</sup>

Education level is a proxy for socioeconomic status (SES),<sup>70</sup> and low neighborhood SES is an independent risk factor for a higher MI incidence and CVD risk factors.<sup>71</sup> Thus, the higher MI hospitalization risks in counties with low education levels may be related to lower accumulation of, and access to, material, economic, and social resources for MI prevention in those counties.<sup>72,73</sup> For instance, supermarkets, which offer

a wide variety of healthy foods at lower prices, tend to be concentrated in affluent neighborhoods. Living in a socioeconomically advantaged area is associated with greater fruit and vegetable consumption,<sup>60</sup> which is inversely associated with the risk of CVD.<sup>74</sup> On the other hand, fast food outlets and small corner grocery convenience stores offering limited selections of lower quality foods and at substantially higher prices predominate in poor neighborhoods.<sup>75</sup> Thus, low SES neighborhoods devoid of supermarkets, referred to as “food deserts,” may lack equal access to the variety of healthy food choices that are available to wealthy communities.<sup>76</sup> Furthermore, residents in low SES neighborhoods lack transport; hence they are less likely to travel to a supermarket outside of their neighborhood.<sup>76</sup>

The distribution of physical activity resources, such as walking trails, is also skewed, with resources being concentrated in neighborhoods with high SES.<sup>77</sup> Long-term exposure to environments with limited access to physical activity resources and healthy nutritious food has been linked to higher incidence/prevalence of chronic diseases that are precursors of MI such as diabetes mellitus, obesity, and hypertension.<sup>71,78</sup> Additionally, low SES neighborhoods tend to have high income inequality, which is associated with disinvestment in social capital, which is in turn linked with increased deaths from CHD, among other causes.<sup>79–81</sup> Low social capital has also been linked with elevated biological stress, that is, allostatic load<sup>52,57,82</sup> and subsequently poor CVD outcomes.<sup>81</sup>

### **Marital Status**

The high MI hospitalization risks we observed for counties with a high proportion of divorced residents is consistent with previous reports of negative impacts of divorce and other disruptive events such as separation or being widowed on cardiovascular health, including increased risk of MI.<sup>83</sup> Venters et al found higher rates of hospitalization for MI/stroke for separated/divorced persons than for married and widowed persons.<sup>84</sup> A recent study found that multiple divorce experiences increased the risks of MI, especially in women.<sup>85</sup>

Divorce is a stressful event that often involves adjustments to a new social role, identity, and living arrangement and is associated with increased psychological distress and a decline in the availability of financial and social capital.<sup>86</sup> Therefore, the high MI hospitalization risks we observed in counties with a high proportion of divorced residents may be attributable to losses of income and health insurance, resulting in decreased ability to prevent, detect, and treat illness.<sup>87,88</sup> The acute and chronic stress associated with divorce may also play a role.<sup>89</sup> Moreover, many individuals respond to stress and depression with

unhealthy coping habits/behaviors such as smoking and alcohol use, among others further exacerbating the risk of MI.<sup>87</sup> By contrast, married individuals tend to have stronger social support, less stress, better mental health status, healthier lifestyles,<sup>90</sup> and greater access to medical insurance, prescription drugs, and overall higher quality of health care.<sup>91</sup>

At the ecologic level, neighborhood social capital, defined as social resources inherent within community networks, and consisting of social support, social leverage, informal social control, and neighborhood organization and participation,<sup>92</sup> may exert a contextual effect on cardiovascular health by: promoting more rapid diffusion of health information thereby increasing the likelihood that healthy norms of behavior are adopted; exerting social control over deviant and unhealthy behavior; providing emotional or material support and mutual respect based on social network and participation, and promoting access to local services and amenities.<sup>93</sup> Thus, neighborhood social cohesion is recognized as an important neighborhood social environment indicator.<sup>13</sup>

Marital and family disruption may decrease informal social controls at the community level and lead to more disorder and lower social capital or social cohesion.<sup>80</sup> Thus, counties with a large proportion of divorced residents may lack collective social control, which has been linked to higher alcohol consumption, smoking, and crime rates.<sup>94</sup> These can increase social disorganization and are associated with depression, lower levels of physical activity,<sup>95–97</sup> reduced access to preventive care,<sup>98</sup> and decreased efficiency and effectiveness of intervention programs.<sup>93</sup> All these are associated with and adverse health outcomes, including diabetes mellitus<sup>71,99,100</sup> and higher CVD risks.<sup>101</sup> Thus, low social capital may have contributed to the high MI hospitalization risks in counties with high divorce rates. On the other hand, based on the results of a study by Sundquist et al,<sup>102</sup> that showed protective effects of social capital on hospitalizations for CHD, the contextual protective effects of social capital may have contributed to lower MI hospitalization risks in counties with low divorce rates.

### **Rural Population**

Our results showing lower MI hospitalization risks in counties with high proportions of rural populations compared with those with low proportions of rural populations are inconsistent with recent ecologic studies showing higher mortality risks from MI<sup>103</sup> and heart disease and ischemic heart disease in rural counties compared with urban counties in Florida,<sup>104,105</sup> and in southeastern United States in general.<sup>106</sup> Our results are also inconsistent with

lower SES,<sup>107,108</sup> lower prevalence of protective health-related behaviors,<sup>109</sup> and higher prevalence of several MI risk factors reported for rural counties in Florida and in the United States in general compared with urban counties. These include unhealthy behaviors/lifestyles such as smoking, physical inactivity, and unhealthy eating patterns<sup>110–114</sup>; being overweight and/or obese<sup>115–118</sup>; hypertension<sup>119</sup>; and diabetes mellitus.<sup>120,121</sup> It is worth noting that food deserts tend to be concentrated in rural neighborhoods, which together with the low SES of these neighborhoods limits accessibility of healthy foods to rural communities.<sup>75,76,114</sup> Additionally, despite the additional burden of risk factors in rural areas, area-level primary and secondary interventions for MI, such regulations around taxation or smoking restrictions, the sale and marketing of tobacco products,<sup>122–124</sup> distribution of primary care providers,<sup>125</sup> cardiologists,<sup>126</sup> and coronary revascularization,<sup>127</sup> disproportionately benefit urban areas.<sup>122–124</sup> Moreover, targeted marketing of tobacco products in rural areas can reinforce pro-tobacco norms in those areas.<sup>128</sup>

The foregoing discussion suggests that it is highly unlikely that the lower MI hospitalization risks we observed for counties with high proportions of rural residents compared with those with low proportions reflect low MI morbidity risks for rural populations. Rather, similar to undiagnosed hypertension, which has been reported to be more prevalent in some rural western Panhandle counties in Florida,<sup>129</sup> undiagnosed MI may be more prevalent in rural counties where the level of knowledge regarding the five classic symptoms of heart attack<sup>130</sup> tends to be lower. Furthermore, cardiac centers/percutaneous coronary intervention-capable hospitals tend to be clustered in metropolitan and large urban areas,<sup>127</sup> thereby impeding timely access to emergency cardiac care.<sup>131</sup> These factors may exacerbate tendencies for rural residents to delay or forgo health care altogether and contribute to the lower MI hospitalization risks and disproportionately higher prehospital MI death rates in rural counties compared with urban counties.<sup>132,133</sup> Thus, higher out-of-hospital MI death risks may potentially explain the lower MI hospitalization risks we predicted in counties with high proportions of rural populations.

### **Black Population**

The lower MI hospitalization risks we observed for counties with higher proportions of black residents are inconsistent with previous reports of higher burdens of CVD and traditional CVD risk factors,<sup>134</sup> and lower prevalence of ideal cardiovascular health metrics among non-Hispanic black compared with white

populations.<sup>1,135</sup> Furthermore, these risk factors often cluster in blacks due to generally low SES for that population.<sup>134</sup> Additionally, black populations are disproportionately and adversely affected by unfavorable neighborhood features including limited access to healthy foods such as fruits and vegetables,<sup>75,76,114</sup> racial segregation,<sup>136</sup> high levels of industrial pollution and poor enforcement of environmental regulations,<sup>137</sup> low SES, low neighborhood walkability, crime, limited access to green spaces and high-quality cardiovascular health care,<sup>138</sup> and low social cohesion.<sup>139</sup> All these factors would be expected to increase MI morbidity risks in predominantly black counties. Moreover, disproportionate burdens of prehospital mortality from MI/CHD<sup>132</sup> and CVD in general<sup>1,106</sup> have been reported among non-Hispanic black compared with white populations. Therefore, lower MI hospitalization risks for counties with high proportions of black compared with white residents may be due to higher prehospital MI-related mortality among black populations, resulting in an underdiagnosis of and lower hospitalization for MI management among blacks. However, this is not captured in our study, perhaps suggesting the need to examine prehospital MI mortality disparities among different racial groups.

Lower rates of utilization for cardiac care by black residents may be attributed to limited knowledge regarding symptom recognition,<sup>130,140</sup> lack of access to high-quality cardiac care,<sup>127,141,142</sup> and mistrust of the healthcare system stemming from historical events such as the Tuskegee syphilis study,<sup>143</sup> reinforced by perceived racial discrimination.<sup>144</sup>

### **Lack of Health Insurance**

The lower MI hospitalization risks observed for counties with high proportions of uninsured population are consistent with the findings of a study by Talbott et al<sup>7</sup> that found a positive association between healthcare coverage and acute MI hospitalization rates. In that study, a large proportion of the population in the New England/Mid-Atlantic region reported that they had health insurance, yet they had the highest acute MI hospitalization rates. Talbott et al<sup>7</sup> also found a negative association between acute MI mortality rates and healthcare coverage.

Taking MI hospitalization risk as a proxy for MI morbidity, the lower MI hospitalization risks for counties with high proportion of uninsured population would suggest lower MI morbidity risks for those counties. However, this is highly unlikely, because lack of health insurance not only impedes timely access to cardiac care when needed but also reduces access to necessary preventive and therapeutic care to minimize future illness.<sup>145</sup> On the other hand, having health insurance leads to higher rates of MI

diagnoses and therapeutic cardiac procedures,<sup>146,147</sup> thereby reducing the risks of major cardiac events. Thus, the disease is more likely to be identified/diagnosed and controlled among the insured. Moreover, it is more difficult to obtain off-site specialty cardiovascular services, including referrals, for the uninsured compared with those with health insurance.<sup>148</sup> Therefore, the association of low MI hospitalization risks with high health uninsured rates is a reflection of lower rates of utilization of cardiac care services in counties with high proportions of uninsured populations.<sup>145</sup>

The stronger association between the proportion of population lacking health insurance and MI hospitalization risks in southern Florida counties may be due to a large proportion of low-income minority population, particularly Haitian, non-Hispanic blacks, and Hispanic immigrants, in that part of the state.<sup>149–151</sup> These demographic groups have been disproportionately affected by Florida's decision not to expand Medicaid under the Affordable Care Act; hence, they have double the likelihood to fall into the "coverage gap" compared with their uninsured white counterparts.<sup>142</sup> Community health centers, such as Federally Qualified Health Centers provide a safety net for the underinsured and uninsured on income-based sliding-fee scales,<sup>152</sup> but they are highly underutilized,<sup>148,151</sup> hence they have not been successful in reducing socioeconomic barriers to advanced treatment for heart disease for the underinsured and uninsured in southern Florida.

To summarize, the results from the NB model suggest that for certain populations, MI hospitalization is not necessarily equivalent to a morbidity measure.<sup>41</sup> Rather, MI hospitalization risks are a proxy of utilization rates for MI care. In our study, this was particularly true for black, rural, and uninsured populations, due to limited access to resources for cardiovascular health such as health insurance and specialized cardiac centers. Furthermore, because our data may have included multiple admissions for the same individual for the same MI event, our MI hospitalization risks are a crude proxy of MI risks in populations with low education levels and high divorce rates.

### Non-Stationarity of Regression Coefficients

The local GWN model allowed geographically varying relationships between MI hospitalization risks and its sociodemographic determinants to be modeled through spatially varying parameter estimates. Our results showing geographic variations of associations between MI hospitalization risks and education and health uninsured rates corroborate findings from previous ecologic studies<sup>17–19,153</sup> that showed that the

impacts of SDOH factors on the risks of various cardiovascular health outcomes vary based on geographic location. For instance, all the coefficients for the associations of age, marital status and rural residence with MI/stroke mortality risks varied with location in middle Tennessee.<sup>18</sup> Ford and Highfield<sup>153</sup> showed significant spatial association between CVD mortality and social deprivation in Harris County in Texas.

Stationarity of regression coefficients for proportions of rural, black and divorced residents suggest that global relationships between MI hospitalization risks and these determinants may be generalized to every county in Florida (the effects of these 3 determinants were constant across Florida). Conversely, variation in the associations between MI hospitalization risks and the proportion of population with less than high school education and uninsured rates based on geographic location suggest that a global relationship between MI hospitalization risks and these determinants cannot be generalized to every county in Florida.

These findings have several policy implications. First, the results imply that "one size fits all" approaches would not be suitable for addressing high MI risks and inequitable utilization of MI care services in Florida. Rather, different parts of the state require slightly different strategies. Therefore, planning for MI control and prevention efforts will need to use a needs-based approach informed by empirical evidence from global regression models supplemented with local models. Specifically, policies for addressing inequitable utilization of MI care services by improving health insurance coverage rates need to focus on southern Florida counties where low MI hospitalization risks may reflect low utilization rates for MI care services. Likewise, policies focusing on reducing MI hospitalization risks by improving literacy levels should pay extra attention to counties within southern Florida which have low education attainment.

### Strengths and Limitations

The data we used were collected using a consistent set of case definitions and included MI hospital admissions for the entire state of Florida, thus allowing us to explore temporal trends and assess geographic variation of MI hospitalization risks for the entire state of Florida. Using hospitalized cases with any discharge diagnosis for MI allowed us to characterize the burden of MI hospitalizations more fully, regardless of whether MI was the principal or secondary discharge diagnosis. This is because a substantial proportion of MIs occur during a hospitalization for other acute illnesses, rather than being the cause of hospitalization. For instance, 37% of adjudicated



MIs had a principal hospital discharge diagnosis of MI whereas 63% had a principal hospital discharge diagnosis other than MI. Further, the elderly population often present with several major comorbidities, making the selection of the single most likely primary cause of hospitalization difficult.<sup>1</sup> Additionally, non-clinical considerations, such as reimbursement, can influence which diagnosis gets coded as principal diagnosis and lead to an underestimation of the current true burden of MI.<sup>12</sup>

The use of a geographically weighted regression model to account for potential local variations in the strength of associations between MI hospitalization risks and its sociodemographic determinants enabled identification of location-specific strategies that may be used to reduce the burden of MI and to increase equitable utilization of MI care in Florida. Without the place-specific perspective of GWNB model, the local associations between MI hospitalization risks and education level and uninsured rates would not be apparent, which would suggest a uniform/“one size fits all” control strategy for the entire state. This is an unrealistic proposition, given the wide variabilities in socioeconomic and environmental conditions that exist within Florida. Moreover, correction for multiple hypothesis testing avoided false-positives in geographically weighted regression.

The findings of this study have some limitations that suggest important areas for future research. This being an ecological study, there is potential for ecological fallacy, because individuals diagnosed with MI may not be the same people who were exposed to the SDoH factors we investigated at the county level. Therefore, interpretations of specific associations between contextual variables and MI hospitalization risks should be made with caution, recognizing that inferences based on aggregate data do not apply to comparable individual-level data.<sup>154</sup> Moreover, there is potential for substantial within-county variations in sociodemographic factors due to the heterogeneous nature of the counties. Thus, a change in spatial unit of analysis (eg, ZIP code or census tract) may alter our findings due to the modifiable areal unit problem.<sup>155</sup> Nonetheless, we chose to study counties rather than a smaller geographic area such as a 5-digit ZIP code or US census tracts or blocks because the former is more relevant to policy action steps.

We based MI hospitalization risks on events rather than individuals due to lack of personal identifiers in the data. As such, multiple admissions for the same individual for the same MI event may be included in the data. Additionally, we lacked statistically robust data at the county level to adjust for important behavioral, clinical, and environmental factors, and our MI data do not include subclinical MIs, patients who never sought care or may have died

before hospitalization. Accordingly, there is potential for confounding and selection bias, which may result in inaccurate estimation of the true associations between MI hospitalization risks and identified sociodemographic predictors.

The American Community Survey has collected 1-, 3-, and 5-year estimates for sociodemographic data since 2005. We selected a time frame for SDoH data based on what was available. Additionally, we used 5-year American Community Survey estimates for the 2008–2012 period because it is in the middle of our study period; hence we deemed data for this period best suited to match the MI hospitalization data. Although people may have been exposed much earlier and could have resided in a different county than where the first signs of the MI occur, our analysis did not consider the lag time between potential exposure and the occurrence of the disease symptoms. This may have resulted in misclassification of some exposures, with consequent underestimation or overestimation of associations between SDoH factors and MI risks.

These limitations notwithstanding, our results are consistent with a broad range of causal biological processes and with studies showing strong associations between cardiovascular events and area-level sociodemographic predictors even after adjusting for relevant confounders.<sup>53,71</sup> Thus, study findings may be useful for guiding policies directed toward reducing disparities related to education attainment, lack of health insurance coverage, divorce rates, rural residence, and race/ethnicity. This would lead to lower MI morbidity risks and/or higher utilization rates for cardiovascular care in Florida. Moreover, the results identify specific areas that may benefit most from place-based public health interventions that address low education levels and high health uninsured rates to improve cardiovascular health in Florida.

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## CONCLUSIONS

Race/ethnicity, marital status, rurality, education level, and lack of health insurance were significant predictors of MI hospitalization risks in Florida. The influence of race/ethnicity, divorce rate, and rurality were constant across Florida. However, the influence of education level and health uninsured rate varied based on geographic location in the state, with their influence being strongest in counties in southern Florida. These results indicate that global models supplemented with local models are more appropriate for exploring the associations between MI hospitalization risks and its demographic and socioeconomic predictors. Study findings may help state and local public health entities allocate scarce

resources more efficiently to reduce cardiovascular health disparities and achieve lasting improvements in population health for all Floridians.

## ARTICLE INFORMATION

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### Affiliations

From the Comparative and Experimental Medicine, College of Veterinary Medicine (E.W.O.), Departments of Geography (N.N.), Business Analytics and Statistics (R.Z.), and Public Health (K.W.K.), The University of Tennessee, Knoxville, TN; Public Health Research (M.J.) and Environmental Public Health Tracking (C.D.), Division of Community Health Promotion, Florida Department of Health, Tallahassee, FL.

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None.

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