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Original Contribution

Geographic variation in predictors of ED admission rates in U.S. Medicare fee-for-service beneficiaries☆

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ABSTRACT

Introduction: We study community-level factors associated with emergency department (ED) admission rates and assessed how they vary across geography.
Methods: We conducted an ecological study using 2012 data from 100% of U.S. Medicare Fee-for-Service beneficiaries to calculate county-level ED admission rates, adjusted by Hierarchical Condition Categories to control for patient health. We tested community-level measures related to healthcare market concentration, healthcare delivery, and socioeconomic factors potentially associated with admission rates and assessed whether these factors predicted ED admission rates across counties using ordinary least squares (OLS) regression and whether they varied across geography using geographically weighted regression (GWR).
Results: In 3031 U.S. counties, the ED admission rate varied from 3.9% to 82.2%. The lowest ED admission rates were concentrated in counties in Kansas, Oregon, and Vermont and the highest ED admission rates were in counties throughout Washington, Wyoming, Texas, and Colorado. The OLS model found several community-level factors that negatively impacted admission rates, specifically hospital market concentration, the rate of hospital beds with urgent care, and the rate of hospital beds. The factors that had a positive impact on the admission rate include the rate of MDs and factors for disadvantage, affluence, and foreign born/Hispanic. However, GWR showed the relationship between the ED admission rate and predictors varied across U.S. counties
Conclusions: The association between healthcare market concentration, healthcare delivery, and socioeconomic factors with ED admissions differed across communities in Medicare beneficiaries. This suggests that policy and interventions to reduce ED admissions need to be tailored to specific community contexts.

1. Introduction

In 2013, there were 130 million visits to hospital-based emergency departments (ED) in the U.S., and 14.5 million (11%) resulted in admissions to an inpatient or observation unit in the hospital [1]. Several studies have demonstrated considerable variation in decisions to admit patients to the hospital. At the provider-level, 2 to 3-fold variation has been demonstrated for hospital admission decisions, even after adjusting for other factors for both a general ED population and for patients with specific conditions, such as pneumonia and injury [2,3]. Similarly, at the hospital level, 2–6 fold variation in adjusted admission rates has been reported [4,5,6,7]. Factors contributing to variation include both patient-level factors (i.e. age, comorbid conditions, and insurance), hospital-level factors (i.e. trauma status), as well as community-level factors (i.e. physicians per population) [4,5]. Two studies have shown that admission rates tend to cluster geographically, where admission rates were more similar at nearby hospitals than distant ones [5,8]. Specifically, Pines et al. demonstrated that nearby EDs had similar admission rates [6]. Caines et al. also explored county-level variation in admission rates among U.S. Medicare beneficiaries and found that admission rates tended to cluster geographically and be similar in nearby counties [8]. Yet, despite this clustering, admission rates varied greatly over wide geographical areas with higher admission rates occurring in the Northeastern and Southern U.S., and lower admission rates in the Midwest. Another recent study by Warner et al. demonstrated that several covariates were associated with hospital-level ED admission rates – specifically for-profit hospitals had higher admission rates and admission rates were lower in communities with lower capita income [9]. However, a key unanswered question in the literature is the degree to which community factors influence ED admission rates at the county-level, and how these relationships vary across communities. Understanding the relationship between covariates and ED

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admission rates is important as policymakers develop strategies to implement interventions (i.e. reducing disparities or increasing the number of physicians) that may also impact ED admission rates, a major economic driver of U.S. healthcare expenditures.

This current study builds off the prior work of Caines et al. by (1) identifying county-level factors associated with the county-level ED admission rate and (2) determining whether these associations vary across geographical areas. We adopt a geographic modeling framework that takes spatial non-stationarity (i.e. a difference in the relationship across space) into account using geographically weighted regression (GWR). This approach takes into account geography and can estimate local rather than global model parameters.

2. Methods

2.1. Study design

We conducted an ecological study using 100% U.S. Fee-for-Service (FFS) patients enrolled in the Medicare Part A and Part B programs in 2012. The data came from several sources: 1) 2012 patient-level data from the Medicare administrative enrollment and claims data extracted from the Centers for Medicare and Medicaid Services (CMS) Chronic Conditions Warehouse (CCW) were used to assess ED encounters and admissions. These data were used to calculate the outcome variable, the county-level ED admission rate, which was adjusted to account for variability in the health status of beneficiaries across counties using the CMS Hierarchical Condition Categories (HCC) scores; 2) 2012 Medicare Inpatient Research Identifiable Files were used to calculate the Herfindahl-Hirschman index (HHI) of Medicare FFS discharges; 3) additional healthcare delivery system measures were created using county-level data from the 2013–2014 Area Health Resources Files (AHRF) [10]; and 4) sociodemographic and socioeconomic factors were created from measures derived from the American Community Survey (ACS) 5-year estimates (2009–2013) [11]. A detailed description of each of the measures used in this analysis can be found in Appendix A.1 Measurement. Data from 2012 were used for this analysis because we sought to build off the results of the prior Caines et al. study [9].

2.2. Study setting and population

This analysis only included counties from the continental U.S., as those counties better fit the adaptive bandwidth selection approach

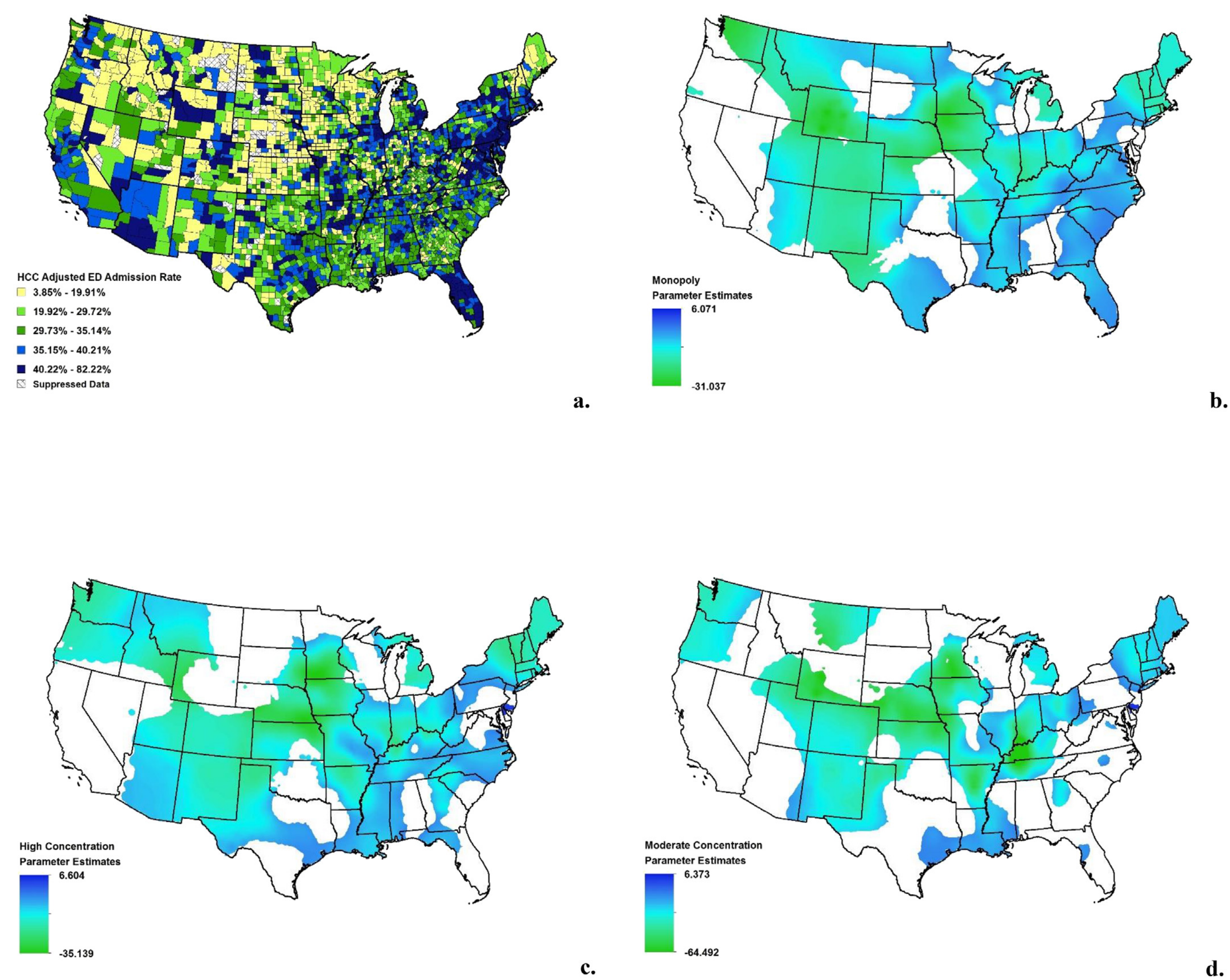

Fig. 1. County-level HCC adjusted emergency department admission rate and geographically weighted regression parameter estimates for healthcare market concentration measures. (a) displays the HCC adjusted ED admission rate by county. The county-level ED admission rate varied across the U.S. with rates ranging from 3.9% to 82.2%. Fig. 2(a)–(c) display the GWR parameter estimates for the healthcare market concentration measures. When compared to counties with no healthcare market concentration, counties with a monopoly, high concentration, or moderate concentration have higher ED admission rates in the areas in blue and lower ED admission rates in counties in green.

that is used in the GWR model due to the fact that counties in Alaska and Hawaii are physical outliers. The county was the unit of analysis, as counties embody a meaningful social space across which economic processes unfold [12], is the smallest analytic unit with useful policy implications [13], and are valid spatial and decisional units of analysis [14]. Limiting the counties to the continental U.S. as well as eliminating counties with fewer than 11 beneficiaries, fewer than 100 ED visits, or 20 ED admissions resulted in a total sample size of 3031 U.S. counties. Similarly, the National Center for Health Statistics releases data with no fewer than 20 units.

2.3. Study protocol

The data presented adhere to CMS standards for privacy as no information based upon fewer than 11 beneficiaries are displayed. The data used are de-identified and do not pose any risk to beneficiaries. The data did not require Institutional Review Board review as determined by CMS as this was an internal project.

2.4. Data analysis

In order to reach the first goal of this study and identify county-level factors significantly associated with the ED admission rate, we employed both ordinary least squares (OLS) regression and geographic weight regression (GWR). OLS is a traditional regression analysis where the dependent variable is continuous and predictors are either binary, categorical, or continuous variables. GWR adds a spatial dimension to OLS, allowing us to determine whether these associations between the dependent and independent variables vary across geographical areas. Specifically, GWR was used to investigate whether the relationship between the ED admission rate and its predictors varies across space. As compared to OLS, GWR accounts for spatial autocorrelation and produces regression coefficients specific to each county (i.e. spatial varying coefficients) [15]. Additional detail regarding the GWR modeling approach is described in Appendix A.2 Data Analysis.

As the GWR modeling generates a large amount of output, the best way to summarize information is to map the distributions of the local estimates and provide a 5-number summary of local statistics [16]. The 5-number summary of parameter estimates shows the extent of the variability in the parameter estimates by including the minimum, lower quartile, median, upper quartile, and the maximum local parameter estimate from the GWR model [15]. To statistically test for spatial non-stationarity in the parameter estimates, the Monte Carlo approach was utilized, which is the appropriate test for a continuous dependent variable [16,17,18]. Spatial non-stationarity exists if the p-value of the Monte Carlo test is less than or equal to 0.05, in which case there is sufficient evidence to reject the null hypothesis and conclude that the effect of the variable of interest on the ED admission rate varies spatially [18].

The GWR model output provides the covariate estimates with their corresponding p-values for all locations, which allowed for the mapping of the spatial variation in the association between the ED admission rate and a predictor of interest. That is, the GWR output generates surface layers for each covariate, which depicted the spatial variation of the relationship with the ED admission rate. Following the method proposed by Matthews and Yang [15], maps display a continuous color scheme for the parameter estimate surface where the significant parameter estimates are displayed in shades of blue to green and the non-significant geographical areas are masked out in white. The maps were created using the Spatial Analyst extension in ArcMap 10.3.1 and the statistical analysis was performed in SAS 9.3 using the macro developed by Chen and Yang [19].

3. Results

3.1. Descriptive results

The map in Fig. 1(a) presents the spatial distribution of the ED admission rate. The county-level ED admission rate varied across the U.S. with rates ranging from 3.9% to 82.2%. Lowest ED admission rates were concentrated in counties in Kansas, Oregon, and Vermont and the highest ED admission rates in counties throughout Washington, Wyoming, Texas, and Colorado. The descriptive statistics are described in Appendix A.3 Descriptive Statistics and displayed in Appendix Table 2.

3.2. Global regression results

Global OLS regression results are displayed in Table 1. Compared to counties with no healthcare market concentration, the ED admission rate was lower in counties with a monopoly, high concentration, and moderate concentration. With every additional MD per 100,000 in a county, the ED admission rate increased by 0.1% (CI: 0.007, 0.013). As the number of hospitals with urgent care per 100,000 increases in a county, the ED admission rate decreases by half a percentage point (CI: −0.716, −0.307). With every additional hospital bed per 1000 in a county, the ED admission rate decreases by 0.4% (CI: −0.473, −0.289). Higher disadvantage, affluence, and foreign born/Hispanic factor scores were all associated with higher ED admission rates; however, the unemployment/public assistance factor was not significant. Multicollinearity was not an issue for this model as indicated by the variance inflation factor as displayed in Table 1.

3.3. Local regression results

The associations identified from the OLS model results are overall assessments of the relationships between the ED admission rate and independent variables; however, GWR was needed to understand these relationships in greater detail (e.g., how these relationships vary across space in both their direction and strength). As such, maps of the significant associations ($p \le 0.05$) between the ED admission rate and predictors are included in Figs. 1(b)–3(d). Estimates that are not statistically significant are shaded out in white.

While the OLS model showed a negative relationship between hospital market monopoly and ED admissions, the GWR results showed

Table 1
OLS regression model predicting the HCC adjusted ED admission rate (Global Regression Model) in Medicare beneficiaries in 2012 across continental U.S. counties (N = 3031)

	Estimate	Lower CI	Upper CI	Standard error	VIF
Intercept	38.637***	37.761	39.512	0.447	0.000
Monopoly	−9.935***	−10.955	−8.915	0.520	2.047
High concentration	−8.475***	−9.753	−7.196	0.652	1.957
Moderate concentration	−7.650***	−9.433	−5.866	0.910	1.805
No market (comparison group)					
MDs per 100,000	0.010***	0.007	0.013	0.001	1.692
Hospitals with urgent care per 100,000	−0.512***	−0.716	−0.307	0.104	1.037
Hospital beds per 1000	−0.382***	−0.473	−0.289	0.047	1.194
Disadvantage factor	1.474***	1.104	1.844	0.189	1.082
Affluence factor	2.692***	2.247	3.136	0.227	1.581
Foreign born/Hispanic factor	0.837***	0.466	1.208	0.189	1.097
Unemployment/Public assistance factor	0.181	−0.184	0.547	0.186	1.061
Adjusted R-square	0.260				
Akaike information criterion	13,939				

OLS = ordinary least squares.
CI = 95% confidence interval.
VIF = variance inflation factor.
ED = emergency department.
*** $p \le 0.001$.

that the association between hospital market monopoly and the ED admission rate varies in both its strength and direction across counties in the U.S. (Fig. 1(b)). While much of the country does show a negative association with decreases in the ED admission rate as large as 31%, in states along the east coast and some areas along the Gulf of Mexico, counties with a monopoly have higher ED admission rates compared to counties with no market. Fig. 1(c) and (d) show a similar pattern; however, there are fewer areas of the country with significant parameter estimates as the hospital concentration lessens. In Fig. 2(a), the areas in blue show a positive association between the rate of MDs per 100,000 population and the ED admission rate (as shown in the OLS model results) with increases in the ED admission rate as high as 0.1%; however, in the New England region of the US, the results show that as the rate of MDs per 100,000 increases the ED admission rate decreases. The OLS model results showed a negative association with ED admission rate for both the hospitals with urgent care per 100,000 and the hospital beds per 1000 measures; however, the GWR model results (Fig. 2(b) and (c)) show areas of both positive and negative associations. For example, in counties throughout New England, Michigan, Wisconsin, Ohio, Indiana, and other states, as the number of hospital beds per 1000 population increases so does the ED admission rate, with increases in the ED admission rate as high as 3.4%.

Geographically-varying associations were also identified for the relationships between the sociodemographic and socioeconomic factors and the ED admission rate (Fig. 3(a)–(d)). Although the OLS model showed a positive association between the disadvantage factor and the ED admission rate, the GWR model results showed a strong negative association in counties located in Michigan, Wisconsin, the Dakotas, and most states throughout the South (Fig. 3(a)). These are areas where higher disadvantage scores were associated with lower ED admission rates, with decreases in the ED admission rate as much as 9.3%. As for affluence factor, higher affluence scores are associated with higher ED admission rates. This was the case in the OLS model as well as all significant areas of the GWR model results (Fig. 3(b)); however, it should be noted that the strength of the association varied across space, with increases in the ED admission rate as high as 13.5%. The OLS model results showed a positive relationship between the foreign born/Hispanic factor and the ED admission rate, which was also the case in the majority of the significant areas of the GWR model results (Fig. 3(c)), with increases in the ED admission rate as high as 19%.

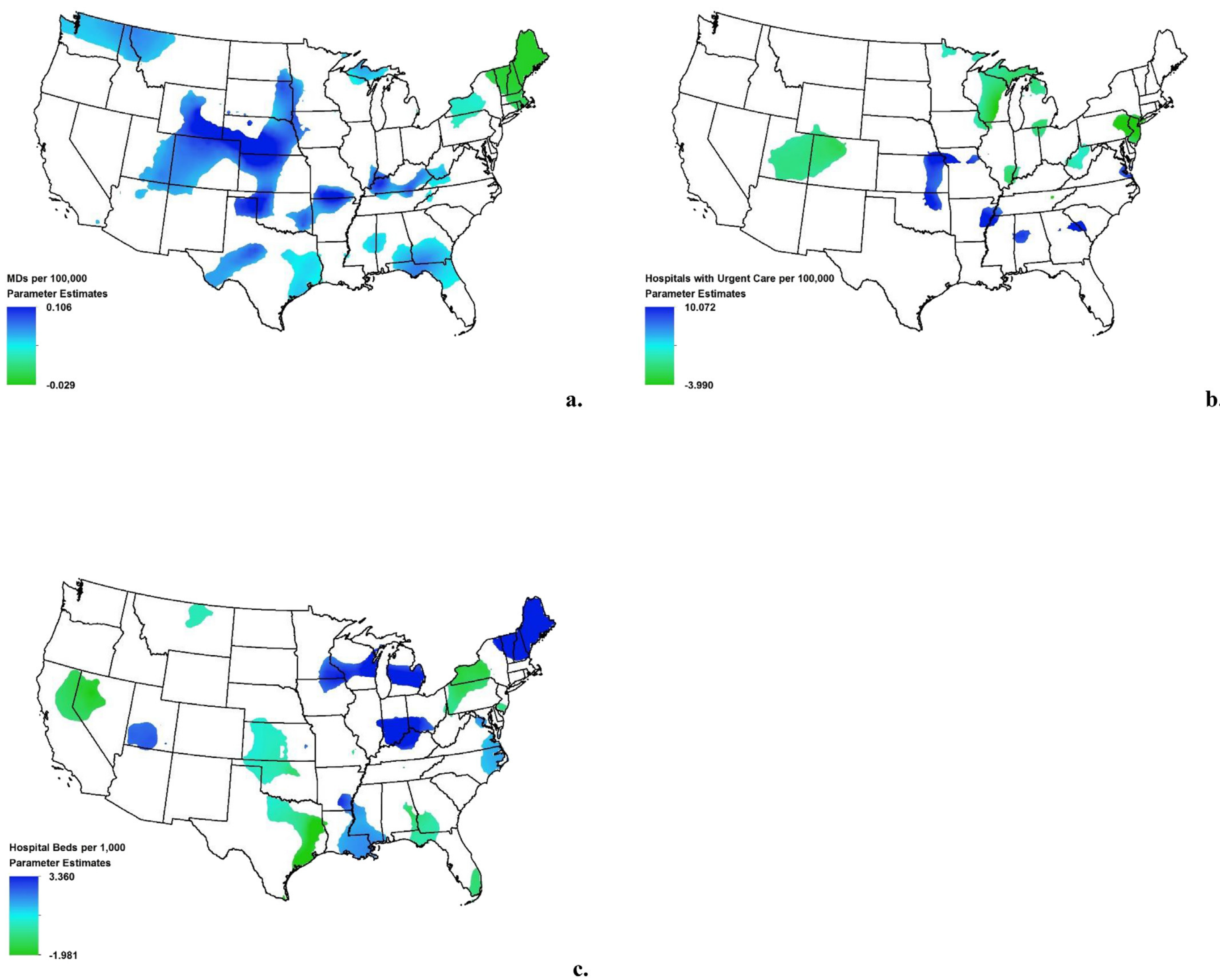

Fig. 2. Geographically weighted regression parameter estimates for healthcare delivery system measures. The maps in (a)–(c) show strong evidence of the existence of spatial non-stationarity in the relationship between the healthcare delivery system measures and the ED admission rate (as indicated by the contrasting shades of dark blue and kelly green). In (a), the areas in blue show a positive association between the rate of MDs per 100,000 population and the ED admission rate with increases in the ED admission rate as high as 0.1%; however, in the New England region of the US, the results show that as the rate of MDs per 100,000 increases the ED admission rate decreases. For the hospitals with urgent care per 100,000 (b) and the hospital beds per 1000 (c) measures, the GWR model results show areas of both positive and negative associations.

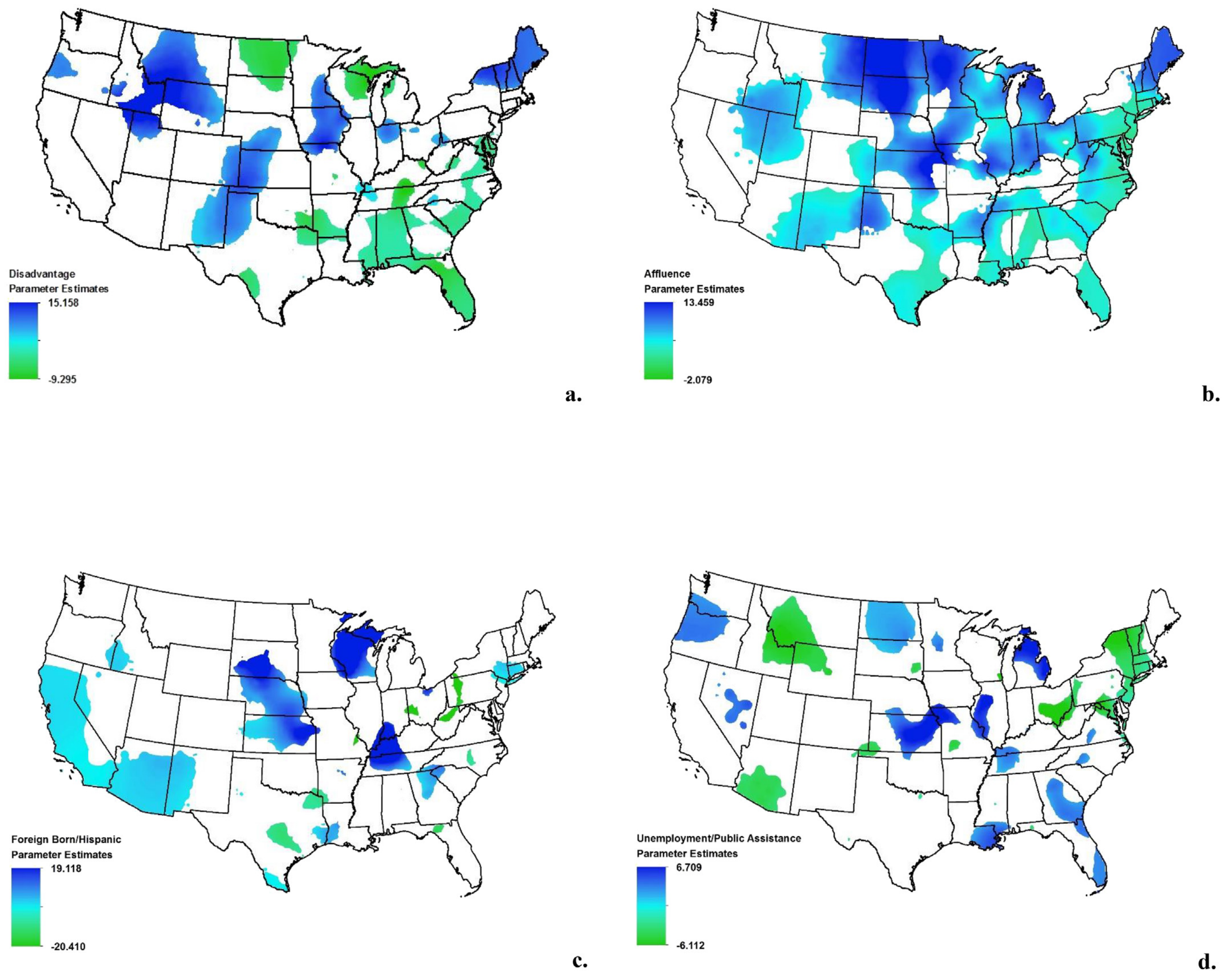

Fig. 3. Geographically weighted regression parameter estimates for socioeconomic and sociodemographic measures. The maps in (a)–(d) show spatially varying associations for the relationships between the sociodemographic and socioeconomic factors and the ED admission rate. The GWR model results showed a strong negative association in counties located in Michigan, Wisconsin, the Dakotas, and most states throughout the South (a). These are areas where higher disadvantage scores were associated with lower ED admission rates, with decreases in the ED admission rate as much as 9.3%. As for affluence factor, higher affluence scores are associated with higher ED admission rates in the significant areas of the GWR model results (b); however, it should be noted that the strength of the association varied across space, with increases in the ED admission rate as high as 13.5%. In the majority of the significant areas of the GWR model results, there was a positive relationship between the foreign born/Hispanic factor and the ED admission rate (c); however, the GWR model results also showed a negative association between the foreign born/Hispanic factor and the ED admission rate in counties in Pennsylvania, Ohio, West Virginia, Texas, North Carolina, and Florida. As for the unemployment/public assistance factor (d), the GWR model results identified both positive and negative significant associations between the unemployment/public assistance factor and the ED admission rate.

However, the GWR model results also showed a negative association between the foreign born/Hispanic factor and the ED admission rate in counties in Pennsylvania, Ohio, West Virginia, Texas, North Carolina, and Florida, with decreases in the ED admission rate as much as 20%. As for the unemployment/public assistance factor, the OLS model results showed no significant relationship with the ED admission rate, but the GWR model results showed otherwise (Fig. 3(d)). The GWR model results identified both positive and negative significant associations between the unemployment/public assistance factor and the ED admission rate.

While these maps showed the presence of non-stationary associations (i.e. geographic variations) between the predictors and the ED admission rate, a formal test for spatial non-stationarity was needed. As previously discussed, the Monte Carlo test was used to test for spatial non-stationarity. The results of the Monte Carlo test are included in Table 2 along with the 5-number parameter summaries. As such, the Monte Carlo test showed that spatial non-stationarity exists and by knowing the geographic location of the model results we were able to determine where the non-stationary relationships are varying. The GWR model had a better model-fit compared to the OLS model as indicated by the Akaike Information Criterion.

4. Discussion

Previous studies have shown that the decision to admit patients to the hospital from an ED visit varies across providers, hospitals, and geography. Our study replicated the spatial distribution of the ED admission rate presented in Caines et al. [8], then used a global (non-spatial) OLS regression model to identify community-level healthcare market, healthcare delivery, and sociodemographic/socioeconomic variables associated with the county ED admission rate. The purpose of this was to assess what modifiable factors (i.e. covariates) at the community-level may be most closely related to ED admission rates, and to help inform decisions of policymakers focused on initiatives to reduce

Table 2
GWR 5-number parameter summary results and Monte Carlo significance test for spatial variability of parameters in 2012 Medicare beneficiaries across counties in the continental U.S. (N = 3031)

	Minimum	Lower quartile	Median	Upper quartile	Maximum	Monte Carlo testing status
Intercept	20.113	36.767	40.225	43.843	56.923	Non-stationary***
Monopoly	−31.623	−16.894	−10.321	−6.238	6.154	Non-stationary***
High concentration	−36.036	−17.595	−10.672	−6.070	6.977	Non-stationary***
Moderate concentration	−67.363	−20.490	−12.457	−5.142	7.758	Non-Stationary***
MDs per 100,000	−0.036	−0.000	0.011	0.026	0.107	Non-stationary***
Hospitals with urgent care per 100,000	−4.169	−0.560	0.061	0.777	10.343	Non-stationary***
Hospital beds per 1000	−2.031	−0.299	−0.036	0.391	3.487	Non-stationary***
Disadvantage factor	−9.529	−1.766	−0.236	2.945	15.259	Non-stationary***
Affluence factor	−2.162	2.444	3.695	6.085	13.509	Non-stationary***
Foreign born/Hispanic factor	−21.436	−0.868	0.934	2.736	19.699	Non-stationary***
Unemployment/Public assistance factor	−6.405	−0.942	0.443	1.965	6.772	Non-stationary***
Akaike information criterion	20,847					

GWR = Geographically-weighted regression.
MDs = Medical doctors.
*** $p \leq 0.001$.

the use of hospital-based care. We found that as the healthcare market concentration increased the ED admission rate decreased and that counties with higher rates of hospitals with urgent care and hospital beds also had lower ED admission rates. Counties with higher concentrations of physicians as well as counties with higher scores for the three socioeconomic and sociodemographic factors demonstrated higher ED admission rates. However, one factor tested – unemployment/public assistance – was not a predictor of the ED admission rate.

These global associations may mask heterogeneity in the likelihood that a patient who lives in a particular area of the country gets admitted to the hospital after arriving at the ED. This is due to the complex interplay among clinical, social, and healthcare economic factors across communities [20]. Our GWR model that tested these global associations for spatial non-stationarity (i.e. that the association between these variables and ED admission rates vary across space, in this case counties) showed that our study variables related to healthcare market concentration, health care delivery, and socioeconomic/sociodemographic status presented different associations with ED admission across different communities. For example, physician concentration, which showed a significant positive association with ED admission rate in the OLS model, showed that this relationship differed across the US, with positive associations in counties in the Northwest, Midwest, and South and negative associations in counties in New England. Similarly, the OLS model showed a positive association between the disadvantage factor and ED admissions, but when using the GWR model that allows for non-stationarity, we found a strong negative association in counties throughout the Southeast as well as Michigan, Wisconsin, and the Dakotas.

We can conclude from this work that there is no clear, geographically stable relationship between the measured covariates and ED admission rates. Therefore, the assumption that changing the measured covariates through policy interventions (i.e. reducing disparities or increasing the number of physicians in a community) will reduce hospital-based care uniformly across communities, and in particular the decision to hospitalize, is likely not correct. Future research with more detailed clinical and physiological information may help shed light on additional contributing factors to geographic variation in admission decisions. However, there is one broad consistency that is confirmed by our work, that admission rates do follow a geographic pattern, suggesting that when benchmarking admission rates at the county, (or perhaps even ED-level) that comparing them with local institutions may be most appropriate because of the shared social and environmental characteristics of a local community.

4.1. Limitations

There are several limitations to this work. First, this study was conducted at the county-level, therefore in larger counties where there are multiple hospitals or within county variation in demographic variables, we represent the average effect. There may have been different results, had smaller units of geographic measurement with greater granularity been used, however this would not be expected to impact the overall findings. Our study was limited because of the attribution of a beneficiary to their home county rather than the county of the hospital where they were admitted. Therefore, if a patient were admitted to a hospital outside their home county the admission was attributed to their home county's admission rate rather than the hospital's county admission rate. We also restricted this analysis to FFS Medicare beneficiaries, so the results are not representative of the entire Medicare population. Admission rates for people with different types of insurance (i.e. Medicare Part C or private insurance) or lack of insurance may demonstrate different relationships with the covariates in both the OLS and GWR models. In particular, admission decisions for Medicare beneficiaries who are older and/or disabled may be predominated more by clinical factors than economics. Finally, we did not directly study the reasons for admission, specifically, admission diagnosis, which is often the most important factor in whether an ED encounter results in an admission. In addition, we did not have access to triage level which may also have predicted ED admission.

5. Conclusion

In this study, we found that the association between healthcare market concentration, healthcare delivery, and socioeconomic/sociodemographic factors with ED admissions differed across communities. By employing a GWR model, our findings illustrate that whether an individual patients' ED visit results in hospital admission is the result of a complex interplay of social, clinical, and environmental factors that vary across communities. An implication of our findings is that policy and interventions need to be tailored to specific community contexts. Our approach is also notable for researchers who seek to explore similar questions in health services research, specifically, studies that aim to better understand the complex interplay between healthcare systems, delivery, and social-economic factors that contribute to variation in healthcare utilization [18].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ajem.2018.08.060.

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