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Identifying Community-Level Predictors of Depression Hospitalizations

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Executive Summary

The goal of this research was to identify rural areas that should be targeted for early adoption of evidence-based depression treatments based on elevated rates of depression related hospitalizations. Using county-level data from the Statewide Inpatient Database, Census, Department of Agriculture, and Area Resource File, predictors of elevated hospitalizations rates were identified using spatial regression models. This investigation demonstrated that: (1) rural counties have lower rates of depression-related hospitalization than urban counties, (2) rurality fails to predict depression-related hospitalization in models that control for community-level demographic, economic and health system risk factors, (3) community-level risk factors explain a respectable ~30% of the variance in depression-related hospitalization rates, and (4) while these risk factors identify high risk areas in the 10 states we studied, they cannot be used to identify high risk areas in other states.

This is the first investigation of potentially preventable mental health hospitalizations in a high quality database that provides systematically coded information on all public and private hospitalizations in 10 states across the country. Merging this database with other national databases allowed us to identify community-level risk factors of unmet need for mental health care that are otherwise subsumed under the umbrella of 'rurality'. We identified rural counties from 10 states with extremely elevated rates of depression related hospitalizations due to observable community-level risk factors. These counties should be prioritized for dissemination/implementation of evidence-based treatments for depression using designs that evaluate whether improved depression treatment produces a cost offset for health plans because it reduces expensive hospitalizations.

Introduction

Most efforts to implement best-practices for depression treatment target health systems serving predominantly urban populations. The goal of this research was to identify rural areas that should be targeted for early adoption of enhanced depression treatment models based on unmet need. Unmet need can be measured in a variety of ways, including prevalence rates, suicide rates, and depression related hospitalization rates. Prevalence rates in small areas must be collected via survey which would be extremely expensive to collect for a nationally representative sample. Suicide rates are available from the Centers for Disease Control (National Vital Statistics).(1) However, it would be difficult to reliably characterize patient need by suicide rates because, as relatively rare events, suicide rates fluctuate greatly in small areas over short periods of time. Therefore, in this project, we used depression related hospitalizations as a proxy for unmet need, recognizing that the delivery of high quality outpatient depression treatment should lead to decreased rates of depression-related hospitalization.(2)

Geographic variation in the population's need for improved depression care is multifaceted and depends on many factors including demographic characteristics of the population, characteristics of the local economy, and characteristics of the local health care system. We expected that rural and urban areas would differ with respect to these risk factors and that rural areas would have greater need for the dissemination and implementation of best-practices for depression treatment. Although prevalence rates have not been found to differ across rural and urban areas,(3) we expect that rurality is associated with higher hospitalization rates due to worse access to outpatient specialty mental health care and poor economic conditions. We also expect that higher rates of hospitalization would be explained by differences in demographic, economic, and health care system characteristics. If these community-level risk factors explain a high proportion of the variance in unmet need, they can be used to identify geographic areas in rural America that. Four hypotheses were tested.

1. Rural counties will have significantly higher depression related hospitalization rates than urban counties.
2. Depression related hospitalization rates will be significantly correlated with demographics (e.g., ethnicity, poverty, and education), economic conditions, and health system characteristics.
3. Rurality, demographics, economic conditions, and health system characteristics will

explain a substantial (e.g., >50%) amount of the variation in depression related hospitalization rates.

4. Predictive models can be used to accurately identify geographic areas with elevated depression related hospitalization rates.

These hypotheses were tested by conducting an analysis of spatially-referenced datasets containing county level information about hospitalizations, rurality, demographics, economics, and health care systems. Our ultimate goal was to identify counties across the U.S. with elevated rates of depression related hospitalizations. However, because comprehensive inpatient datasets containing both diagnostic and patient zipcode of origin information are not available at the national level for all adults, it was necessary to 1) identify a nationally representative sub-set of U.S. counties with available data, 2) identify significant predictors of depression related hospitalizations in this sub-set of U.S. counties, 3) determine whether a predictive model with external validity could be developed, and if so, 4) predict hospitalization rates in all U.S. counties using nationally available data about rurality, demographics, economics, and health care systems.

Methods

Data Sources

Depression related hospitalizations were extracted from the Statewide Inpatient Database (SID) which contains the universe of hospital discharge records from all community hospitals in participating states. States in the SID with patient zipcode information in 1995 included Arizona, Colorado, Florida, Iowa, New Jersey, New York, Oregon, South Carolina, Washington and Wisconsin. By 2000, data were also available from four other states (Kentucky, Maine, North Carolina, and West Virginia). These states represent all regions of the US and have a wide range of demographic, economics, and health system characteristics. The SID database includes one record for each hospitalization and includes data about the age, gender, zipcode and up to 10 primary and secondary diagnoses. Counties were defined as the unit of analysis because demographic, economic, and health system data are widely available at this unit of analysis and because a smaller geographical unit would have yielded zero observed hospitalization too frequently to be analyzed efficiently. Zipcodes were used to identify the patient’s county of residence using a geocoding algorithm developed for the Missouri Census Data Center which identifies the county in which the majority of the land area of the zipcode is contained (http://mcdc2.missouri.edu/webrepts/geography/ZIP.resources.html). Data about the demographic, economic and health system characteristics of the counties were obtained from the U.S. Census, the U.S. Department of Agriculture, and the Area Research File.

Depression Related Hospitalization Rates

Following traditional methods, age-sex adjusted depression related hospitalization rates in 2000 were calculated for each county.[1] Using categories defined by the U.S. Census, each inpatient was categorized into on of 20 age-sex groups.[2] The observed hospitalization rate for each age-sex group in the ten states was calculated by dividing the number of hospitalizations in each group by the population in the group as reported in the 2000 U.S. Census. The expected number of hospitalizations for each county was calculated as the product of the age-sex hospitalization rate for the ten-state area and the number of persons in the county in the age-sex category. The indirectly standardized hospitalization rate for each county k (SHR_k), is the ratio of the observed to the expected number of hospitalizations calculated according to the following equation:[(4)]

$$SHR_k = \frac{\sum_j x_{jk}}{\sum_j n_{jk}\bar{\lambda}_j} = \frac{O_k}{E_k}$$

where n_{jk} is the population in the j^{th} age-sex group and the k^{th} county, x_{jk} is the number of depression related hospitalizations in the j^{th} age-sex group and the k^{th} county, and $\bar{\lambda}_j$ is the depression rate for in the j^{th} age-sex group in the ten-state area. If O_k denotes the observed number of hospitalizations in each county and E_k denotes the expected number of hospitalizations, the SHR is $\frac{O_k}{E_k}$. Values greater than one indicate a greater number of hospitalizations than expected and values less than one indicate fewer hospitalizations than expected.

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[1] Admissions with primary or secondary diagnoses of ICDN-9 296.2x, 296.3x, 298.0, 300.4 309.1, 311 were extracted from the SID database. These are the diagnostic codes used for the HEDIS depression performance measure.

[2] The 10 age groups were 20-24, 25-29, 30-34, 35-44, 45-54, 55-59, 60-64, 65-74, 75-84, and 85+.

Explanatory Variables

Rurality was measured at the county level using two different indicators. The first was the Office of Management and Budget's (OMB) definition of a non Metropolitan Statistical Area (MSA). The OMB defines a county as a MSA if it contains an urbanized area (population greater 50,000) or it is adjacent to an MSA county and 25% of the employed population commutes to the urbanized area (or visa versa). The second measure of rurality was Urban Influence Codes developed by the WWAMI Rural Health Research Center.[5] Counties are divided into 12 categories according to their population and the proportion of workers commuting to urban areas (see Table 1).

Demographic variables included percent of population African American, Hispanic, Asian American, and Native American as defined by the U.S. Census. Other Census variables included percent of population below the federally designated poverty level, percent with a high school education, and percent of the population 16 and older who were unemployed. Economic data generated by the Department of Agriculture included and indicator of housing stress, and six mutually exclusive dummy variables indicating whether the economy of county was dependent on farming, mining, manufacturing, federal government, services, or not dependent on a specialized sector. Health system data from the Area Resource File included the number non-psychiatrist physicians per 1000 people, the number of psychiatrists per 1000 people, the number of psychologists per 1000 people, the number of social workers per 1000 people, the number of hospital beds per 1000 people, and dummy variables indicating whether the county had a community mental health center, whether the county was federally designated as a health profession shortage area, and the penetration rate of health maintenance organizations (HMO). Finally, we also included the longitude and latitude of the county, as the hospitalization rates varied seem to vary east to west and north to south.

Statistical Analysis

The unit of the ecological regression analysis was the county. The analysis was conducted in three stages. First, we conducted non-parametric bivariate analyses of the impact of rurality on depression related hospitalization rates. We used a Kruskal-Wallis Rank Sum Tests to compare the SHR rankings of MSA and non-MSA counties and to compare the SHR rankings of the 12 UIC categories of counties. Second, because the spatial regression models used in the third stage of the analysis were computationally intensive, it was necessary to first identify a parsimonious model specification. Therefore, we used backward selection techniques in conjunction with ordinary least squares regression analysis to first identify significant predictors of depression related hospitalizations. To remain in the parsimonious specification, variables had to achieve a significance cutoff level of $p<0.2$. Because we had no a priori expectations about how the independent variables would interact to impact hospitalization rates, we did not test for interaction effects. Because the dependent variable (SHR) does not conform to the distributional assumptions of ordinary least squares regression, a more flexible spatial regression model was used to test the hypotheses and generate predictions.

In the third stage, we conducted a Poisson regression analysis to estimate the impact of the explanatory variables on SHR. Two main analytical problems complicated the analysis. First, the hospitalization rates among neighboring counties are likely to be highly correlated resulting in a violation of the assumption that observations are independently distributed.[6] This problem was addressed using a Conditional Autoregressive (CAR) model to account for potential spatial autocorrelation among neighboring counties. Second, extremely high or low observed hospitalization rates are likely to occur in counties with small populations due to random variation. This problem was addressed using Bayesian smoothing methods, which took advantage of the spatial autocorrelation present in the data.[7]

To account for these two problems, we specified the Bayesian Poisson Conditional Autoregressive (CAR) Model proposed by Besag et al.[8], as implemented in the statistical software GeoBUGS.[9] This model specifies the observed count of hospitalizations to follow a Poisson distribution conditional on the expected hospitalization count and the relative risk for the county: $O_i \mid \delta_i \sim Poisson(E_i e^{\delta_i})$ Where i denotes the i-th county, O_i is the *observed* count of depression related hospitalizations in the i-th county, E_i is the *expected* count in the i-th county, e^{δ_i} is the relative risk of the i-th county. The following equation specifies the log relative risk ($\log\left(e^{\delta_i}\right)=\delta_i$): $\delta_i = \beta_0 + \beta_1 x_{i(1)} + \beta_2 x_{i(2)} + \ldots + \beta_k x_{i(k)} + \Phi_i$, where x_i are the county level variables and β are the regression coefficients. The spatial autocorrelation is modeled as:

$$\Phi_i \sim N(\overline{\Phi}_i, \frac{1}{\delta m_i})$$

$$\overline{\Phi}_i = \frac{1}{m_i} \sum_{k \in \partial_i} \Phi_k$$

∂_i : neighbor set of county i

m_i : number of neighbors of county i

δ : inverse of the overall variance parameter (controls the degree of smoothing imposed)

External Validation

The predictive validity of the Bayesian Poisson CAR model (with Urban Influence Codes as the measure of rurality) was determined using additional data from the four states added to the SID database in 2000. Using the estimated coefficients from the Bayesian Poisson CAR model and the values of the explanatory variables, the SHR was predicted for each county in Kentucky, Maine, North Carolina, and West Virginia. Then for each state we used Pearson Rank Correlations to compare the predicted and actual SHR for each state.

Results

In 2000, the 10 states had 520 counties and a population of 74,422,609. The SID database contained 9,289,440 hospital discharges for the 10 states. Among the 54,012,886 residents aged 20 and above, 448,752 cases of depression related hospitalizations were recorded in the SID database. The overall rate of depression related hospitalizations in these 520 counties was 8.3 per 1000 residents ages 20 and above. This rate is slightly lower than the national estimates based on the CDC National Hospital Discharge Survey 2002 which reports 9.2 depression related hospitalizations per 1000 residents ages 15 and above (using the same ICD9 codes). Table 1 presents the mean values of the county level risk factors.

The results of the bivariate analyses clearly demonstrate that rural counties have lower rates of depression related hospitalizations (MSA SHR=1.02 and non-MSA SHR=0.94). According to the Kruskal-Wallis Rank Sum Test, non-MSA counties have significantly (χ^2 = 8.9771, p<0.01) lower rates of hospitalization than MSA counties. Likewise, the 12 UIC classifications had significantly (χ^2 = 36.3379, p<0.01) different rates of depression related hospitalizations. These findings contradict our first hypothesis that rurality is positively correlated with depression related hospitalizations.

The results of the multivariate analysis for the MSA v.s. non-MSA model identified 15 covariates (in addition to rurality) with p-values <0.2 including: demographic characteristics (percent of population African American and Asian American), economic conditions (percent of population below the federally designated poverty line, percent of the population 16 and older who were unemployed, housing stress indicator, manufacturing dependent economy, non-dependent economy), and health system characteristics (number non-psychiatrist physicians per 1000 people, the number of psychiatrists per 1000 people, the number of hospital beds per 1000 people, the HMO penetration rate, presence of a community mental health center, and federal designation as a health profession shortage area). Longitude and latitude of the county was also a significant predictor in the bivariate analyses. Non-MSA status was not a significant predictor (p>0.2) in the multivariate analysis.

The results of the multivariate analysis for the UIC model also identified 15 covariates with p-values <0.2. In contrast to the MSA v.s. non-MSA model, the Health Profession Shortage Area variable dropped out and percent of population with a high school education was added. Only one of the UIC categories (non-metropolitan county not adjacent to metropolitan or micropolitan county without own town) was a significant predictor ($\beta<0$, $p<0.01$). No variable had a variance inflation factor >3.2 suggesting that multi-collinearity among the explanatory variables was not a problem. The R^2 for the MSA model was 0.30 ($F= 9.74$, $p<0.01$) and the R^2 for UIC model was 0.34 ($F=-13.5$, $p<0.01$). While these risk factors explain much of the variance in rurality's impact on depression related hospitalization rates, the results do not confirm our third hypothesis that the explanatory variables can explain >50% of the variation in depression related hospitalization rates.

The results of the Bayesian Poisson CAR model are depicted in Table 2. The table presents the median parameter estimate for each explanatory variable. If the upper and lower confidence limits within which 95% of the parameter estimates are included include zero, the parameter estimate is not considered statistically significant at the $\alpha=0.05$ level. Rurality was not significantly correlated with depression related hospitalization rate in either the MSA v.s. non-MSA model or the UIC model (although UIC category 12 had a negative and significant coefficient indicating that the most rural counties had the lowest rates of hospitalization). Both the MSA v.s. non-MSA model and the UIC models indicate that counties with a higher percentage of African Americans had significantly (i.e., the parameter estimate was positive 95%

of the time) lower rates of depression related hospitalization. In the UIC model, counties with higher proportions of Asian Americans also had significantly lower rates of hospitalization. In both models, counties with higher poverty rates and counties whose economies were dependent on manufacturing had significantly higher rates of hospitalization. Results from both models indicated that the non-psychiatrist MDs per population and the presence of a community mental health center were positively and significantly correlated with hospitalization rates. In the UIC model, the number of psychiatrists per population was negatively correlated with hospitalization rates. In the MSA v.s. non-MSA model, the HMO penetration was positively associated with hospitalization rates. Overall, these results partially support our second hypothesis that demographics, economic conditions, and health system characteristics are significantly correlated with hospitalization rates.

Extreme values of SHR were defined as <0.75 and >1.333. These cutoff values represent 25% less than the standardized rate and 33% greater than the standardized rate (note that 1/1.33=0.75). Maps 1 and 2 depict the counties with extreme hospitalization rates based on the raw data and rates based on predictions from the Bayesian Poisson CAR Model (UIC model which had a lower deviance information criteria value than the MSA vs. Non-MSA model, 4,842.550 versus 4,850.940). The map of observed SHR depicts a large number of counties with extreme observations (153 counties with SHR <0.75 and 80 counties with SHR >1.33), highlighting the problem of estimating hospitalization rates in counties with small populations. However, the map of estimated SHR from Bayesian Poisson CAR Model depicts fewer counties with extreme observations (66 counties in the smallest group and 8 in the highest group). This second map is more reliable for detecting counties with elevated SHRs because it reduces the risk of identifying counties which have extreme values due to increased random variation resulting from small populations. Specifically, information form neighboring counties is used to reduce this random variation. This finding suggests that the predictive models can be used to identify geographic areas with elevated hospitalization rates for counties included in the analysis, which partially supports our fourth hypothesis.

The external validation indicated that the model estimated from the 10 states does not generalize to the four states added to the SID database in 2000. The rank correlation between the observed SHR and the predicted SHRs from the Bayesian Poisson CAR Model were all small and insignificant: Kentucky (r=0.09, p=0.32), Maine (r=-0.48, p=0.06), North Carolina (r=0.02, p=0.84), and West Virginia (r=0.10, p=0.48). Note that correlation coefficient for Maine was negative. The correlation coefficient between the observed SHR in the 10 SID states and the predicted SHRs in the 10 SID states was much higher and statistically significant (r=0.47, (p<0.01). If the model had external validity to the four states, the correlation coefficients would have approached this value and level of significance. This finding suggests that the predictive models cannot be used to identify geographic areas with elevated hospitalization rates for counties not included in the analysis. This result does not support our fourth hypothesis.

Discussion

This investigation demonstrated that: 1) rural counties have lower rates of depression-related hospitalization than urban counties, 2) that rurality fails to predict depression-related hospitalization in models that control for community-level demographics, economic conditions, and health system risk factors, 3) that these risk factors explain about a third of the variance in depression-related hospitalization rates, and 4) that while these risk factors identify high risk areas in the 10 states we studied, they cannot be used to identify high risk areas in other states.

Our finding that rurality is not a risk factor for depression related hospitalizations as hypothesized is not consistent with a previous study of community residents with depression which found that those located in rural areas were more likely to be hospitalized.[(2)] With respect to demographic characteristics, our finding that depression related hospitalization rates are lower in counties with higher proportions of African Americans is consistent with epidemiological studies which find lower prevalence rates of depression and lower treatment seeking rates among minorities.[(13-16)] With respect to economic conditions, our finding that poverty rates were significantly correlated with hospitalization rates is consistent with findings from observational studies that poverty is a risk factor for depression.[(14;17-19)] Our finding that unemployment rates are not correlated with depression related hospitalization rates is not consistent with previous studies which report that unemployment (measured at the level of the individual) contributes directly to an increased need for depression treatment.[(20-22)] The finding that counties with manufacturing dependent economies have higher rates of depression related hospitalizations has not been reported previously in the literature.

With respect to health care system characteristics, our findings point to a rather complicated relationship between outpatient service availability and hospitalizations. On one hand, hospitalization rates are higher when the number of non-psychiatrist physicians per person is higher and when there is a community mental health center in the county. The first finding is consistent with a study reporting that increased access to primary care (as measured at the level of the individual) results in higher inpatient admission rates for mental health problems.[23] The finding that counties with community mental health centers have higher rates of depression related hospitalizations supports a previous study by Hendryx and Rohland that found that psychiatric inpatient admission rates were higher in areas closer to a community mental health center.[12] Hendryx and Rohland suggest that this finding may be due to supplier-induced demand. It could also be that the greater availability of non-psychiatrist physicians and Community Mental Health Center staff increases the likelihood that individuals in need of hospitalization are being detected (a hypothesis also put forth by Hendryx and Rohland). On the other hand, hospitalization rates are lower when the number of psychiatrists per person is greater, which indicates that when psychiatrists are available for referral or consultation it reduces the risk of hospitalization. In contrast, we found no significant relationship between hospitalization rates and the number of psychologists or social workers per person. Likewise, we found no relationship between hospitalization rates and the number of hospital beds per person. This latter finding is inconsistent with Wennberg's previous findings that bed supply is correlated with hospitalization rates across a range of physical health diagnoses.[24] Our non-finding may be due to the fact that we could only observe the total number of hospital beds per person, rather than the number of psychiatric beds per person. The finding that HMO penetration rates are positively correlated with hospitalization rates for depression seems counter-intuitive, although managed care cost containment strategies tend to reduce costs per admission rather number of admissions.[25;26]

Limitations and Strengths

There are several known limitations to the analysis. The first limitation is the modifiable areal unit problem, which states that results may differ depending on the geographical unit of analysis. Although counties are an appropriate geographical unit of analysis, results may have differed if we had specified zipcodes to be the unit of analysis. In particular, the amount of border crossing (e.g., individuals using outpatient health services outside the county) decreases as the size of the geographic unit increases. A second known limitation is edge effects.[27]

Although the statistical analysis controlled for spatial autocorrelation, we did not account for hospitalizations in adjacent counties located in states not in the SID database. Although, we could have imputed hospitalizations from adjacent counties with missing data this would have complicated the analysis considerably and it is not likely that results would have changed substantially. The third potential limitation concerns variations and inaccuracies in the diagnosis of depression during hospitalizations. It is possible that some of the variations and correlations observed in the data resulted from differences in diagnostic coding procedures across geographic areas rather than true differences in the need for inpatient services due to depression or complicated by depression. Fourth, whenever the unit of analysis is a geographic area (e.g., county) rather than an individual, there is the potential for the ecological fallacy. While it would have been preferable to analyze individual level data, this was not feasible because large nationally representative datasets containing both clinical data and risk factor data measured at the level of the individual are not available.

Despite the limitations described above, these are the first nationally representative data that have been presented about the risk factors for depression related hospitalizations. The analysis was conducted in a high quality database that provided systematically coded information on all hospitalizations in 10 states across the country. The depression related hospitalizations rates were very similar to national estimates from the CDC. Using spatial regression techniques, we were able to successfully identify counties from 10 states with elevated rates of depression related hospitalizations. These counties should be prioritized for dissemination/implementation of evidence-based treatments for depression. However, the predictive models were not found to have external validity when compared to observed hospitalization rates in the four states added to the SID database in 2000. Therefore, we conclude that these models cannot be used to identify areas outside the 10 states that are in greatest need for early adoption of evidence-based depression treatment.

References:

1. Gibbons RD, Hur K, Bhaumik DK, Mann JJ. The relationship between antidepressant medication use and rate of suicide. *Arch Gen Psychiatry.* 2005; 62:165-172.
2. Rost K, Zhang M, Fortney J, Smith J, Smith GR, Jr. Rural-urban differences in depression treatment and suicidality. *Med Care.* 1998; 36(7):1098-1107.
3. Kessler RC, McGonagle KA, Zhao S, Nelson CB, Hughes M, Eshleman S et al. Lifetime and 12-month prevalence of DSM-III-R psychiatric disorders in the United States: Results from the National Comorbidity Survey. *Arch Gen Psychiatry.* 1994; 51(1):8-19.
4. Gotway C, Waller L. *Applied Spatial Statistics for Public Health Data*. Hoboken, NJ: John Wiley and Sons, 2004.
5. Hart LG, Larson EH, Lishner DM. Rural definitions for health policy and research. *Am J Public Health.* 2005; 95(7):1149-1155.
6. Clayton DG, Bernardinelli L, Montomoli C. Spatial correlation in ecological analysis. *Int J Epidemiol.* 1993; 22(6):1193-1202.
7. Clayton D, Kaldor J. Empirical Bayes estimates of age-standardized relative risks for use in disease mapping. *Biometrics.* 1987; 43(3):671-681.
8. Besag J, York J, Mollie A. Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics.* 1991; 43:1-59.
9. Thomas A, Best N, Arnold R, Spiegelhalter D. GeoBugs User Manual (Version 1.1 Beta). 2002. Ref Type: Electronic Citation
10. Wisconsin Department of Health and Family Services DoPHMHP. The health of racial and ethnic populations in Wisconsin: 1996-2000. (Wisconsin Minority Health Report). PPH 0281. 2004. Madison, WI, Department of Health and Family Services. Ref Type: Report
11. Richman VV, Richman EM, Richman A. Patterns of hosptial costs for depression in general hosptial wards and specialized psychiatric settings. *Psychiatr Serv.* 2000; 51(2):179-181.
12. Hendryx MS, Rohland BM. A small area analysis of psychiatric hospitalizations to general hospitals: Effects of community mental health centers. *Gen Hosp Psychiatry.* 1994; 16:313-318.
13. Kessler RC, Berglund P, Demler O, Jin R, Walters EE. Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. *Arch Gen Psychiatry.* 2005; 62:593-602.
14. Riolo SA, Nguyen TA, Greden JF, King CA. Prevalence of depression by race/ethnicity: Findings from the National Health and Nutrition Examination Survey III. *Am J Public Health.* 2005; 95(6):998-1000.
15. Wang PS, Lane M, Olfson M, Pincus HA, Wells KB, Kessler RC. Twelve-month use of mental health services in the United States: Results from the National Comorbidity Survey Replication. *Arch Gen Psychiatry.* 2005; 62:629-640.
16. Wang PS, Berglund P, Olfson M, Pincus HA, Wells KB, Kessler RC. Failure and delay in initial treatment contact after first onset of mental disorders in the National Comorbidity Survey Replication. *Arch Gen Psychiatry.* 2005; 62:603-613.
17. Eibner C, Sturn R, Gresenz CR. Does relative deprivation predict the need for mental health services? *Journal of Mental Health Policy and Economics.* 2004; 7(4):167-175.
18. Egede LE, Zheng D. Independent factors associated with major depressive disorder in a national sample of individuals with diabetes. *Diab Care.* 2003; 26(1):104-111.
19. Mirowsky J, Ross CE. Age and the effect of economic hardship on depression. *J Health Soc Behav.* 2001; 42(2):132-150.
20. Dooley D, Cotalano R. Recent research on the psychological effects of unemployment. *J Soc Issues.* 1988; 44(4):1-12.
21. Fergusson DM, Horwood LJ, Lynskey MT. The effects of unemployment on psychiatric illness during young adulthood. *Psychol Med.* 1997; 27(2):371-381.
22. Montgomery SM, Cook DG, Bartley MJ, Wadsworth ME. Unemployment pre-dates symptoms of depression and anxiety resulting in medical consultation in young men. *Int J Epidemiol.* 1999; 28(1):95-100.
23. Fortney J, Steffick D, Burgess J, Maciejewski M, Petersen L. Are primary care services a substitute or complement for specialty and inpatient services? *Health Serv Res.* In press.

24. Dartmouth Medical School, Center for the Evaluative Clinical Sciences. *The Dartmouth Atlas of Health Care*. Chicago: American Hospital Publishing, Inc., 1996.
25. Merrick EL. Treatment of major depression before and after implementation of a behavioral health carve-out plan. *Psychiatr Serv.* 1998; 49(12):1563-1567.
26. Leslie DL, Rosenheck R. Shifting to outpatient care? Mental health care use and cost under private insurance. *Am J Psychiatry.* 1999; 156:1250-1257.
27. Vidal Rodeiro C, Lawson A. An evaluation of the edge effects in disease map modeling. *Computational Statistics and Data Analysis.* 2005; 49:45-62.

Table 1 – Definition of Urban Influence Codes

Urban Influence Code	Definition
1	large metropolitan county (population greater than 1,000,000)
2	small metropolitan county (1,000,000>population>50,000)
3	micropolitan county (50,000>population>10,000) adjacent to large metropolitan county
4	non-metropolitan county (population <10,000) adjacent to large metropolitan county
5	micropolitan county (50,000>population>10,000) adjacent to small metropolitan county
6	non-metropolitan county (population <10,000) adjacent to small metropolitan county with own town (population >2,500)
7	non-metropolitan county (population <10,000) adjacent to small metropolitan county without own town (population >2,500)
8	micropolitan county (50,000>population>10,000) not adjacent to a metropolitan county
9	non-metropolitan county (population <10,000) adjacent to micropolitan county with own town (population >2,500)
10	non-metropolitan county (population <10,000) adjacent to micropolitan county without own town (population >2,500)
11	non-metropolitan county (population <10,000) not adjacent to metropolitan or micropolitan county with own town (population >2,500)
12	non-metropolitan county (population <10,000) not adjacent to metropolitan or micropolitan county without own town (population >2,500)

Table 2 – Descriptive Statistics

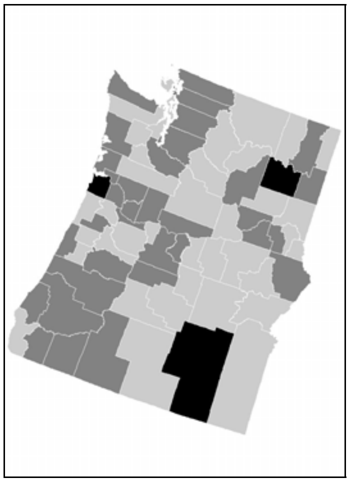
Variables	Mean (s.d.)/Proportion
Dependent Variable	
Standardized Hospitalization Ratio	0.96 (0.38)
Explanatory Variables	
Non-MSA	65.8%
Urban Influence Code - 1	15.0%
Urban Influence Code - 2	25.6%
Urban Influence Code – 3	3.9%
Urban Influence Code – 4	1.9%
Urban Influence Code – 5	11.2%
Urban Influence Code – 6	15.2%
Urban Influence Code – 7	5.8%
Urban Influence Code – 8	5.4%
Urban Influence Code – 9	5.0%
Urban Influence Code – 10	3.3%
Urban Influence Code – 11	3.7%
Urban Influence Code – 12	4.2%
Covariates	
% African American	6.89 (12.62)
% Hispanic	6.97 (10.48)
% Asian American	1.12 (1.74)
% Native American	1.50 (5.94)
% Poverty	11.49 (4.64)
% Unemployed	2.10 (1.03)
% High School Education	81.38 (7.15)
House Stress Indicator	31.35%
Mining Dependent	0.96%
Farming Dependent	8.65%
Federal Government Dependent	12.88%
Services Dependent	21.35%
Manufacturing Dependent	25.58%
Not Dependent	30.58%
Health Professional Shortage Area	0.66 (0.67)
Physicians Per 1000 Pop	1.38 (1.23)
Psychiatrists Per 1000 Pop	0.063 (0.10)
Psychologists Per 1000 Pop	0.21 (0.39)
Social workers per 1000 Pop	0.84 (1.22)
Hospital Beds Per 1000 Pop	3.4 (3.36)
CMHC in County	21.2%
HMO Penetration Rate	0.17 (0.16)
Latitude	39.89 (5.57)
Longitude	-93.52 (14.97)

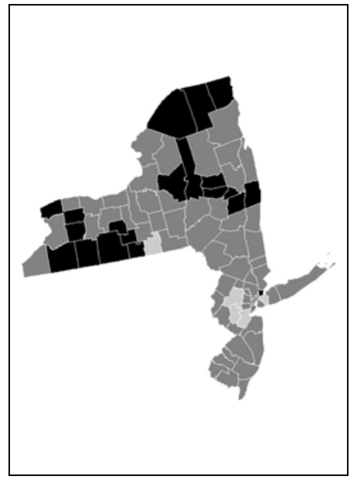
Table 3 – Bayesian Poisson CAR Model Results

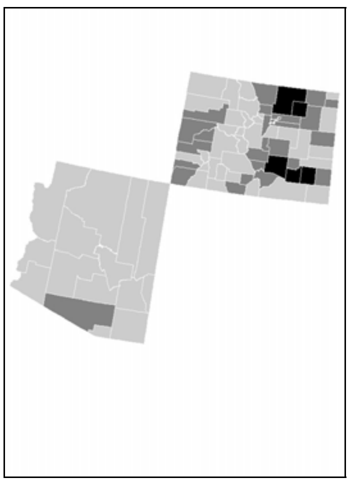
Variable	Model 1 Coefficients	Model 2 Coefficients
Intercept	-0.484*	0.135
Non-MSA	-0.023	-
UIC - 1	-	-
UIC - 2	-	0.017
UIC – 3	-	0.041
UIC – 4	-	-0.195
UIC – 5	-	0.012
UIC – 6	-	-0.053
UIC – 7	-	-0.050
UIC – 8	-	0.017
UIC – 9	-	-0.04034
UIC – 10	-	-0.087
UIC – 11	-	-0.178
UIC – 12	-	-0.485*
% African American	-0.006*	-0.007*
% Asian American	-0.019	-0.023*
% Poverty	0.019*	0.023*
% Unemployed	0.041	0.044
% High School Education	_	-0.000
House Stress Indicator	-0.077	-0.095*
Manufacturing Dependent	0.147*	0.119*
Not Dependent	0.106	0.091*
HPSA	0.017	-
Physicians Per Pop	0.102*	0.090*
Psychiatrists Per Pop	-0.485	-0.436*
Hospital Beds Per Pop	0.007	0.010
CMHC in County	0.112	0.092*
HMO Penetration Rate	0.373*	0.254
Latitude	-0.008	-0.007
Longitude	-0.002	0.004

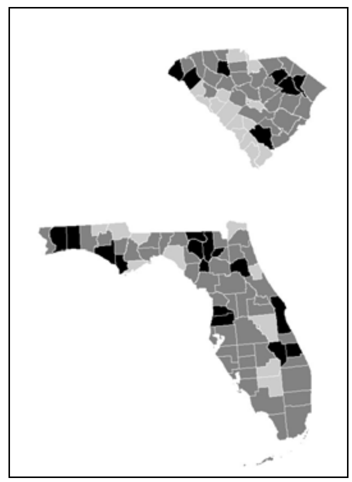
MSA – Metropolitan Statistical Area
UIC – Urban Influence Code
* $p<0.05$

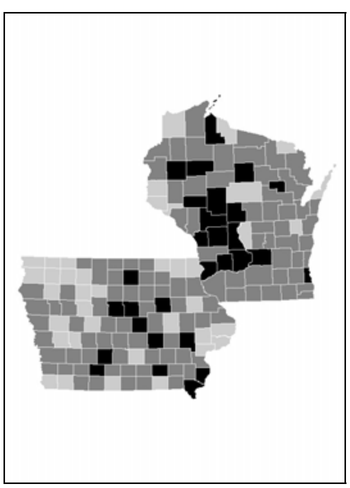
Map 1 – Indirectly Standardized Depression Related Hospitalization Rate









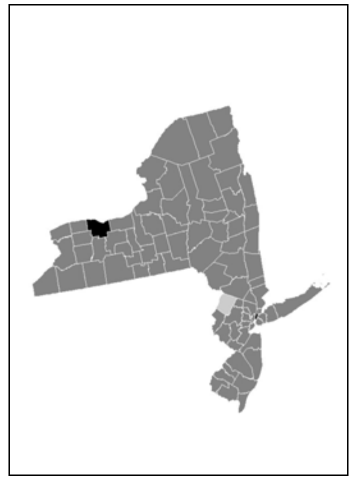


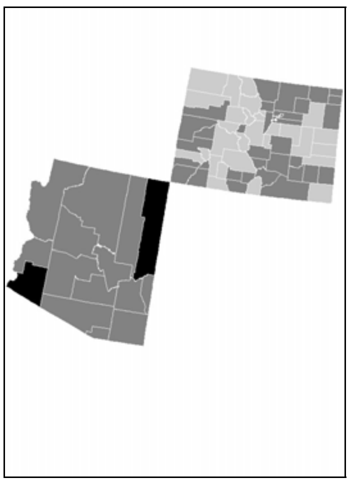
Legend

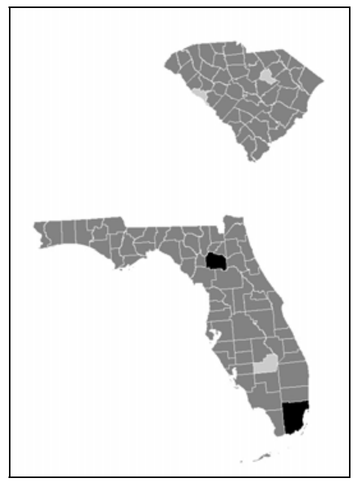
Standardized Hospitalization Rates

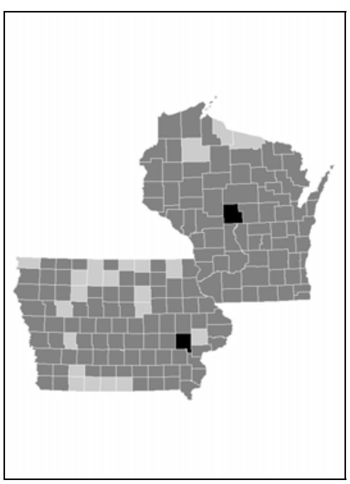
	Lowest – 0.750
	0.751 – 1.333
	1.334 - Highest

Map 2 – Depression Related Hospitalization Rates from Bayesian Poisson CAR Model









Legend

Standardized Hospitalization Rates

	Lowest – 0.750
	0.751 – 1.333
	1.334 - Highest

The WICHE Center for Rural Mental Health Research was established in 2004 to develop and disseminate scientific knowledge that can be readily applied to improve the use, quality and outcomes of mental health care provided to rural populations. As a General Rural Health Research Center in the Office of Rural Health Policy, the WICHE center is supported by the Federal Office of Rural health Policy, Health Resources and Services Administration (HRSA), Public Health Services, grant number U1CRH03713.

The WICHE Center selected mental health as its area of concentration because: (1) although the prevalence and entry into care for mental health problems is generally comparable in rural and urban populations, the care that rural patients receive for mental health problems may be of poorer quality, particularly for residents in outlying rural areas and (2) efforts to ensure that rural patients receive similar quality care to their urban counterparts generally requires restructuring treatment delivery models to address the unique problems rural delivery settings face. Within mental health, the Center proposes to conduct the research development/dissemination efforts needed to ensure rural populations receive high quality depression care.

Within mental health, the Center will concentrate on depression because: (1) depression is one of the most prevalent and impairing mental health conditions in both rural and urban populations, (2) most depressed patients fail to receive high quality care when they enter rural or urban treatment delivery systems, (3) outlying rural patients are more likely to receive poorer quality care than their urban counterparts, (4) urban team settings are adopting new evidence-based care models to assure that depressed patients receive high quality care for the condition that will increase the rural-urban quality chasm even further, and (5) urban care models can and need to be refined for delivery to rural populations.

The WICHE Center is based at the Western Interstate Commission for Higher Education. For more information about the Center and its publications, please contact:

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