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Spring 3-22-2018

Spatial Analysis of County Level Influenza Vaccination Coverage Estimates

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ABSTRACT

Spatial Analysis of County Level Influenza Vaccination Coverage Estimates

By

Seth Abram Meador

3/22/18

INTRODUCTION: The Centers for Disease Control and Prevention (CDC) reported 43.3% of adults (>18) received a flu vaccination in the 2016-17 season (FluVaxView, 2018). Despite long-standing recommendations and the enormous burden caused by the virus, vaccination coverage for flu is consistently low across seasons.

AIMS: This study examines influenza vaccination coverage among adults at the county level, in the contiguous United States (U.S.), to identify clusters of high and low coverage as well as assess access to care variables that could impact coverage levels.

METHODS: County level influenza vaccination coverage estimates from the 2014 Behavioral Risk Factor Surveillance System (BRFSS) were examined to identify statistically significant clusters using global (Moran's I) and local (Local Indicators of Spatial Association (LISA)) spatial clustering tests in GeoDa 1.10. To examine spatial effects of area provider supply and population demand variables, regression analyses were performed in GeoDaSpace. Independent variables were obtained from the Area Health Resource File (AHRF) and the National Council for Prescription Drug Program (NCPDP).

RESULTS: The Moran's I value comparing coverage estimates to the spatially lagged values was 0.48, indicating the coverage estimates are not spatially random. Five hundred sixty five counties were considered 'High-High', four hundred sixty three were 'Low-Low', and sixty seven had high coverage but were surrounded by counties with low coverage, designated as 'High-Low'. 'Low-High' counties are defined as counties with low coverage surrounded by counties with high coverage. Forty counties were considered 'Low-High' in this analysis. The final regression model used a regime to stratify counties by states that expanded Medicaid under the Affordable Care Act and those that did not. Among counties in states that did not expand Medicaid, the variables per capita pharmacies, per capita clinics, and percent less than sixty five years with no health insurance had no statistically significant associations with the outcome. In counties that were part of the Medicaid expansion, only per capita pharmacies and per capita clinics were not significant.

DISCUSSION: Per capita health care providers were statistically significant and positively associated with influenza vaccination coverage in both regime models, but had a larger regression coefficient in the expanded Medicaid regime model.

Key Words: Spatial Analysis, GIS

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by

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A Thesis Submitted to the Graduate Faculty
of Georgia State University in Partial Fulfillment
of the
Requirements for the Degree

MASTER OF PUBLIC HEALTH

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APPROVAL PAGE

Spatial Analysis of County Level Influenza Vaccination Coverage Estimates

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Acknowledgments

My sincerest gratitude to Drs. Lee Mobley and Stacie Greby for sharing their knowledge, for providing guidance, and support through this process. I am truly honored to have the opportunity to learn from such talented individuals.

I would also like to thank my family, and most importantly, my wife Sarah for her unwavering love and support.

Author's Statement Page

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TABLE OF CONTENTS

List of Tables

List of Figures

Introduction

Annually, the U.S. experiences an influenza (flu) epidemic with unpredictable gradients

of severity. The virus is responsible for thousands of deaths and hospitalizations (CDC, 2018).

The Centers for Disease Control and Prevention (CDC) reported 43.3% of adults (>18) received

a flu vaccination in the 2016-17 season (FluVaxView, 2018). Receiving an annual flu

vaccination is considered an effective method of preventing the flu, and is recommended for

everyone six months of age and older without contraindications by the Advisory Committee on

Immunization Practices (Grohskopf et al., 2017). Different vaccine types are available for use,

including unadjuvanted, egg-based trivalent and quadrivalent inactivated influenza vaccines

(IIV3 and IIV4), adjuvanted trivalent egg-based inactivated influenza vaccines (aIIV3), high-

dose trivalent egg-based inactivated influenza vaccines (hd IIV3), quadrivalent cell culture–

based inactivated influenza vaccines (ccIIV4), and recombinant trivalent influenza vaccines

(RIV3) (Budd, et al., 2016). The quadrivalent live attenuated intranasal influenza vaccine

(LAIV4) was not been recommended for use in the 2017-18 season because of concerns about

effectiveness (Budd, et al., 2016). Despite long-standing recommendations and the enormous

burden caused by the virus, vaccination coverage for flu is consistently low among adults 18-64

years across seasons. Examining contextual factors of vaccination coverage at a finer geographic

resolution (county) may provide clues to better target specific populations.

Using spatial data this analysis sought to answer the following: 1) were 2014 county level

flu vaccination coverage estimates clustered locally among U.S. counties, or were the estimates

spatially random? It was hypothesized that statistically significant clusters of both high and low

coverage estimates will be detected. Findings of significant clusters would suggest that

regression analyses include spatial effects. 2) In spatial regression, was the variation in coverage

across counties in the U.S. statistically and significantly related to area provider supply and population demand variables? If so, which independent variables seem to have the greatest impact? The ability to assess whether a county was influenced by adjacent counties, also known as spillover effect, is an additional benefit from estimating spatial regression. As discussed in Trogdon and Ahn (2015) such spillovers would suggest that targeting interventions to increase influenza vaccination in one area could have spillover benefits that would lead to increases in neighboring areas as well.

Literature Review

The selection of literature regarding adult vaccination coverage and spatial analysis is limited in scope. However, similar methods have been utilized to assess childhood vaccination (Omer et al. 2008; Trogdon and Ahn, 2015) as well as stroke hospitalization clusters over time (Schieb, et al, 2013). An analysis of immunization registry data from North Carolina revealed clusters of low coverage rates among uninsured and publicly insured children, concluding coverage was lower in areas of persistent poverty and shortages of providers, indicating out-of-pocket costs are only one of numerous factors contributing to low coverage (Trogdon and Ahn, 2015). Using the 2014 county level estimates provided by the Behavioral Risk Factor Surveillance System (BRFSS), this project provides a new perspective on identifying both clusters of above-average and below average-vaccination, the provider supply and population demand characteristics that define those areas, and how those characteristics compare across the two types of areas. Additionally, this project can demonstrate the value of applying spatial techniques to gain new knowledge in public health.

Barriers to influenza vaccination uptake have been identified consistently throughout the literature. Coverage for adults (≥18) in the 2016-17 flu season was 43.3%, well below the

Healthy People 2020 target of 70% (HP2020, 2017). With their analysis of the 2009 BRFSS data, Takayama et al. found a negative association between receiving the flu vaccine and having an income less than $35,000, as well as those without health insurance (2012). This association continued despite increased coverage with advanced age. Higher levels of flu coverage are generally seen among adults older than sixty five years as compared to adults eighteen to sixty four (FluVaxView, 2017), which is likely the result of mandatory coverage of the vaccine by Medicare and generally utilize health care more often than those less than sixty five years. Lu et al. found similar results when analyzing data from the National Health Interview Survey (2013). They concluded that adults 18-64 years were more likely to have received the vaccine if they were employed, living at or above poverty, and had health insurance.

Disparities in flu vaccination coverage by race were identified in the 2011-12 season by Lu et al. (2014) and remains a consistent theme throughout the literature. In the 2016-17 season coverage for Asians was 52.8% while coverage for non-Hispanic whites was 47.5%, non-Hispanic blacks 43.0%, Hispanics 46.2%, American Indian/Alaska Natives was 41.8%, and people of other or multiple races was 46.7% (FluVaxView, 2018). Addressing the enduring coverage gaps are difficult given the combination of factors, including: socio-demographic characteristics, patients and provider attitudes toward vaccination, awareness of recommendations, systems used in clinics serving different patient populations, preventive care, propensity to seek and accept vaccination, and quality of care received by racial/ethnic populations (Lu et al. 2014). Quinn et al. noted a similar list of contributing factors for disparities in coverage in their study of flu vaccination among African Americans specifically (2018).

Healthcare providers, both medical and pharmacy trained, are instrumental in increasing flu vaccine uptake. These providers are in a unique position to educate their patients and address potential concerns, with one literature review citing pregnant women rely almost entirely on their medical provider for information during pregnancy (Myers, 2016). Routine visits to healthcare providers are essential to increasing coverage, and the inability to pay for the visit has been negatively associated with receiving the influenza vaccine in numerous studies (Takayama et al., 2012; Lu et al., 2016; La et al., 2017). However, few studies have examined the association between healthcare provider density and influenza vaccination coverage. Gai & Gu combined individual level data from BRFSS and healthcare provider data from the Area Health Resource file and concluded an increase in provider density was associated with greater odds of receiving the flu vaccine (2014). Associations between vaccination coverage and pharmacy density has been explored in greater detail. Examining the same data set, but replacing per capita physicians with per capita pharmacies, Gai and Feng concluded the number of pharmacies per 1000 people was associated with greater odds of receiving a flu shot (2017). Murphy et al. found that pharmacies in medically underserved areas administered one third of all influenza vaccinations in the 2009-10 flu season (2012).

Knowledge, attitudes, and beliefs have tremendous influence on the decision to receive the flu vaccine. In a systematic review of the literature Yeung et al. concluded that perceived vaccine efficacy and safety were main deterrents to receiving the vaccine, and were more influential factors than an increase in knowledge of influenza (2016). Internet panel surveys of pregnant women revealed concern of the vaccine's safety and effectiveness. However, women that were hesitant to get the vaccine but received a recommendation from their provider were

more likely to be vaccinated than those that did not receive the recommendation (Ding et al., 2017).

Data Sources

County level influenza vaccination coverage estimates were obtained from the BRFSS Small Area Estimation (SAE) project. Due to an increased demand for local level data, BRFSS developed methods to produce county level prevalence estimates for flu vaccinations as well as other public health indicators for health policy and program evaluation (BRFSS, 2018). The BRFSS SAE method relied on data from 4 sources: 1) the 2013 BRFSS (n = approximately 430,000 individual survey responses), which provides data on health behaviors, demographic characteristics, and county; 2) the 2008–2012 American Community Survey (ACS) Public Use Microdata Sample (PUMS), which provided individual-level data with person weights (n = approximately 11,600,000) and Public Use Microdata Areas (PUMAs); 3) the Missouri Census Geographic Equivalency File (GEOCORR), which matched counties and PUMAs; 4) the 2013 Nielsen Claritas population totals used for weighting to county-level populations (Pierannunzi et al, 2016). Prevalence estimates were created by aggregating individual level probabilities, generated by linear random effects models, to the county level. Variables used in the final specified model included demographic factors such as age, sex, race or ethnicity, and used county as the random effect. Internal validity was checked by comparing imputed estimates to estimates generated directly from BRFSS data. To verify external validity, imputed estimates for the proportion of the population (18-64 years) without health insurance were compared to proportions generated by the ACS.

In the empirical model estimated here, demographic variables were explicitly excluded because these had been used to generate the influenza vaccination coverage (outcome) estimates.

Predictor variables in the empirical model included provider supply characteristics and population demand characteristics thought to be important in this ecological model of flu vaccination uptake. Most of these variables were obtained from The Area Health Resource File (AHRF), 2016-17. This data set acts as a repository for dozens of population health related data sources and provides estimates at the county, state, and national levels. More than fifty sources are combined in the AHRF under eight categories: Health Care Professions, Health Facilities, Population Characteristics, Economics, Health Professions Training, Hospital Utilization, Hospital Expenditures, and Environment (HRSA, 2018). In conjunction with AHRF data, pharmacy location data from the National Council for Prescription Drug Program (NCPDP) was used in the final model. NCPDP provides unique identification numbers to pharmacies to improve interactions with the federal government. All data provided to NCPDP is self-reported from each pharmacy.

Measures

To determine the influence of supply variables such as access to care on influenza vaccination, variables were created for per capita healthcare providers, per capita clinics, and per capita licensed pharmacists by county. Healthcare providers included primary care doctors, obstetricians and gynecologists (OB/GYNs), Physician's Assistants, and Nurse Practitioners. Federally Qualified Health Centers were combined with Rural Health Clinics to calculate the variable per capita clinics. A file from NCPDP containing pharmacy addresses was geocoded using ESRI's ArcMap to determine the number of pharmacies per county. After completing a quality assurance check on the unmatched addresses, the geocoded addresses were spatially joined to a U.S. county shapefile. When specified, a new variable is created during the join

process that produces a sum of all points in each polygon (county). The sum was divided by the total population in each county to calculate the per capita pharmacist variable.

Because of strong evidence correlating insurance status with vaccination status, the variable percent of persons under sixty five years without health insurance, from the AHRF, was included in the model. Socioeconomic factors reflecting population demand included percent persons in poverty, and percent urban population of each county.

Methods

Spatial autocorrelation is defined as the correlation among values of a single variable with adjacent values in terms of their geospatial location. When groups of values are similar among neighboring locations, there is spatial clustering in the values. When being more similar to a neighbor is due to some reciprocation – also known as a 'spillover' effect – then neighboring observations are not independent, which can cause problems in regression analysis (Griffith, 1987). Since the early 1950s the global Moran's I test has been used to quantify the presence of spatial clustering and is applicable to nearly any discipline that incorporates spatially referenced data. Subsequently, a statistical procedure was developed using the global Moran's I logic that allows for the decomposition of global indicators into the local contribution of each individual observation to detect statistically significant high and low local clusters, relative to the mean of all observations (Anselin, 1995).

County level vaccination coverage clusters were assessed using global and local spatial clustering tests. All spatial analyses were conducted with GeoDa 1.10. Assessment began with creating a spatial weights matrix to establish spatial relationships among counties in the data set. Because the data are aggregated into county polygons, queen contiguity weights will be used to

identify the spatial neighbors for each county. The Global Moran's I is used to determine if the data are spatially random or if clustering is present. If the Moran's I is a positive number between 0 and 1 and the p-value is significant ($\alpha \leq .05$), then we can say local clustering is occurring somewhere among the map features. To locate the local clusters, we conduct the Local Moran's I test. The output is displayed on a map with five classifications as either 'Not Significant', 'High-High Cluster', 'Low-Low Cluster', 'High-Low Outlier', or 'Low-High Outlier'. A 'High-High Cluster' is defined as the central county and its neighbors have values that are statistically significantly different than the mean. 'Low-Low Clusters' are defined in the same way except their values are below the mean. 'High-Low' or 'Low-High' indicate a central county with a statistically significantly different value that is the inverse of its neighbors.

Next, if significant clusters were found, we would expect that the regression analysis should include spatial effects. The exploratory Ordinary Least Squares (OLS) regression analysis included all areas and all predictor variables together, and specification tests on the residuals of the regression were used to determine what refinements to the simple OLS model are required for producing reliable estimates. These explorations revealed that spatial spillovers were present in the data. Further analysis grouping the Medicaid expansion and non-expansion states suggested that groupwise heteroscedasticity was confounding the estimates in a single-equation model. The final spatial regression model was stratified into two separate equations to represent the group of states that expanded Medicaid under the Affordable Care Act in 2014 (ACA, 2018), versus the group that did not.

To address unmodeled spatial heterogeneity and spatial autocorrelation, GeoDaSpace was used to estimate a third model, including both lag and error terms, and used a spatial regime that differentiated states which expanded Medicaid under the Affordable Care Act (ACA) by 2014.

The model was specified with General Method of Moments and 'KP-HET' which accounts for spatial heteroskedasticity to produce robust standard errors. Results are estimated separately for each of the two groups of states (based on the predefined regimes). The method used allowed for groupwise heteroskedasticity, estimating separate equations while correlating errors across equations to enhance efficiency. The results also provided a Chow test of whether the coefficients were stable across the Regimes.

Using the descriptive statistics for each covariate and the outcome variable, the standard deviations are used to interpret the quantitative results for the significant regression coefficients. We answer the question: by how much does flu coverage change (in terms of its own mean and standard deviation) when the explanatory variable is increased one standard deviation from its mean? This approach allows the interpretation to bypass the units of measurement, which can make estimates appear very large or small, and focuses on the quantitative impacts rather than solely the statistical significance (Kuo & Mobley, 2016).

Spatial Clustering Analysis

It's hypothesized that flu vaccination coverage among adults is not spatially random among counties in the U.S. The univariate global Moran's I test can detect clustering across the area of interest by comparing the coverage estimate for each county to the mean of the data set. A Moran's I value between zero and one indicates clustering somewhere in the areas of interest. A value between zero and negative one suggests spatial randomness among counties. Prior to running the test, a spatial weights matrix is generated using queen contiguity to specify the neighboring structure for each county. The Moran's I value comparing coverage estimates to the spatially lagged values was 0.48, indicating the coverage estimates are not spatially random. The univariate local Moran's I tool was used to locate clusters of high and low coverage.

The results of the Local Indicators of Spatial Association (LISA) test display only the 'core' counties at the center of the statistically significant ($\alpha < .05$) cluster in the map (Figure 1). Five hundred sixty five counties were considered 'High-High', four hundred sixty three were 'Low-Low', and sixty seven had high coverage but were surrounded by counties with low coverage, designated as 'High-Low'. Forty counties had low coverage surrounded by counties with high coverage, designated as 'Low-High'. The significant Moran's I also provides a rational to conduct a spatial regression to assess the variables with the most impact on influenza coverage.

Regression Analysis

Because it is hypothesized that influenza vaccination coverage does not exhibit a spatially random pattern among U.S. counties, spatial considerations are needed in regression modeling. There are possibly two separate spatial processes at work, spatial regimes and spatially correlated variables and errors across the counties.

A correlation matrix was created using the correlation procedure in SAS to limit problems associated with multicollinearity among predictor variables. Not all variables initially selected for the analysis were included in the final model due to the effect of measuring similar county characteristics. For example, percent of the county population in poverty and median household income both measure wealth among the county populations, and appear to be highly correlated with a correlation coefficient of -0.78. This would be an expected outcome as one would assume that as income increases, the poverty rate decreases. The percent poverty variable resembled a similar pattern as the LISA results and was chosen for the final model. Because the flu vaccine should be covered by health insurance for everyone six months and older, and Medicare provides vaccinations for those older than sixty five years, the variable measuring the

percent of those less than sixty five years without health insurance was also included in the final model. Using quantile classification, thematic maps were created of all variables and visually compared to the results of the LISA analysis map. The map displaying urbanicity showed little similarity to the LISA map, but was included in the model because of prior studies showing associations between living in an urban area and receiving a flu vaccine (Galarce, et al., 2011). Per capita health care provider, clinic, and pharmacy were included in the final model as well to identify associations between flu vaccination coverage and access to care.

Results

To discover the model that best fits the data, one starts with OLS, and uses a series of diagnostic tests on the residuals to further refine the model. OLS was used to specify the first model using the spatial weights file created for the cluster analysis to assess spatial effects that may be left over in the OLS model residuals. Model diagnostics suggested that some improvements were needed over the OLS model. The multicollinearity condition number (11.9) is significantly lower than the suggested limit of 50 indicating the explanatory variables are not correlated with one another, so no problems with multicollinearity are evident with the group of regressors chosen. The Moran's I test of spatial dependence in the residuals was significant, as expected. However, to determine the best alternative model (lag or error), a comparison was made between the Robust Lagrange Multiplier lag and error tests. Both non-robust tests were significant, but only the robust lag test was significant, thus the subsequent regression estimated was the spatial lag model.

The spatial lag model improved fit as evidenced by the reduced log likelihood values (-9920 compared to -9406). With the exception of per capita clinic and per capita pharmacy, all variables were statistically significant. Percent urban (-0.021), percent poverty (-0.098), and

percent less than sixty five years without health insurance (-0.077) had negative coefficients, suggesting an inverse relationship to influenza vaccination coverage. The additional lag variable in the model was highly significant, illustrating the significant spillover effects among adjacent counties. The Breusch-Pagan test for heteroskedasticity was highly significant, suggesting that the lag model was not sufficient to explain all of the spatial heterogeneity in the data.

Among counties in states that did not expand Medicaid variables per capita pharmacies, per capita clinics, and percent less than sixty five years with no health insurance were not statistically significant. In counties that were part of the Medicaid expansion, only per capita pharmacies and per capita clinics were not significant. Additionally, results of the Chow test comparing variables across regimes revealed only per capita healthcare providers was statistically significantly different between states that expanded Medicaid and those that did not.

Discussion

Figure 2 shows the states that expanded Medicaid. Comparing this to Figure 1, it is evident that there may be some relationship between Medicaid expansion status and vaccination coverage. The counties designated 'High-Low' and 'Low-High' in the spatial clustering analysis are particularly interesting because they are considered outliers. This designation indicates they are statistically significantly different from their neighboring counties with regards to flu vaccination coverage. Further investigation is required to determine which factors would lead a particular county to have higher or lower vaccination coverage than surrounding areas.

Per capita healthcare provider was statistically significant and positively correlated with flu vaccination coverage in both regimes, however the regression coefficient was larger in the expanded Medicaid regime compared to unexpanded. This larger effect suggests that Medicaid expansion may have enhanced the effect of additional healthcare providers on access to

vaccinations following the coverage of preventative health services by health insurance plans as specified by the ACA. Corriero et al. found increases in human papillomavirus (HPV) vaccination coverage in their examination of The National Health and Nutrition Examination Survey (NHANES) data pre and post implementation of ACA (2018). Providers may also be more inclined to recommend the vaccine to patients because of improvements in reimbursement that accompany expansion of the percentage of populations covered by health insurance (Hurley et al., 2017). Results of a 2013 survey of providers showed physicians reported not recommending vaccinations to their adult patients and patients frequently refusing vaccines for financial reasons (Hurley et al., 2017).

Among states that did not expand Medicaid, the effect of a one standard deviation change in per capita healthcare providers increased influenza vaccination coverage by about a quarter of a percent (0.265). States that expanded Medicaid saw an increase of about three quarters of a percent (0.748) for one standard deviation change in per capita healthcare provider. Quantifying the magnitude of effects was done only for per capita healthcare provider because of results of the Chow test showed these effects were significantly different across the Regimes. These effects are small relative to the standard deviations of influenza vaccination coverage (6.35-did not expand Medicaid; 6.11-did expand Medicaid). However, it provides further evidence that increased access to and affordability of the flu vaccine may increase vaccination coverage.

Negative correlation coefficients for percent poverty in both models was an expected outcome as previous studies have reported lower influenza vaccination coverage among those living in poverty (Lu, et al.2016; Redelings, et al. 2011). Among states that expanded Medicaid, the percent less than sixty five years with no health insurance was statistically significant with a correlation coefficient of -0.12, meaning for every one percent increase in those without

insurance, there was a twelve percent decrease in influenza vaccination coverage. There is some speculation as to what is responsible for this outcome. This uninsured variable is capturing those in the population that make too much money to qualify for Medicaid (under the new, more generous rules) but not enough to buy insurance. The Chow test does not find this negative effect to be significantly different across the regimes. Generally, one would expect a higher uninsured rate to be associated with a lower vaccination rate. Another postulation would be that coverage is consistently lower for those less than sixty five years (FluVaxView, 2018) and thus health insurance status would not affect their decision to be vaccinated. Further investigation is required to determine possible associations.

Several limitations should be taken into consideration for interpretation of the results. 1) The influenza vaccination coverage estimates from BRFSS were modeled using SAE methods and might not reflect the true coverage status in a particular county. These estimates have gone through validity checks but may be problematic where data for independent variables was sparse. This could also account for the strong need to include both spatial error and spatial lag terms in the final models. Some of the spatial autocorrelation could have been a result of the estimation methods used to produce the vaccination coverage variable, which highlights the need for using correctly specified spatial regression models when analyzing these data. 2) Alaska, Hawaii, and island counties in Washington and Massachusetts were excluded due to the requirement for contiguity among polygons to complete the analysis. Counties in these areas are considered 'spatial islands' and would therefore not have neighbors. 3) Areas of high or low coverage in the cluster analysis are in relation to the mean coverage estimate of all counties included in the data set. Influenza vaccination coverage may not be considered high or low according to state health

department standards. 4) Flu vaccination coverage is based on self-report from survey respondents and may be subject to recall bias.

The application of spatial analysis to vaccination coverage data is a relatively new technique. With the availability of vaccination coverage data at higher geographic resolutions (county, zip code, etc.), investigators can identify pockets of low coverage in need of vaccination services during an outbreak or an epidemic. These techniques may also provide insight on identifying disparities that may not be revealed in large surveys. Future research should focus on local level effects of campaigns to increase coverage. Despite state and national efforts to increase access by reducing the cost burden of flu vaccination, other factors are equally as important and should include providing consistent access to healthcare providers.

Table 1. Sample Statistics for States that did not Expand Medicaid

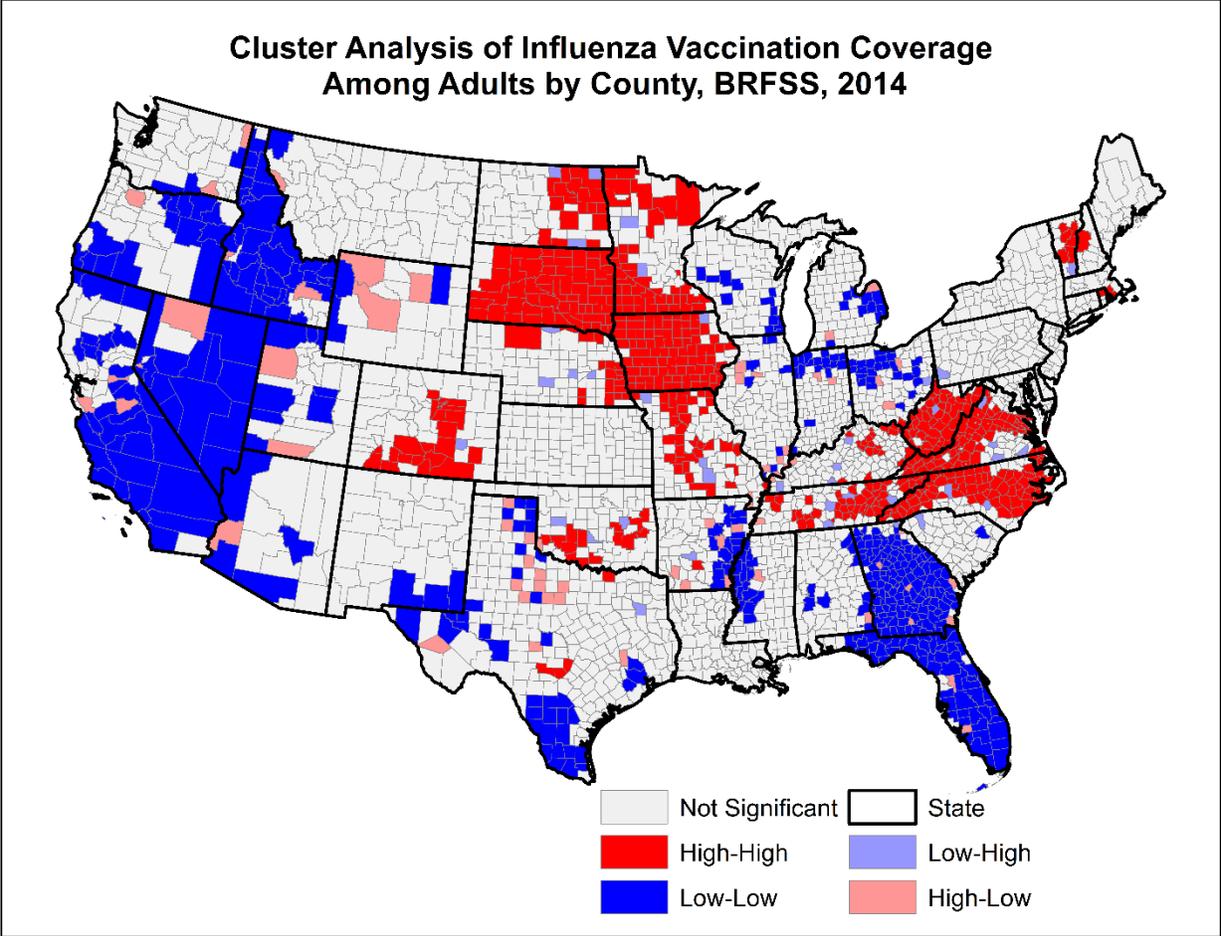| Variable	Mean	SD
Economic Conditions		
Percent Persons in Poverty	17.5385	6.5644
Health Insurance		
% <65 without Health Insurance	16.5525	4.6697
Access to Care		
Per Capita Healthcare Providers	162.3827	120.2696
Per Capita Clinics	18.1491	24.3520
Per Capita Licensed Pharmacists	31.2386	16.6917
Rural/Urban		
Percent Urban Population	39.3341	31.3692
Influenza Vaccination Coverage	39.1635	6.3532

Table 2. Sample Statistics for States that did Expand Medicaid

Variable	Mean	SD
Economic Conditions		
Percent Persons in Poverty	15.8126	6.1191
Health Insurance		
% <65 without Health Insurance	10.7487	3.4161
Access to Care		
Per capita Healthcare Providers	179.7315	102.5019
Per Capita Clinics	17.0611	24.0202
Per Capita Licensed Pharmacists	29.8400	14.0473
Rural/Urban		
Percent Urban Population	44.8907	31.2227
Influenza Vaccination Coverage	40.1431	6.1157

Table 3. Spatial Regime Regression Analysis of Influenza Vaccination Coverage Among Adults in U.S. Counties

Variable	Medicaid Not Expanded			Medicaid Expanded		
	Coeff	St. Error	p-value	Coeff	St. Error	p-value
Percent Persons in Poverty	-0.0728	0.0182	0.0000	-0.0561	0.0204	0.0060
% <65 without Health Insurance	-0.0428	0.0259	0.0980	-0.1202	0.0530	0.0235
Per capita Healthcare Providers*	0.0022	0.0010	0.0263	0.0073	0.0018	0.0000
Per Capita Clinics	0.0000759	0.0046	0.9869	0.0069	0.0071	0.3279
Per Capita Licensed Pharmacists	0.0068	0.0070	0.3293	0.0042	0.0095	0.6574
Percent Urban Population	-0.0200	0.0047	0.0000	-0.0164	0.0066	0.0137
Flu Vaccination Lag	0.7514	0.0644	0.0000	0.7692	0.0749	0.0000
Lambda (Error)	-0.6813	0.0783	0.0000	-0.6035	0.0836	0.0000

*Variable was statistically significantly different across regimes.

Figure 1. Cluster Analysis Results

Cluster Analysis of Influenza Vaccination Coverage
Among Adults by County, BRFSS, 2014

Figure 2. Medicaid Expansion States

States That Expanded Medicaid Under the Affordable Care Act, 2014

Expanded (26)
Not Expanded (23)

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