Geo-spatial Patterns in Influenza Vaccination: Evidence from Uninsured and Publicly-Insured Children in North Carolina

Justin G. Trogdon, PhD,[a]* and Thomas Ahn, PhD[b]

* Corresponding author

a.
Department of Health Policy and Management
Gillings School of Global Public Health
University of North Carolina at Chapel Hill
1101-B McGavran-Greenberg Bldg.
135 Dauer Dr., CB-7411
Chapel Hill, NC 27599-7411
justintrogdon@unc.edu
1-919-962-2433

b.
Department of Economics
Gatton College of Business and Economics
University of Kentucky
335X Gatton College of Business and Economics
Lexington, KY 40506
thomas.ahn@uky.edu
1-859-257-5975

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Abstract:

Objective: To explore geo-spatial patterns in influenza vaccination

Methods: We conducted an ecological analysis of publicly-funded influenza vaccinations at the ZIP code tabulation area (ZCTA) level using secondary data for publicly-funded influenza vaccinations among eligible school-aged children (ages 5 to 17) for the 2010-2011 and 2011-2012 influenza seasons from the North Carolina Immunization Registry (NCIR). NCIR data were merged by ZCTA with other publicly available data. We tested for spatial autocorrelation in unadjusted influenza vaccination rates using choropleth maps and Moran's I. We estimated non-spatial and spatial negative binomial models with spatially correlated random effects adjusted for demographic, economic, and healthcare variables. The study was conducted at the University of North Carolina at Chapel Hill in the spring of 2014.

Results: The NCIR demonstrated spatial autocorrelation in publicly-funded influenza vaccinations among uninsured and means-tested, publicly insured school-aged children; ZCTAs tended to have influenza vaccination rates that were similar to their neighbors. This result was partially explained by included ZCTA characteristics, but not wholly.

Conclusions: To the extent that the geo-spatial clustering of vaccination rates is due to causal influences, targeting interventions to increase influenza vaccination among school-aged children in one area could also lead to increases in neighboring areas.

Keywords: influenza; vaccination; spatial analysis

Introduction

School-aged children are an important population for influenza vaccination policy. School-aged children experience high rates of influenza infection, absenteeism, hospitalization, and death (1-3). In addition to the effects of influenza on children, they are also a major source for the transmission of influenza within families, schools, and communities due to high infection rates, prolonged viral shedding, and close contact with other classmates (4-8). Thus, from a policy perspective, increasing influenza vaccination rates in school-aged children can reduce influenza illness in the larger susceptible population (7, 9) and can be a potentially cost-effective way to prevent influenza in the population as a whole (10, 11).

As a result, beginning with the 2008-2009 influenza season, the Advisory Committee on Immunization Practices (ACIP) recommend annual influenza vaccination for all children aged six months to 18 years (12). This recommendation meant that uninsured and low-income children could receive influenza vaccinations at no cost through the Vaccines for Children (VFC) program, which provides ACIP-recommended vaccines at no cost to children who might not otherwise be vaccinated because of inability to pay (13). Despite the VCF and other state programs to remove access and cost barriers, influenza vaccination rates among school-aged children remain low: median coverage across states was 41.2% during the 2009-2010 influenza season (14).

Vaccination is of particular importance for under- and uninsured children, more so than school-aged children with private insurance. Because these students are from poor families without access to private insurance, they may lack many of the family and financial safety nets of their peers. Short, acute illnesses that can be shrugged off with a visit to the pediatrician's office and parent(s) taking a few days off from work for relatively affluent children will be more problematic for the vulnerable population in our study. These children may not be able to receive proper, timely medical treatment. Absence from school results in lower test scores, and as students in poverty score lower, all else equal, each day of schooling missed is more costly, relative to their classmates (15). In addition, due to parent(s)' work schedule inflexibilities, they may be forced to return to school earlier than is ideal, inadvertently increasing the risk of transmitting the flu to their schoolmates.

Several simulation models of the geo-spatial spread of influenza suggest that spatial targeting of influenza vaccination could be an effective strategy to reduce the spread of pandemic influenza (16, 17). However, within the United States, regional estimates of influenza vaccination are rare and have not been studied in-depth using geo-spatial techniques (18-20). Previous studies have focused on spatial patterns of influenza infections (21, 22), hospitalizations (23, 24), or deaths (25). With the exception of Yousey-Hindes and Hadler (24), we know of no other studies that have focused on influenza outcomes for children. Spatial patterns are important not only for targeting high-need areas, but also because if vaccination rates are causally related from one area to another (e.g., through information networks), targeting interventions to increase influenza vaccination among school-aged children in one area could lead to positive spillover effects in neighboring areas.

This study explores geo-spatial patterns in publicly-funded influenza vaccination among uninsured and means-tested, publicly-insured school-aged children in North Carolina. North Carolina has had one of the highest levels of intrastate variation in influenza vaccination coverage (20).This study is one of the first to investigate geo-spatial patterns in influenza *vaccination*. Using vaccination registry data, we conducted an ecological analysis of publicly-funded influenza vaccination rates to determine if vaccination rates tend to cluster geographically. The analysis tests the extent to which influenza vaccination rates cluster geographically due to similar demographic, economic, and health characteristics in nearby areas. The results of this study will inform efforts to increase vaccination rates among school-aged children and prevent transmission of influenza in the population by identifying correlates with low rates in certain areas and highlighting areas where interventions are needed.

Data

We collected data for publicly-funded influenza vaccinations among school-aged children (ages 5 to 17) for the 2010-2011 and 2011-2012 influenza seasons from the North Carolina Immunization Registry (NCIR), provided by the North Carolina Department of Health and Human Services. The NCIR is a secure, web-based clinical tool to provide official immunization information to the state (26). This study is one of the first to use vaccination registry data. We are aware of only three other studies that utilized registry data and they all focused on H1N1 vaccination in non-U.S. settings (18, 27, 28). A major benefit of vaccination registries is that they are objectively reported by providers and avoid recall and reporting bias from self-reported measures in surveys (28).

Providers receiving any state-supplied vaccine were required to report influenza vaccinations during the 2008-2009 and 2009-2010 influenza seasons. However, due to budget limitations, in the 2010-2011 and 2011-2012 influenza seasons included in this study, only influenza vaccination doses funded by the federal VFC program were required to be reported to the NCIR. To assess whether there were any changes in reporting patterns by providers, we analyzed data from the National Immunization Survey (NIS)-Teen for North Carolina. Among 13 to 17 year olds in North Carolina with provider-confirmed influenza vaccinations for the 2010-2011 season (N=89 teens), 72.0% of respondents' providers reported to the state registry and another 19.4% had at least some of their providers report to the registry. This rate of registry reporting was comparable to the 2009-2010 season during which reporting was required in North Carolina: 75.4% of teens had all providers report to registry and 18.6% has some but not all providers report to registry. The rates of providers reporting to the registry in North Carolina were higher than the national average in both influenza seasons.

We aggregated the number of children vaccinated against influenza using public funds in each season by patient ZIP code, which we then cross-walked to ZIP code tabulation area (ZCTA) (29). ZCTAs are generalized area representations of ZIP code service areas developed by the U.S. Census Bureau to overcome the difficulties in precisely defining the land area covered by each ZIP code. For our analysis, ZCTAs provide sufficient variation across geographic areas while also having data available for area-level characteristics. We collected geographic boundary and demographic characteristics for North Carolina ZCTAs from the U.S. Census Bureau: 2013 TIGER shape files (30), 2010 U.S. Census, and 2008-2012 (5-year) American Community Survey (ACS). Data at the ZCTA level were only available at one point in time, centered around 2010.

We measured the severity of the influenza season using county-level data on influenza-like illness (ILI) visits to the emergency department (ED) for the 2009-2012 seasons from the North Carolina Disease Event Tracking and Epidemiologic Collection Tool (NC DETECT). NC DETECT receives data daily from 113 of the 115 24/7 EDs in North Carolina. The NC DETECT definition of ILI includes any case with the term “flu” or “influenza”, or at least one fever term and one influenza-related symptom.

We also collected county-level characteristics from the 2012-2013 Area Resource File (ARF). All variables at the county level, which cross ZCTA boundaries, were converted to ZCTAs using weighted averages of the county-level data. For count variables, we used Census calculations of the percentage of the total population of the 2010 county represented by the ZCTA/county overlap for the weights (e.g., a ZCTA that accounted for 10% of the county population received 10% of the county’s medical providers). For dichotomous variables, all counties touched by the ZCTA must have a positive indicator for the ZCTA to receive a positive value. For per-capita variables, we used Census calculations of the percentage of the total population of the 2010 ZCTA represented by the ZCTA/county overlap for the weights (e.g., a ZCTA with 90% of its population in county A and 10% in county B will weight per capita variables from county A at 90% and per capita variables from county B at 10%). Data at county level were available for each influenza season: 2010 for the 2010-2011 season and 2011 for the 2011-2012 season.

Variables

The dependent variable in the analysis was the number of school-aged children (ages 5 to 17) vaccinated for influenza using public funds in each ZCTA in each influenza season. The explanatory variables included the following demographics: the population of uninsured and means-tested, publicly-insured school-aged children (logged when used as exposure in count models, 2008-2012 ACS); percent female (2010 Census); percent Hispanic; percent black, Non-Hispanic; percent other or multi-race/ethnicity (white, non-Hispanic omitted; 2010 Census); percent with less than high school diploma; and percent with at least some college (high school diploma omitted; 2008-2012 ACS). Based on previous literature (31), we expected ZCTA's with more females, minorities, and higher levels of education to have higher influenza vaccination rates.

We adjusted for access to vaccinations using two economic variables: percent in poverty (2008-2012 ACS) and unemployment rate, ages 16+ (ARF). We hypothesized that higher rates of poverty and unemployment rate would be associated with lower influenza vaccination rates due to higher financial costs of the vaccinations. However, this effect could be offset by the VCF program. We also adjusted for the number of providers (physicians, physicians assistants, and nurse practitioners) with National Provider Identifier per 100 population (ARF) and whether the ZCTA was a Health Professional Shortage Area (HPSA) as defined by the Health Resources and Services Administration (ARF). Fewer providers per 100 population and HPSA designation should reduce access to vaccinations.

We also adjusted for outpatient visits per capita in the lagged influenza season (e.g., 2009 for 2010-2011 influenza season; ARF), 3-year influenza and pneumonia deaths per 1,000 population ending in the lagged influenza season (e.g., 2007-2009 for 2010-2011 influenza season; ARF), and lagged ILI ED visits per 100 school-aged children (NC DETECT). We lagged these variables to avoid simultaneity bias/reverse causality in the regression models. We expected more severe influenza seasons to be associated with higher vaccination rates the following season.

Analysis

Because the ZCTA-level variables were only available for 2010, we conducted the following analyses separately for each influenza season. First, we tested for spatial autocorrelation in the unadjusted influenza vaccination rates visually using choropleth maps and quantitatively using Moran's I (32). Choropleth maps color code each ZCTA using quintiles for influenza vaccination rates. Moran's I is a statistic used to test for spatial autocorrelation. Values of I greater than the expected value (E(I)) indicate positive spatial autocorrelation: nearby ZCTAs tend to exhibit similar publicly-funded influenza vaccination rates among eligible school-aged children. Values of I less than E(I) indicate negative spatial autocorrelation: nearby ZCTAs tend to exhibit dissimilar influenza vaccination rates among eligible school-aged children. We used two definitions of neighbors. Contiguous neighbors share a common border or a single common point (i.e., contiguity). We also used a weighted average of all ZCTAs with each ZCTA's contribution weighted by the inverse of the Euclidean distance between the centroids of the ZCTA and the other ZCTA.

Second, we estimated non-spatial count data models for influenza vaccinations at the ZCTA level. These models explore how much of the spatial autocorrelation in influenza vaccination rates is explained by observable ZCTA characteristics. Specification tests revealed evidence of over dispersion in the number of vaccinations per ZCTA, so we estimated negative binomial models. The models adjusted for the variables discussed above. We then tested for spatial autocorrelation of the negative binomial residuals (expressed as the difference between the actual and predicted values divided by the school-aged population) using choropleth maps and Moran's I.

Lastly, we estimated negative binomial models with spatially correlated random effects known as conditional autoregressive (CAR) models (33). The vaccination rate was a function of ZCTA characteristics and two error terms: a standard negative binomial dispersion term and a spatial error term whose mean (conditional on the other ZCTAs) is equal to the average spatial error term among adjacent ZCTAs. We estimated the model in a Bayesian framework using Markov chain Monte Carlo (MCMC) implemented in WinBUGS. We ran 200,000 simulations of the MCMC and report summary statistics from the posterior distribution of the model's parameters using the last 50,000 simulations.

See the appendix for details of the model and estimation. We also report choropleth maps showing the quintiles of influenza vaccination rates attributable to the conditional autoregressive random effects.

Results

Average publicly-funded influenza vaccinations were 181 per ZCTA in 2010-2011 and 205 in 2011-2012, with standard deviations larger than the mean (Table 1). ZCTAs had 1,014 eligible school-aged children on average, ranging from 1 to nearly 9,000. On average, ZCTAs were evenly divided between males and females, 20% black, non-Hispanic, and 6% Hispanic. ZCTAs had over 50% of the population with at least some college, poverty rates of about 18%, and 60% were HPSA.

Unadjusted influenza vaccination rates showed clustering of high and low vaccination rates among ZCTAs in North Carolina (Figure 1). Overall, publicly-funded vaccination rates reported in the NCIR were generally low: a rate above 27% in 2010-2011 (30% in 2011-2012) would put a ZCTA in the upper quintile. Moran's I (Table 2) indicated significant positive clustering of influenza vaccination rates by ZCTA using contiguous neighbors (0.139 p=0.000 in 2010-2011, 0.203 p=0.000 in 2011-2012) and inverse distance to other ZCTAs (0.021 p=0.000 in 2010-2011, 0.026 p=0.000 in 2011-2012).

The following variables were associated with higher levels of publicly-funded influenza vaccination among eligible school-aged children in the non-spatial negative binomial models (Table 3, MLE columns): share of the population that was Hispanic (relative to white, non-Hispanic), providers per 100 population, three-year influenza and pneumonia deaths per 1000 population (2011-2012), and ILI in the prior influenza season. Conversely, these variables were associated with lower levels of influenza vaccination: share of the population that was in poverty and unemployed (2010-2011), HPSA, and outpatient visits per capita. The estimates of α, the parameter for the distribution of the negative binomial error, were statistically significantly different from zero, indicating over dispersion in the data.

We then calculated residuals as the difference between observed publicly-funded vaccinations and predicted vaccinations and divided the residuals by the population of eligible school-aged children.

Conditional on the explanatory variables, there was still significant geo-spatial clustering of influenza vaccination rates. Moran's I values were lower once we adjusted for the covariates, but the p-values indicated statistically significant clustering in the residuals using contiguous neighbors (Table 2).

The CAR models explicitly model spatial autocorrelation in the random effects of a negative binomial model (Table 3, CAR columns). Compared to the maximum likelihood estimates (MLE) that did not account for spatial autocorrelation, the coefficients (point estimates for MLE and posterior means for CAR) for Hispanic, below poverty, unemployed (2010-2011), and lagged ILI among school-aged children (2011-2012) were very similar. However, the coefficients for providers per 100 population (2010-2011), outpatient visits per capita, and lagged ILI among school-aged children (2010-2011) were no longer significant in the CAR model (i.e., the posterior 95% credible interval included zero). In addition, the coefficients for HPSA were smaller in magnitude in the CAR model relative to the MLE estimates. The CAR estimates indicated that ZCTAs with higher shares of black, non-Hispanic and other race/ethnicity had higher levels of publicly-funded influenza vaccinations among school-aged children. The CAR model's estimate of α still indicated significant over dispersion in vaccination rates, but the estimates were much smaller than MLE; the CAR model attributed a larger portion of the over dispersion to spatial correlation in the error terms.

To give a sense of the contribution of the ZCTA characteristics to publicly-funded influenza vaccinations for school-aged children, we calculated the incidence rate ratio from the 2011-2012 CAR estimates. A one percentage point increase in the share of the population that was Hispanic was associated with a two percent increase in the publicly-funded influenza vaccination rate (IRR = 1.02 = exp(2.096/100)),[1] holding the other covariates constant. Some of the covariates are more amenable to changes in policy. For example, HPSA status was associated with a 12 percent lower influenza vaccination rate among school-aged children (IRR = 0.88). It appears that parents responded to the

[1] Coefficient was scaled to express the variable as a percentage instead of a fraction.

severity of the previous year's influenza season; each additional ILI ED visit per 100 school-aged children in the prior influenza season was associated with a six percent increase in the publicly-funded vaccination rate ($p < 0.10$).

Figure 2 shows quintile choropleth maps of influenza vaccination rates attributable to the conditional autoregressive random effects in the CAR model, which represent spatial heterogeneity conditional on population size and the covariates included in the model. Clustering of influenza vaccination rates was evident, with areas of relatively low rates concentrated in the northeast, south, and west-central portions of the state.

Discussion

Registry data from North Carolina demonstrated substantial spatial autocorrelation in publicly-funded influenza vaccinations among school-aged children—ZCTAs tended to have influenza vaccination rates that were similar to their neighbors. This result was partially explained by demographic, economic, and healthcare characteristics and prior influenza cases in the ZCTAs, but not wholly. For the 2010-2011 and 2011-2012 influenza seasons, there were identifiable clusters of ZCTAs with very low vaccination rates.

The results of this study could be useful in helping to target areas to increase influenza vaccinations and reduce the spread of influenza within the state. Simulation models of pandemic influenza have suggested geo-spatial targeting as an effective strategy (16, 17). To the extent that the geo-spatial clustering of vaccination rates is due to causal influences from one ZCTA to another (e.g., through information networks), targeting interventions to increase influenza vaccination among school-aged children in one area could also lead to increases in neighboring areas. There is support for an important role for social pressure, norms, and neighborhood social capital in the uptake of influenza vaccinations (31, 34-36). Low vaccination rate areas may also be ideal candidates for school-based vaccination clinics (37).

The results of our ecological analysis are consistent with evidence from individual-level uptake of influenza vaccination among children. For example, the Centers for Disease Control and Prevention has also reported higher influenza vaccination rates among Hispanic children vs. non-Hispanic whites (38). In addition, the literature suggests that vaccination rates respond to the severity of the influenza season (36).

This study has limitations that are important for the interpretation and application of the results. The NCIR may under-report influenza vaccinations among school-aged children. For example, state-wide influenza vaccination rates for adolescents ages 13 to 17 in the NIS-Teen were 24.7% (2010-2011) and 26.0% (2011-2012). The NCIR did not capture vaccinations given by pharmacies during this period. We focused on publicly-funded vaccinations, for which reporting was required, to minimize the extent of under-reporting. The benefit of registry data is that it avoids recall and self-reporting bias present in surveys (14, 28).

ZCTAs and ZIP codes were not created as geographic markers and their use in spatial analysis may lead to representational errors (39). There are several other Bayesian specifications for spatial effects other than the model estimated here (40, 41). The details of the spatial patterns and clusters may be different under these alternative specifications. Finally, there could be other factors not measured that would explain the observed geo-spatial patterns. We believe the results motivate further analysis of individual vaccination decisions and the potential role of network effects through information transmission about influenza vaccination (positive and negative) and potential free-rider problems caused by perceived herd immunity (i.e., relying on others to vaccinate to protect your child from exposure).

Table 1. Summary Statistics for ZIP Code Tabulation Areas (ZCTA) in North Carolina (N=769 ZCTAs; proportions unless otherwise noted)

	Mean	SD	Min	Max
Eligible pop.[a] (# of children)	1,014	1,241	2	8,786
Female	0.51	0.03	0.16	0.60
Hispanic[b]	0.07	0.06	0.00	0.47
Black, non-Hispanic	0.20	0.19	0.00	0.99
Other race/ethnicity	0.04	0.07	0.00	0.79
Less than high school[c]	0.18	0.09	0.00	0.50
At least some college	0.51	0.15	0.12	0.96
Below poverty	0.18	0.10	0.00	0.71
2010-2011 Influenza Season				
Publicly-funded influenza vaccinations (# of vaccinations)	181	239	0	1,805
Unemployed	0.11	0.02	0.07	0.17
Providers per 100 pop.	0.12	0.06	0.00	0.38
Health Professional Shortage Area	0.60	0.49	0.00	1.00
Outpatient visits[d] (# visits per capita)	1.97	1.49	0.00	10.86
3-year influenza & pneumonia deaths[d] (# of deaths per 1000 pop.)	0.14	0.13	0.00	0.61
Influenza-like illness ED visits[d] (# of visits per 100 school-aged children)	1.65	0.85	0.00	7.83
2011-2012 Influenza Season				
Publicly-funded influenza vaccinations (# of vaccinations)	205	274	0	2,126
Unemployed	0.11	0.02	0.07	0.18
Providers per 100 pop.	0.12	0.06	0.00	0.40
Health Professional Shortage Area	0.60	0.49	0.00	1.00
Outpatient visits[d] (# visits per capita)	1.83	1.28	0.00	7.71
3-year influenza & pneumonia deaths[d] (# of deaths per 1000 pop.)	0.15	0.14	0.00	0.68
Influenza-like illness ED visits[d] (# of visits per 100 school-aged children)	1.43	0.82	0.00	7.13

a. Uninsured and means-tested, publicly-insured children ages 5 to 17

b. White, Non-Hispanic is the reference group

c. High school is the reference group

d. Lagged values (i.e., 2009 for 2010-2011 and 2010 for 2011-2012)

Table 2. Global Test of Spatial Autocorrelation in Publicly-funded Influenza Vaccination Rates: Moran's I[a]

	2010-2011 Influenza Season		2011-2012 Influenza Season	
	Unadjusted	Negative Binomial Residuals	Unadjusted	Negative Binomial Residuals
Contiguity Matrix				
Moran's I	0.139	0.037	0.203	0.060
p-value	0.000	0.038	0.000	0.002
Inverse-Distance Matrix				
Moran's I	0.021	0.001	0.026	0.002
p-value	0.000	0.191	0.000	0.053

a. The expected value of Moran's I for 769 ZCTAs is -0.001.

Table 3. Publicly-funded Influenza Immunizations: Negative Binomial Models

	2010-2011		2011-2012	
	MLE	CAR	MLE	CAR
Female	0.433 [-1.212, 2.078]	-0.026 [-1.168, 1.119]	0.949 [-0.738, 2.635]	0.605 [-0.521, 1.698]
Hispanic[a]	1.607** [0.857, 2.358]	1.897** [1.184, 2.635]	1.983** [1.183, 2.783]	2.096** [1.418, 2.772]
Black, non-Hispanic	0.029 [-0.239, 0.297]	0.479** [0.167, 0.787]	0.097 [-0.181, 0.375]	0.543** [0.214, 0.844]
Other race/ethnicity	0.214 [-0.441, 0.870]	0.530* [-0.089, 1.144]	0.354 [-0.281, 0.989]	0.546* [-0.074, 1.171]
Less than high school[b]	-0.926 [-2.122, 0.271]	-0.484 [-1.283, 0.305]	-0.611 [-1.798, 0.577]	-0.193 [-0.959, 0.576]
At least some college	-0.471 [-1.078, 0.135]	-0.051 [-0.557, 0.437]	-0.179 [-0.805, 0.447]	-0.053 [-0.526, 0.399]
Below poverty	-0.904** [-1.668, -0.141]	-1.310** [-1.839, -0.791]	-0.809** [-1.520, -0.098]	-1.332** [-1.855, -0.820]
Unemployed	-3.770** [-6.495, -1.044]	-3.118* [-6.597, 0.043]	-1.587 [-4.316, 1.141]	-2.076 [-5.507, 0.989]
Providers per 100 pop.	2.195** [1.228, 3.163]	0.764 [-0.290, 1.762]	1.955** [1.077, 2.833]	0.947* [-0.104, 2.018]
Health Professional Shortage Area	-0.215** [-0.296, -0.133]	-0.127** [-0.227, -0.034]	-0.192** [-0.275, -0.108]	-0.131** [-0.227, -0.036]
Outpatient visits per capita[c]	-0.034** [-0.065, -0.002]	-0.000 [-0.041, 0.038]	-0.048** [-0.084, -0.011]	-0.011 [-0.060, 0.041]
3-year influenza & pneumonia deaths per 1000 pop.[c]	0.037 [-0.372, 0.445]	-0.031 [-0.419, 0.385]	0.485** [0.102, 0.868]	0.099 [-0.301, 0.524]
Influenza-like illness ED visits per 100 school-aged children[c]	0.068** [0.013, 0.124]	0.031 [-0.028, 0.092]	0.053** [0.003, 0.103]	0.054* [-0.005, 0.116]
ln(Eligible pop.)[d]	0.799** [0.751, 0.848]	0.831** [0.804, 0.860]	0.786** [0.739, 0.833]	0.837** [0.808, 0.866]

Constant	4.487**	4.394**	4.607**	4.502**
	[4.442, 4.532]	[4.371, 4.419]	[4.562, 4.651]	[4.480, 4.525]
α (parameter of negative binomial distribution)	0.226**	0.066**	0.236**	0.058**
	[0.194, 0.263]	[0.048, 0.086]	[0.202, 0.275]	[0.043, 0.076]
σ^2_u (variance of spatial error)		0.444**		0.445**
		[0.350, 0.550]		[0.360, 0.538]
Observations	769	769	769	769

MLE = maximum likelihood estimation, CAR = conditional autoregressive.

Point estimates (MLE) and posterior means (CAR) reported. 95% confidence intervals (MLE) and 95% credible intervals (CAR) in brackets.

* $p < 0.10$, ** $p < 0.05$

a. White, Non-Hispanic is the reference group

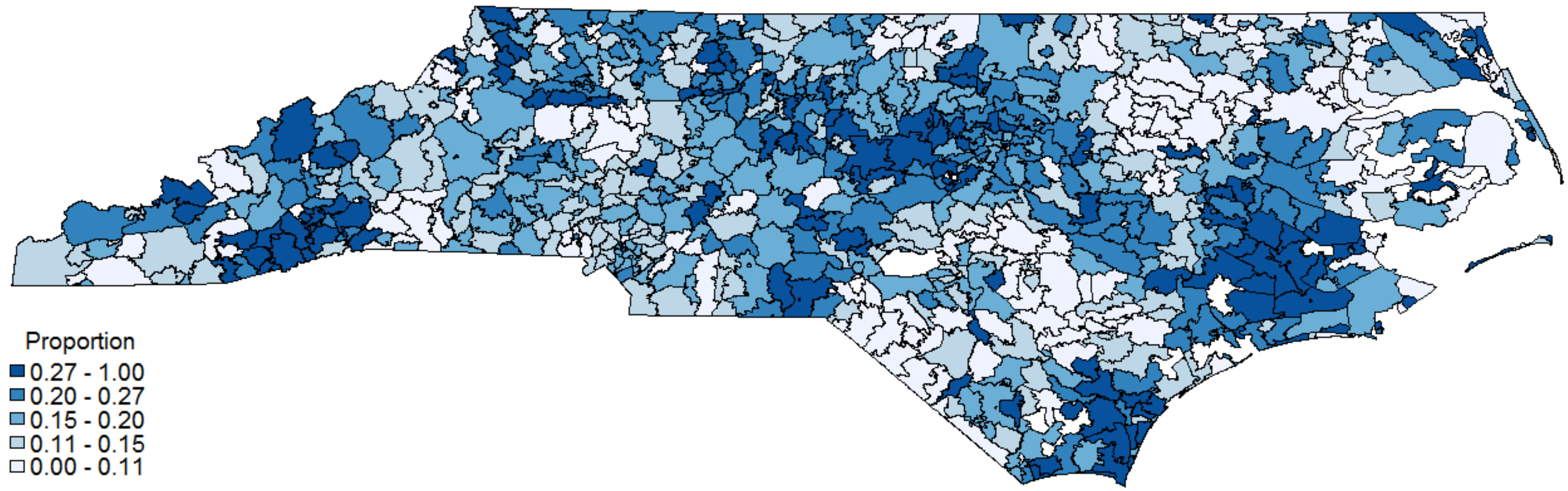
b. High school is the reference group

c. Lagged values (i.e., 2009 for 2010-2011 and 2010 for 2011-2012)

d. Uninsured and means-tested, publicly-insured children ages 5 to 17

Figure 1. Proportion of uninsured and means-tested, publicly-insured children ages 5 to 17 vaccinated against influenza using public funds (unadjusted rates)

A. 2010-2011



B. 2011-2012

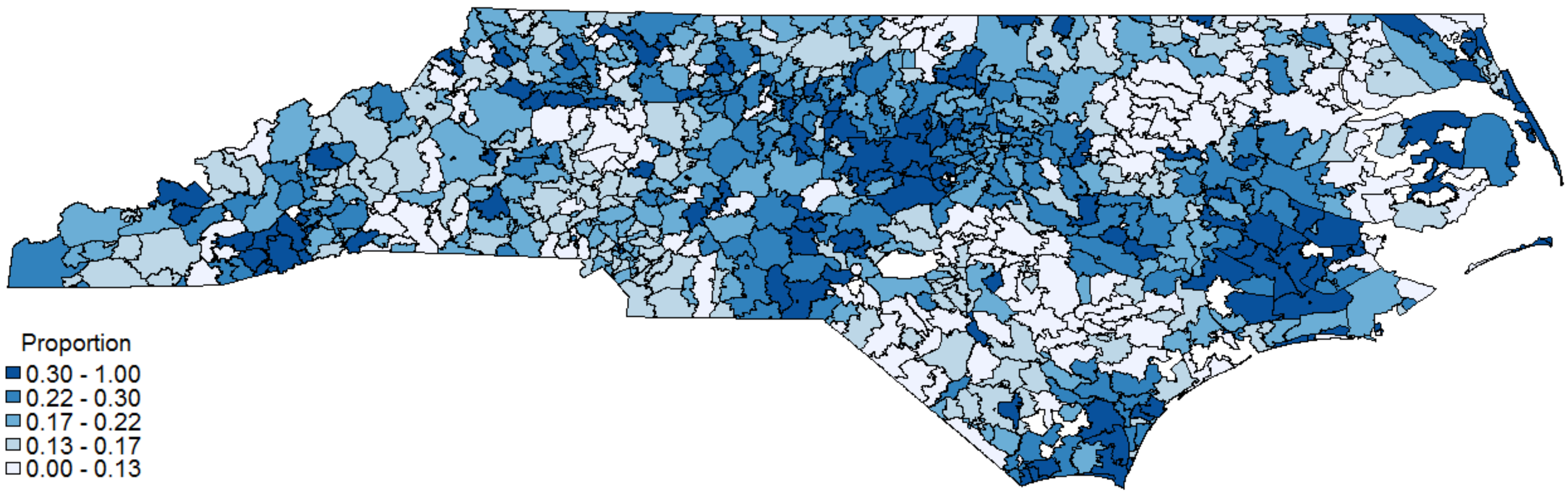
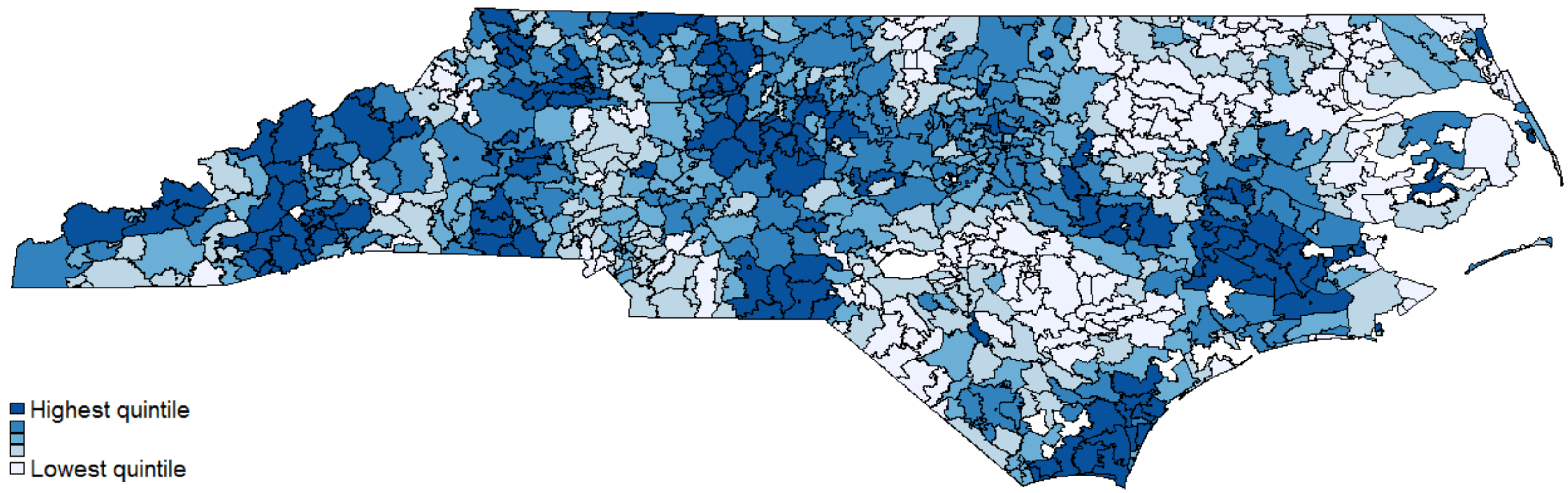
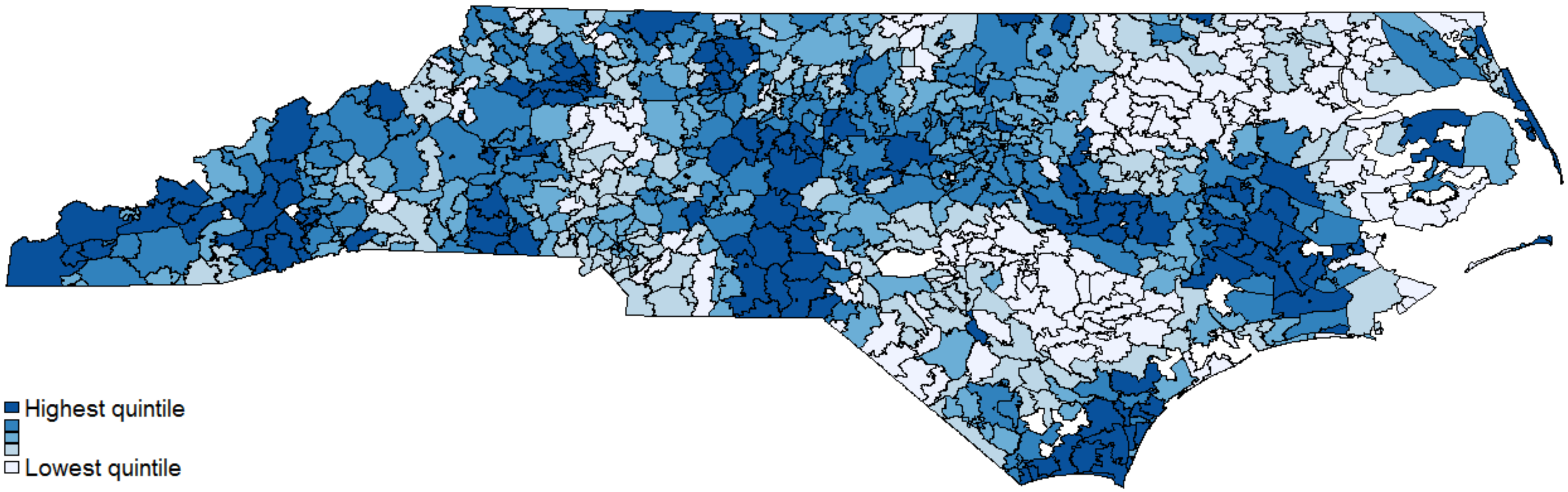


Figure 2. Publicly-funded influenza vaccination rates attributable to conditional autoregressive random effects

A. 2010-2011



B. 2011-2012



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