Emulation of Community Water Fluoridation Coverage Across U.S. Counties

Authors

John A. Curiel, Political Science, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, United States.

Anne. E. Sanders, Division of Pediatrics and Public Health, UNC Adams School of Dentistry, Chapel Hill, North Carolina, United States.

Gary D. Slade, Division of Pediatrics and Public Health, UNC Adams School of Dentistry, Chapel Hill, North Carolina, United States.

Word count

Word count: Introduction to Acknowledgments: 3,163

Total word count (Abstract to Acknowledgments): 3,440

Total number of tables/figures: 2 Tables, 3 Figures

Number of references: 33

Six keywords: Fluoridation; Health Literacy; Socioeconomic Factors; United States; Geographic Locations; Regression Analysis
ABSTRACT

Expansion of community water fluoridation has stalled in the United States, leaving 115 million Americans without fluoridated drinking water. This study used spatial regression methods to assess contributions of supply side factors (neighboring counties' fluoridation coverage) and demand side factors (health literacy, education, and population density of the local county) in predicting extent of fluoridation in U.S. counties. For this cross-sectional ecological analysis, data from the 2014 Water Fluoridation Reporting System for all 3,135 U.S. counties were merged with sociodemographic data from the 2014 American Community Survey and county-level estimates of health literacy based on the National Association of Adult Literacy Survey. We employed multilevel geographically weighted autoregressive models to predict fluoridation coverage of each county as a function of fluoridation coverage of neighboring counties and local-county covariates: either health literacy or sociodemographic characteristics. Akaike's Information Criterion (AIC) was used to distinguish the better model in terms of explanatory power and parsimony. In the best-fitting model, an increase equivalent to the interquartile range of neighboring counties' fluoridation coverage was associated with an increase of 25 percentage points (95% confidence limits[CL]=24.12, 30.14) in local county's fluoridation coverage while an increase equivalent to the interquartile range of local county's health literacy was associated with an increase of eight percentage points (95%CL=6.00,9.81). The results are consistent with a process of emulation, in which counties implement fluoridation based upon their population's health literacy and the extent of fluoridation practiced in neighboring counties. These results suggest that demand for community water fluoridation will increase as health literacy increases within a county. Furthermore, when considering expansion of fluoridation, non-fluoridated communities can benefit from precedents from nearby communities that are fluoridated.
INTRODUCTION

Community water fluoridation, a great public health achievement of the last century, is under threat. Following the initial growth phase of fluoridation in America during the early to mid-twentieth century,(Banfield and Wilson 1963) implementation of fluoridation slowed down considerably.

Within the U.S., local governments, such as water districts, townships, and counties, bear primary responsibility in deciding whether or not to fluoridate public water systems. Given the historical contentious politics surrounding fluoridation and misinformation arising from anti-fluoridation groups,(Crain et al. 1969) many local governments succumb to electoral pressure and decide against fluoridation. Nowadays, as opposed to the mid-20th century wave, access to fluoridation spreads locality by locality, often in bitter electoral battles.

Roger’s Theory of Diffusion (Rogers 2003) might explain the stalled spread of fluoridation. Roger’s Theory posits that diffusion of innovative policies requires more than demonstrable evidence of policy success and effectiveness. Additionally, the people and organizations who adopt innovations must assess a policy as advantageous as dependent upon their capability to learn. Potential adopters assess a successful policy as effective conditional upon two factors, supply and demand side. Supply side factors in learning consist of the body of evidence in favor of a policy or the credibility and association of those vouching for the policy, i.e. environmental level variables. Demand side factors includes features related to the potential for the policy adopter in question to process information and benefit from the policy in question (Des Jarlais et al. 2006).

There are precedents for states and localities to emulate the successful practices of neighbors. Office holders and administrators from neighboring innovative localities learn of the costs and savings, and its citizens are more likely to interact with those who benefitted from a policy (Karch 2007; Walker 1969). For many policies, emulation has been difficult to demonstrate because objective signs of policy success have not been readily apparent (Barabas et al. 2014; Karch 2007). However, this does not apply to fluoridation, given objective evidence that it reduces dental caries, and the fact that there is no tangible drawback other than the initial costs to implement (Centers for Disease Control and Prevention 1999). Therefore, we expect that as the total coverage of fluoridation in neighboring areas increases, so too will fluoridation within the local county.

We posit that these supply and demand side factors help to account for localities’ adoption of fluoridation. Specifically, we hypothesize that a county’s decision to adopt fluoride is determined by whether neighboring counties adopt fluoride on the supply side and the local county’s ability to process and understand the benefits of fluoride via health literacy on the demand side (Curiel et al. 2018; Curiel et al. 2019). Following an emulation model, where policy diffusion is influenced by potential adopters’ capability to learn from geographic neighbors, we expect that a local county’s extent of fluoridation coverage will be influenced by greater fluoridation coverage in in neighboring counties and the local county’s health literacy, with the latter signifying the local county’s ability to discriminate scientific from pseudo-scientific evidence.
METHODS

Study Design and Dependent Variable

This ecological analysis used cross sectional data from WFRS on the percentage of public water systems fluoridation coverage within American counties for the year 2014 as our dependent variable. The dataset calculates coverage as the number of county residents with access to a fluoridated public water system, divided by the total number of residents on a public water system. The data covers 3,135 counties. A spatial linear regression with state fixed effects analyzed the extent to which factors of interest associate with fluoridation coverage within U.S. counties for the year 2014. We use.

Independent variables

Our primary independent variable of interest is the health literacy for a given county. Health literacy is a latent variable, which we approximate given how health literacy correlates with measurable variables at the county level. We calculated county health literacy scores from the predictive model established to analyze health literacy in voter precincts (Curiel et al. 2019), which calculates factors of health literacy for geographic units using Multilevel Regression with Post-stratification (MRP) from the National Association of Adult Literacy (NAAL) survey conducted in 2003. The model predicts health literacy as a combination of sociodemographic factors, including education, race, age, income, marital status, and region (Curiel et al. 2019). MRP methods guarantee the best sub-national level estimates of a construct of interest, and prevents temporal instability (Buttice and Highton 2013), making it ideal for this study. We employ the American Community Survey’s (ACS) 2014 estimates for population and sociodemographic characteristics, as acquired from Social Explorer (Social Explorer 2014). Through MRP, we weight the predictor sociodemographic variable effects by the proportion of the population matching the sociodemographic factors of interest present within each county.

The model additionally controlled for population density, population growth, and racial segregation. Population density was used because CWF becomes more economically viable in more urban areas (Saman et al. 2011). Hence, we expect sparsely populated and large geographic counties to be less amenable to initiating CWF. We measure density as the population per square mile of a county. Adjustment was made for population growth given that counties with large population growths might initially have some difficulty in connecting everyone to fluoridated water before catching up a few years later. It was expressed as the county’s percentage increase in population from the year 2000. Segregation was used as another covariate, given that some of the first cities to initiate fluoridation are legacy cities in regards to fluoridation (Banfield and Wilson 1963; Crain 1966), and we expect that highly segregated cities capture the historical progressive roots of fluoridation that maintain CWF to this day. It was measured using the Duncan and Duncan segregation index, which measures the proportion of a population that would need to move in order for every census block group of a county to reflect the county’s racial proportions (Duncan and Duncan 1955; Hong et al. 2014).

Given that the potential confounders, in the form of sociodemographic variables, were used in construction of county-level health literacy variable, separate models were used for sensitivity analysis: one used the derived,
health literacy variable, and the other used sociodemographic variables. These two models contrast the explanatory power of health literacy versus its component parts, which determine whether health literacy, as a function of its components, is superior. Failing to do so would lead to a null effect for health literacy given the complete multicollinearity. Akaike’s Information Criterion (AIC) was used to determine the better model in terms of explanatory power and parsimony.

**Statistical analytic approach**

The linear regression geographically weighted autoregressive models (GWAM) used a contiguous neighbors approach to control for the primary potential source of potential bias and the supply side of emulation, neighboring county fluoridation coverage. The model weights the average fluoridation of neighboring counties based upon a spatial matrix coded as 1 for neighboring counties, and 0 otherwise. Within the spatial error term are two potential effects. First is the general error caused by aggregation bias (Gotway Crawford and Young 2004), where aggregating water system level fluoridation to the county level might cause measurement error. Although water systems correlate with county boundaries, as only several to a dozen water companies aggregate up to counties, there is the potential for a scaling problem when water systems cross county boundaries. Therefore, fluoridation coverage should be correlated between neighboring counties. Additionally, given the learning nature of emulation, the supply side effect of counties with successful experiences with fluoridation that might teach neighboring non-fluoridated counties is also captured within the spatial error term. Although GWAM usually treats spatial errors as a nuisance, we are interested in the effect of spatial neighbors given that the spatial variable captures at least partially the diffusion mechanism (Calvo and Escolar 2004), and can therefore proceed with neighbor effects as the best method to reduce the inefficiency and bias that arises from spatial correlated errors. In the final model, the spatial error therefore comprises the upper limit of the impact of supply side effects. The model was created with the spatial moving error formula from R’s spdep package.

**RESULTS**

Summary statistics for the dependent and independent variables (Table 1) confirm sufficient variance within the dataset to conduct the analyses of interest. Health literacy scores ranged from 209 to 340 across counties, while health literacy among individuals ranged from 0 – 500, with higher scores reflecting greater health literacy. Within aggregated geographic unit data, the range of scores was narrower, but offered sufficient variance. Population coverage of water fluoridation coverage varied from 0 to 100 percent, with a mean of 49 percent.

Figure 1 presents an example of observed spatial dependence and spatial clustering within California. The Figure demonstrates how fluoridation coverage is far from uniform, in addition to the network of influences for each county within the state. Most counties had between 3-6 neighbors that might influence the local county’s decision to adopt fluoride. For example, the northern part of California had low fluoridation coverage, meaning that most counties are expected to remain fairly static in their decision to not fluoridate so long as they do not have fluoridated neighboring counties and water systems to emulate.
Figure 2 presents a cartogram of fluoride coverage by county. The cartogram presents the fluoride coverage for U.S. counties, where county size is weighted by population so that more populated counties appear larger despite their small geographic size. It draws attention to the clustering of fluoridated counties, with largest non-fluoridated county populations in the western and northeastern United States.

Table 2 presents results of the GWAM models for fluoridation coverage based upon the county level covariates. Model 1, showed a positive and significant effect for both health literacy and neighbors with fluoridation. A one unit increase in health literacy was associated with a 0.43 percentage point increase in fluoridation coverage. With other variable held equal, an increase in health literacy from the 25th to the 75th percentile was associated with an increase fluoridation coverage by nearly eight percentage points (95% confidence limits[CL]=6.00, 9.81). An increase in the fluoridation coverage of neighbors with fluoridation from the 25th to 75th percentiles was associated with an average increase of 25 (95%CL=24.12, 30.14) percentage points in fluoridation coverage, all else equal.

The estimates for model 2, which comprised the theoretical sociodemographic variables of interest, outperformed the health literacy model, with a lower Akaike Information Criterion by 218. This suggests that the explanatory power of the sociodemographic variables exceeds the penalty for the increased number of covariates. Variables present in both models exhibit the same direction of association and reach statistical significance. This includes the local county’s population density, segregation, and population growth.

For the variables unique to model 2, the education and age variables also were associated with fluoridation coverage. For age, a one percentage point increase of individuals 25 – 45 years of age was associated with an increase of 0.5 percentage points of fluoridation coverage, relative to those under the age of 25. However, a one percentage point increase of individuals over the age of 45 was associated with an approximate 0.9 decrease in fluoridation coverage relative to those under the age of 25. For education, a one percentage point increase of the percentage of population with greater-than high school education is associated with an increase in fluoridation coverage by 0.67 percentage points.

In order to visualize the impact of some of the key explanatory variables of interest, predicted effects are plotted in Figure 3. Positive associations with local county fluoridation coverage are seen for health literacy and neighboring counties’ fluoridation, and both exhibiting similar confidence intervals, with only a slight difference in intercepts. The magnitude of the predicted increase in local county fluoridation is of public health relevance: for example, an increase in fluoridation coverage from 20 percent to 60 associated with both reduced caries and reduced income-inequality in caries for children (Sanders et al. 2019). Figure 3 also shows that the effect of population density is largely driven by the majority of counties with a population under 10,000 individuals per square mile. That said, increasing the people per square mile from the least populated counties to 10,000 per square mile is associated with an increase in fluoridation by over ten percentage points.
Overall, these results demonstrate support for emulation in explaining distribution of CWF among U.S. counties. Knowledge, whether it take the form of health literacy or the percentage of a population with education beyond high school, both significantly increase the percentage of fluoridation coverage. The positive effects for knowledge capture the demand side of emulation based diffusion. The effect estimate for knowledge are of public health important and are the multilevel spatial regression model means that the results are robust to geographic clustering and state effects. Although the spatial error captures both omitted variables and the supply side of diffusion, the estimated effect of diffusion appears strong enough so as to imply a substantive supply side effect for emulation. Even should three quarters of the spatial error term be due to omitted variable bias, the impact would still reach substantive significance. These results also speak to the objective nature of fluoridation benefits. Were it the case that fluoridation did not benefit dental health, and even harmed the health of individuals, there would not be such a strong positive effect for geographic neighbors.

These results have particular relevance for fluoridation in the United States. Unlike the indirect influence of public support for fluoridation in most other industrialized democracies (Akers et al. 2005), the U.S., and some cities in Canada, allow citizens to decide directly upon the initiation and funding of public water fluoridation (Hahn 1968). The mere presence of opposition to fluoride is often sufficient to throw elections to initiate fluoride into doubt(Mueller 1966), and fluoride is among the most contentious of local issues decided in local politics (Hahn 1968). Although the scientific field has thoroughly rebutted the myths surrounding the dangers of fluoridation, from cancer (Chilvers 1982), arthritis (Phipps et al. 2000), and proclivity to communism (Crain 1966), the emotional appeals and scientific sounding arguments of fluoridation’s opponents is sufficient so as to lead risk averse voters to maintain the status quo (Christoffel 1985; Curiel et al. 2018). Only if voters can distinguish between the methods, or discern reliable sources from unreliable ones, might they discard unsound arguments employed by anti-fluoridation campaigners (Curiel et al. 2019; Sapolsky 1968; Sapolsky 1969). The Freidan Health Impact Pyramid (FHIP) as applied to dental health suits the fluoridation adoption process fairly well. At the bottom of the FHIP are socioeconomic factors that form the foundation of the determinants of health, which includes health literacy (Frieden 2010; Kumar and Rosanna 2018). Unlike race and age, however, health literacy, the “capacity to obtain, process and understand basic oral health information and services needed to make appropriate oral health decisions” (AMA Council on Scientific Affairs 1999; Kumar and Rosanna 2018), health literacy can be improved. It is important to note that the FHIP applied to dental health places fluoridation as the base for environmental interventions to improve public health. However, whether a locality can implement CWF depends upon whether elected officials do not suffer backlash from concerned voters over fluoridation, or if voters themselves in deciding CWF feel that the benefits of CWF outweigh the minimal costs. Whether voters vote an official out of office or vote against fluoride directly depends upon the voter’s understanding of the scientific basis for fluoride. Therefore, we expect that as the knowledge base of a county increases, so too will fluoridation coverage.

These results are both promising in understanding how and why fluoride expands, along with concerning. Given that the strongest predictors of fluoridation are an educated populace and neighbors with fluoride, this suggests
that access to fluoridation will remain clustered and unequal. Prior research on economic development suggests that the greatest determinant of county economic and population growth to be an educated populace (Hoyman and Faricy 2009), and metropolitan areas (Nall 2018). Therefore, the areas with the least access to fluoridation and dentists, dental crisis areas, are also the places least hospitable to fluoridation adoption. Without some exogenous shock, fluoridation diffusion will be slowest in aiding the places most in need of fluoride. On a positive note, although most public health initiatives tend to suffer in the presence of racial segregation (Nall 2018), fluoride’s origins in urban areas that also happened to be segregated by income has carried over to aid racial minorities in segregated counties. Although segregation is far from ideal from a societal perspective, it is fortunate that at least in regards to dental health, racial minorities do not suffer from yet another structural barrier to health care (Zaslavsky and Ayanian 2005).

Therefore, if fluoridation is to expand to the places most in need, it will take a concerted effort and strategy. In particular, fluoridation advocates should seek to expand fluoridation to counties neighboring counties with higher levels of fluoridation. In the event that anti-fluoridation forces seek to scare voters or elected officials with pseudo-science and emotionally laden rhetoric, fluoridation advocates can point to both the large body of research supporting fluoride, and their neighbors to disprove the anti-fluoride message. Additionally, for fluoridation deserts where no counties in the area have access to fluoridation, pro-fluoridation advocates should target areas with the highest levels of health literacy or education overall. Upon gaining a foothold with the initiation of fluoride, fluoride advocates and expand fluoridation from there. In regards to identifying areas of interest, either health literacy or proportion with above a high school education seems appropriate. Although the ACS sociodemographic model outperforms health literacy, it should be noted that such a finding should not be unexpected given that we employed counties as our unit of analysis. Health literacy works best at the individual level, or small geographic units, such as census block groups, ZIP codes, or voter precincts. This is the case given the scaling problem that occurs whenever aggregating up individuals to larger units of geography (Gotway Crawford and Young 2004). Health literacy might also be better to employ when targeting potential areas for fluoridation expansion, given that it collapses the relevant sociodemographic factors onto a single dimension that is easier to map out than its component parts.

One shortcoming of this work is the cross sectional analysis using county fluoridation data from a single year. We were forced to employ a cross section of counties given that the historical data on fluoridation coverage is only by state, not county. However, it should be noted that the spatial regression model employed addresses much of the concerns associated when employing cross sectional data. Additionally, these results found here mirror the results found in analyzing voter support for fluoridation (Curiel et al. 2019). The impact for health literacy and those with above a high school education are positive and significant in both studies. Therefore, these works combined strongly suggest that knowledge, and health literacy in particular, are crucial in explaining support and adoption of community water fluoridation.

**ACKNOWLEDGEMENT**

Supported by NIH/NIDCR UH2DE025494
REFERENCES


FIGURES

Figure 1: Choropleth map of fluoride coverage within California counties, 2014.

Hollow dots reflect the centroids of each county, and solid lines reflect the neighboring counties’ contributions to the spatial error term.
Figure 2: Cartogram of fluoride coverage by county.

County sizes are weighted by population following the Gastner-Newman method in ArcGIS. Smaller polygons reflect counties with smaller populations, and larger polygons larger populations. Counties in darker blue reflect greater fluoridation coverage.
Figure 3: Predicted county-level fluoridation from geographically weighted autoregressive models

The plots demonstrate the predicted fluoridation coverage for health literacy (Model 1, Table 1), neighboring fluoridation coverage (Model 1, Table 1), population density (Model 1, Table 2), and education (Model 2, Table 2). The independent variables are plotted on the x-axes, with a rug plot marked by ticked lines demonstrating the distribution of the independent variables of interest. Solid lines reflect predicted percent fluoridation coverage, with dashed lines reflecting the 95% confidence intervals.
## Tables

### Table 1: Summary statistics

<table>
<thead>
<tr>
<th>County statistic</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>25th pct.</th>
<th>75th pct</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population per square mile</td>
<td>3,142</td>
<td>264.1</td>
<td>1763.8</td>
<td>0.0</td>
<td>16.8</td>
<td>114.8</td>
<td>70893.2</td>
</tr>
<tr>
<td>% of population fluoridated</td>
<td>3,137</td>
<td>49.1</td>
<td>34.3</td>
<td>0.0</td>
<td>15.2</td>
<td>79.2</td>
<td>100.0</td>
</tr>
<tr>
<td>% population growth</td>
<td>3,135</td>
<td>5.3</td>
<td>13.2</td>
<td>-46.6</td>
<td>-2.5</td>
<td>10.2</td>
<td>110.4</td>
</tr>
<tr>
<td>Health literacy index</td>
<td>3,142</td>
<td>276.9</td>
<td>14.0</td>
<td>209.0</td>
<td>267.5</td>
<td>285.9</td>
<td>340.6</td>
</tr>
<tr>
<td>Segregation index</td>
<td>3,143</td>
<td>29.2</td>
<td>13.9</td>
<td>0.0</td>
<td>19.0</td>
<td>37.7</td>
<td>88.4</td>
</tr>
<tr>
<td>% educated beyond high school</td>
<td>3,142</td>
<td>50.2</td>
<td>10.7</td>
<td>21.3</td>
<td>42.3</td>
<td>57.3</td>
<td>87.9</td>
</tr>
<tr>
<td>% educated high school only</td>
<td>3,142</td>
<td>34.8</td>
<td>7.0</td>
<td>8.7</td>
<td>30.3</td>
<td>39.7</td>
<td>64.5</td>
</tr>
<tr>
<td>% non-White</td>
<td>3,142</td>
<td>16.3</td>
<td>16.6</td>
<td>0.0</td>
<td>4.4</td>
<td>22.7</td>
<td>95.9</td>
</tr>
<tr>
<td>% aged ≥45 years</td>
<td>3,142</td>
<td>44.6</td>
<td>6.7</td>
<td>13.5</td>
<td>40.6</td>
<td>48.4</td>
<td>79.7</td>
</tr>
<tr>
<td>% aged 25 - 44 years</td>
<td>3,142</td>
<td>23.5</td>
<td>3.3</td>
<td>9.7</td>
<td>21.5</td>
<td>25.2</td>
<td>44.1</td>
</tr>
<tr>
<td>% below poverty level</td>
<td>3,142</td>
<td>16.8</td>
<td>6.5</td>
<td>1.0</td>
<td>12.1</td>
<td>20.3</td>
<td>52.6</td>
</tr>
</tbody>
</table>
Table 2: geographically weighted autoregressive model predicting county fluoridation coverage and county level covariates, 2010

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Model 1: Health literacy model</th>
<th>Model 2 Sociodemographic model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>S.E.</td>
</tr>
<tr>
<td>Population per square mile</td>
<td>0.0002 ***</td>
<td>0.0003</td>
</tr>
<tr>
<td>Health literacy index</td>
<td>0.439 ***</td>
<td>0.054</td>
</tr>
<tr>
<td>Segregation index</td>
<td>0.484 ***</td>
<td>0.041</td>
</tr>
<tr>
<td>% population growth</td>
<td>-0.096 **</td>
<td>0.047</td>
</tr>
<tr>
<td>% educated high school only</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% educated beyond high school</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% aged 25 - 44 years</td>
<td>0.517 **</td>
<td>0.247</td>
</tr>
<tr>
<td>% aged ≥45 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% non-White</td>
<td>0.039</td>
<td>0.057</td>
</tr>
<tr>
<td>% below poverty level</td>
<td>-0.016</td>
<td>0.135</td>
</tr>
<tr>
<td>Constant</td>
<td>-79.952 ***</td>
<td>22.701</td>
</tr>
<tr>
<td>Spatial Error</td>
<td>0.424 ***</td>
<td>0.024</td>
</tr>
<tr>
<td>State fixed effects</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>3,135</td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-14,808.7</td>
<td></td>
</tr>
<tr>
<td>Akaike Information Criterion</td>
<td>29,731.3</td>
<td></td>
</tr>
</tbody>
</table>

* p<0.1, **p<0.05, ***p<0.01