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Emulation of Community Water Fluoridation Coverage Across US Counties

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Abstract: ***Introduction:*** *Expansion of community water fluoridation has stalled in the United States, leaving 115 million Americans without fluoridated drinking water.*

Objective: *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 the extent of fluoridation in US counties.*

Methods: *For this cross-sectional ecological analysis, data from the 2014 Water Fluoridation Reporting System for all 3,135 US 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 was used to distinguish the better model in terms of explanatory power and parsimony.*

Results: *In the best-fit model, an increase from the first to third quartile of neighboring counties' fluoridation coverage was associated with an increase of 27.76 percentage points (95% confidence limits [CI] = 27.71, 27.81) in a local county's fluoridation coverage, while an increase from the first to third quartile of local county's health literacy was associated with an increase of 2.8 percentage points (95% CL = 2.68, 2.89). 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.*

Conclusion: *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.*

Knowledge Transfer Statement: *Expanded coverage of community water fluoridation has stalled in the United States. The economic theory of diffusion describes how, over time and space, policy enacted in one community can influence public opinion in a neighboring community. This study applies geospatial analysis of county-level data and the theory of policy diffusion to demonstrate that fluoridated counties can promote the implementation of community water fluoridation in their neighboring, non-fluoridated communities.*

Keywords: health literacy, socioeconomic factors, United States, geographic locations, regression analysis, public health dentistry

Introduction

Community water fluoridation, a great public health achievement of the last

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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 considerably.

Within the United States, local governments, such as water districts, townships, and counties, bear the primary responsibility in deciding whether or not to fluoridate public water systems. Given the historical contentious politics surrounding fluoridation and misinformation arising from antifluoridation groups (Crain et al. 1969), many local governments succumb to electoral pressure and decide against fluoridation. Presently, as opposed to the mid-twentieth century support, access to fluoridation spreads locality by locality, often in bitter electoral battles. Furthermore, public skepticism about community water fluoridation is now amplified by “fake news” and the perception of nanny state laws (i.e., the belief that government policy interferes unduly in personal choice). Meanwhile, the debate for (Cockcroft and Donaldson 2007) and against (Cheng et al. 2007) fluoridation continues in the general medical literature as it does in the public health literature (both for [Friedman 2016] and against [Carstairs 2015] fluoridation).

Rogers’ Theory of Diffusion (Rogers 2003) might explain the stalled spread of fluoridation. Rogers’ 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, which itself is dependent upon their capability to learn. Potential adopters assess a successful policy as effective conditional upon 2 factors: supply side 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 include 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 citizens are more likely to interact with those who benefitted from a policy (Walker 1969; Karch 2007). For many policies, emulation has been difficult to demonstrate because objective signs of policy success have not been readily apparent (Karch 2007; Barabas et al. 2014). 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 fluoridation is determined by whether neighboring counties adopt fluoridation on the supply side and the local county’s ability to process and understand the benefits of fluoridation 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 neighboring counties and the local county’s health literacy, with the latter signifying the local county’s ability to discriminate credible science from misleading assertions.

Methods

Study Design and Dependent Variable

This ecological analysis used cross-sectional county-level data from the Water Fluoridation Reporting System (Slade et al. 2018) that lists the percentage of people receiving water from a fluoridated public water system for the year 2014. The dataset calculates the percentage 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 cover 3,135 counties. A spatial linear regression with state fixed effects analyzed the extent to which factors of interest associate with fluoridation coverage within US counties for the year 2014. The model used state as a fixed effect, which means that any findings are less likely to be due to unmeasured variances between the states.

Independent Variables

Our primary independent variable of interest is the health literacy of 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 estimates the best predictors of health literacy among survey respondents, and then applies the factors to geographic units, a method known as multilevel regression with poststratification (MRP). The initial survey results used to estimate health literacy were 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 subnational 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 demographic 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, wealth inequality, and racial segregation. Logged population density was used because fluoridation 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 fluoridation. We measure density as a county's logged population per square mile. 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. Wealth inequality, as measured by the Gini coefficient for counties, was employed as a potential covariate of interest. Segregation was used as another covariate, given that some of the first cities to initiate fluoridation are legacy cities in regard to fluoridation (Banfield and Wilson 1963; Crain 1966), and we expect that highly segregated cities capture the historical progressive roots of fluoridation that maintain fluoridation 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 a 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 2 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 2 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 up to a dozen water companies aggregate up to counties (Gotway Crawford and Young 2004), 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 nonfluoridated 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 the "spdep" package in the statistical program R.

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 ranges from 0 to 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%, with a mean of 49%.

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 showing the network of influential factors for each county within the state. Most counties had between 3–6 neighbors that might influence the local county's decision to adopt fluoridation. 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 fluoridation coverage by county. The cartogram presents the fluoridation coverage for US 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 the largest nonfluoridated county populations located in the western and northeastern United States.

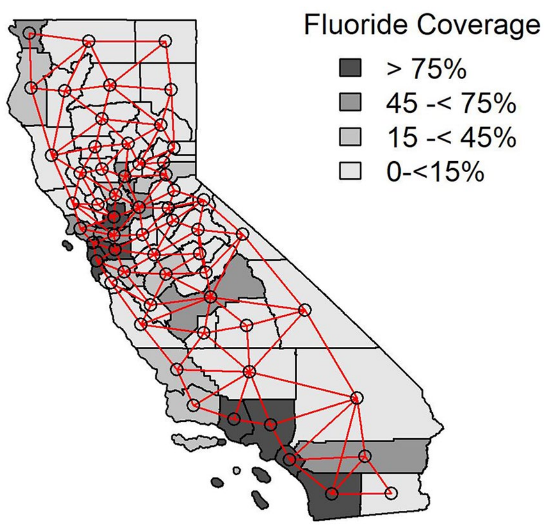
Table 2 presents results of the GWAM models for fluoridation coverage based upon the county level covariates. Model 1 showed a positive and significant effect for both health literacy

Table 1.
Summary Statistics.

County Statistic	*n*	Mean	SD	Min	25th pct	75th pct	Max
Log population per square mile	3,142	3.8	1.8	–3.3	2.8	4.7	11.2
% of population fluoridated	3,137	49.1	34.3	0.0	15.2	79.2	100.0
% population growth	3,135	5.3	13.2	–46.6	–2.5	10.2	110.4
Health literacy index	3,142	276.9	14.0	209.0	267.5	285.9	340.6
Segregation index	3,143	29.2	13.9	0.0	19.0	37.7	88.4
% educated beyond high school	3,142	50.2	10.7	21.3	42.3	57.3	87.9
% educated high school only	3,142	34.8	7.0	8.7	30.3	39.7	64.5
% non-White	3,142	16.3	16.6	0.0	4.4	22.7	95.9
% aged ≥45 y	3,142	44.6	6.7	13.5	40.6	48.4	79.7
% aged 25–44 y	3,142	23.5	3.3	9.7	21.5	25.2	44.1
Gini coefficient	3,142	44.0	3.6	33.5	41.8	46.1	65.2
% below poverty level	3,142	16.8	6.5	1.0	12.1	20.3	52.6

pct, percentile.

Figure 1. Choropleth map of fluoridation 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.



and neighbors with fluoridation. A 1-unit increase in health literacy was associated with a 0.13 percentage point increase in fluoridation coverage. With other variables held equal, an increase in health literacy from the 25th to the 75th percentile was therefore associated with an increase fluoridation coverage by nearly 3 percentage points (95% confidence limits [CL] = 2.68, 2.89). An increase in the fluoridation coverage of neighbors with fluoridation from the 25th to 75th percentiles was associated with an average increase of nearly 28 (95% CL = 27.71, 27.81) 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 AIC by 50. 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. Demand-side factors include the local county's population density, segregation, wealth inequality, and population growth.

For the variables unique to model 2, the education and age variables also were associated with fluoridation coverage. For age, a 1 percentage point increase of individuals over the age of 45 was associated with an approximate 0.6 decrease in fluoridation coverage relative to those under the age of 25. For education, a 1 percentage point increase of the percentage of population with greater-than high school education is associated with an increase in fluoridation coverage by 0.36 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

Figure 2. Cartogram of fluoridation coverage by county. County sizes are weighted by population following the Gastner-Newman method in ArcGIS software. Smaller polygons reflect counties with smaller populations, and larger polygons larger populations. Counties in darker blue reflect greater fluoridation coverage.

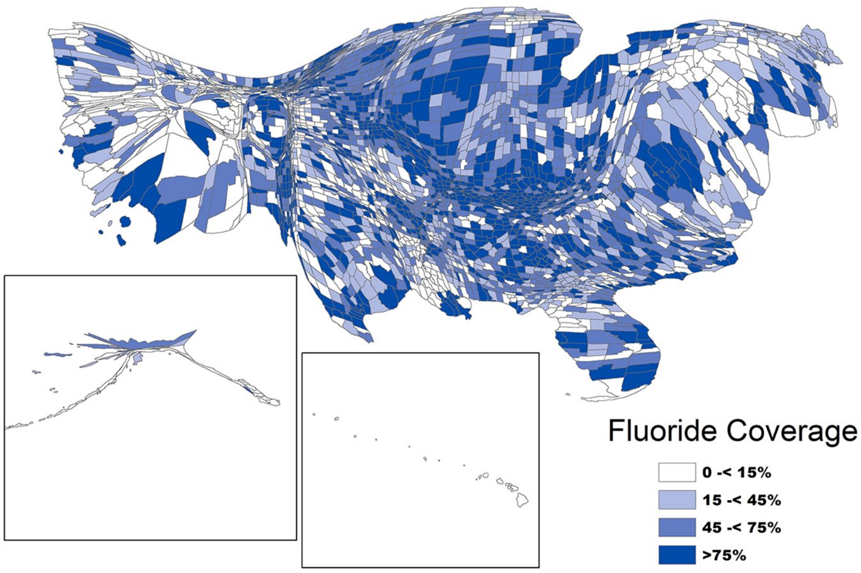
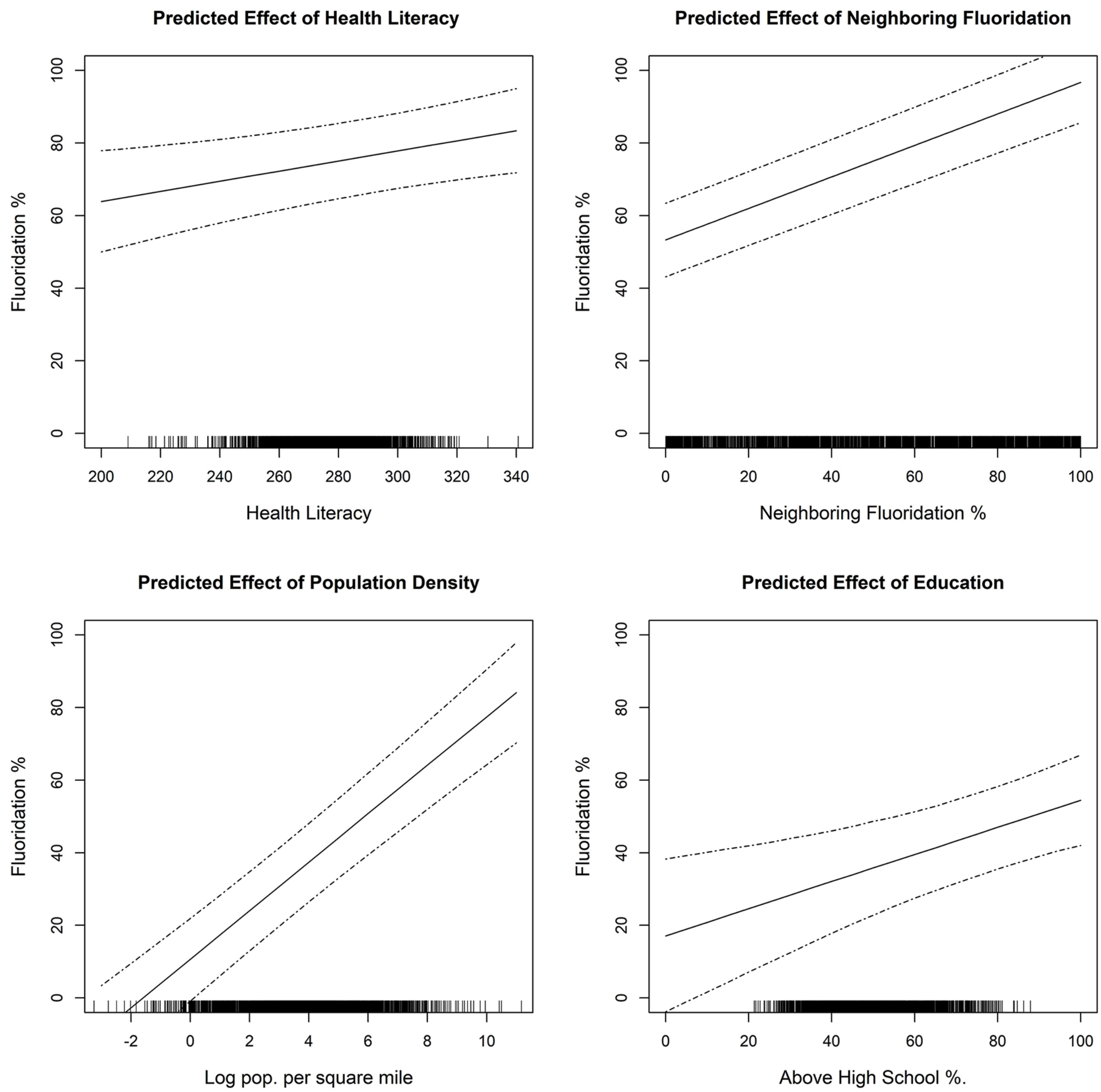


Table 2.
Geographically Weighted Autoregressive Model Predicting County Fluoridation Coverage using County Level Covariates, 2010.

Covariate	Health Literacy Model		Sociodemographic Model	
	Coefficient	SE	Coefficient	SE
Population per square mile	8.99***	0.50	6.68***	0.57
Health literacy index	0.14***	0.05		
Segregation index	0.21***	0.04	0.16***	0.04
Gini coefficient	0.39**	0.16	0.35*	0.19
% population growth	–0.31***	0.05	–0.44***	0.05
% educated high school only			–0.01	0.18
% educated beyond high school			0.37***	0.13
% aged 25–44 y			0.30	0.13
% aged ≥45 y			–0.57***	0.24
% non-White			0.03	0.06
% below poverty level			–0.10	0.15
% married			0.32	0.34
Constant	–57.59***	22.44	–30.94	40.45
Spatial error	0.43***	0.02	0.41***	0.02
State fixed effects	Yes		Yes	
Number of observations	3,135		3,135	
Log likelihood	–14,660		–14,630	
Akaike Information Criterion (AIC)	29,437		29,388	

SE, standard error.
**P* < 0.1. ***P* < 0.05. ****P* < 0.01.

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% CIs.



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% to 60% was associated with both reduced caries and reduced income inequality in caries for children (Sanders et al. 2019). Figure 3 also shows that logged population density is strongly associated with fluoridation, moving from no fluoridation to over 80% fluoridation from the least to most populous counties. These results suggest that logged population largely capture the feasibility of fluoridation, where rural counties are not susceptible to widespread public water systems, and, in turn, public water fluoridation. Though the uncertainty is greater for educational attainment, the covariate is also associated with an over 20 percentage point increase in fluoridation.

Discussion

Overall, these results demonstrate support for emulation in explaining distribution of fluoridation among US counties. Knowledge, in the form of health literacy and the percentage of a population with education beyond high school, associated with significant increases in the percentage of fluoridation coverage. The positive effects for knowledge capture the demand side of emulation-based diffusion. The effect estimate for knowledge is of public health importance and 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 fits the necessary condition for emulation to work as the causal mechanism (Rogers 2003), albeit not the sufficient condition. It is still possible that some omitted variable that cannot be captured with ACS variables might explain the spatial error, though at this time it is unclear what that might be. Even should 3 quarters of the spatial error term be due to omitted variable bias, the impact would still reach substantive significance. These results also suggest general positive experiences with fluoridation. Were it the case that fluoridation did not benefit dental health, and even harmed the health of individuals, it would be less likely to observe such a strong positive association with fluoridation between geographic neighbors, health literacy, and education.

These results have particular relevance for fluoridation in the US. Unlike the indirect influence of public support for fluoridation in most other industrialized democracies (Akers et al. 2005), the US, and some cities in Canada, allows citizens to decide directly upon the initiation and funding of public water fluoridation (Hahn 1968). The mere presence of opposition to fluoridation is often sufficient to throw elections to initiate fluoridation into doubt (Mueller 1966), and fluoridation is among the most contentious of local issues decided in local politics (Hahn 1968). Although the scientific field has thoroughly rebutted the initial anxieties over alleged negative externalities of fluoridation, from cancer (Chilvers 1982), arthritis (Phipps et al. 2000), and proclivity to communism (Crain 1966), controversial claims continue to this day (Editorial Expression of Concern 2019). The emotional appeals and scientific-sounding arguments of fluoridation's opponents are 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 (Sapolsky 1968, 1969; Curiel et al. 2019). The Friedan 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 include 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 fluoridation depends upon whether elected officials do not suffer backlash from concerned voters over fluoridation, or, when considering fluoridation, if voters themselves feel that the benefits of fluoridation outweigh the minimal costs. Whether voters vote an official out of office or vote against fluoridation directly depends upon the voters' understanding of the scientific basis for fluoridation. Therefore, we expect that as the knowledge base of a county increases, so too will fluoridation coverage.

These results also bear some importance to nations besides the US. While not all nations make fluoridation decisions at the local level or via direct democracy, ultimately all representative democracies require public buy-in for approved policies to varying extents. If a low–health-literate public perceives fluoridation as questionable, then it would be difficult to approve or expand fluoridation. Whether decision makers or organized interests might make use of these results to initiate greater health literacy or fluoridation is uncertain, though the first necessary condition to policy change is strong empirical evidence that demonstrates the problem (Baumgartner and Jones 1993).

These results are both promising as well as concerning in understanding how and why fluoridation expands. Given that the strongest predictors of fluoridation are population density, 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, i.e. 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 fluoridation. On a positive note, although most public health initiatives tend to suffer in the presence of racial segregation (Nall 2018), fluoridation'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 regard 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 that neighbor other counties with higher levels of fluoridation. In the event that antifluoridation forces seek to frighten voters or elected officials with information rooted in flawed science, poor methodology, or emotionally laden rhetoric, fluoridation advocates can point to both the large body of research supporting fluoridation and to their neighbors to disprove the antifluoridation message. Additionally, for fluoridation deserts where no counties in the area have access to fluoridation, fluoridation advocates should target areas with the highest levels of health literacy or education overall. Upon gaining a foothold with the initiation of fluoridation, fluoridation advocates could expand fluoridation from there.

With regard to identifying interventions, either health literacy or proportion of the population above a high school education seems appropriate. Whether one seeks to increase health literacy or educational attainment, it will likely require increased funding in education. While such an investment would be difficult to justify if its only goal was to increase support for fluoridation, a focus on education and comprehension would benefit society at large. Also, population-based measures to improve health literacy are more appealing than interventions restricted to people with low health literacy, given evidence from a systematic review which found that simply providing more information to patients with low health literacy produces only "mixed results" (Pignone et al. 2005).

The ACS sociodemographic model performed slightly better than the health literacy model, suggesting that fluoridation coverage is explained by aspects of sociodemographics in addition to health literacy. However, better performance of the sociodemographic model is not unexpected given that we employed counties as our unit of analysis. Health literacy works best at the individual level, or in 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 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 had to employ a cross section of counties given that the historical data on fluoridation coverage is available only by state, not county. Also, population estimates of health literacy in 2014 were reliant on parameter estimates from the NAAL survey conducted a decade earlier, though this would only be an issue for MRP methods under 2 conditions. First, if the coefficients of the demographic estimators of health literacy had substantively and significantly changed, and second, if the first condition is met and the study employed time series panel data (Curiel et al. 2019). Additionally, the use of aggregations of county demographics leads to an indirect measure of the independent variables of interest. We can say that there are associations between the covariates of interest and the dependent variable, though we lack the means to get at true causality due to the design limitation. However, it should be noted that the spatial regression model employed addresses many of the concerns associated when employing cross-sectional data. Additionally, the 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 suggest that knowledge in general, and health literacy in particular, might explain support and adoption of community water fluoridation.

Author Contributions

J.A. Curiel, contributed to conception, design, data acquisition, analysis, and interpretation, drafted and critically revised the manuscript; A.E. Sanders, contributed to conception and data interpretation, critically revised the manuscript; G.D. Slade, contributed to design, data acquisition, and analysis, critically revised the manuscript. All authors gave final approval and agree to be accountable for all aspects of the work.

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