Evaluating how licensing-law strategies will impact disparities in tobacco retailer density: a simulation in Ohio

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ABSTRACT

Objectives To assess tobacco licensing-law strategies (eg, restricting the sale of tobacco near schools, banning the sale of tobacco in pharmacies) in terms of the equity of their impact and ability to correct existing disparities in tobacco retailer density.

Methods We geocoded all 11 392 tobacco retailers in Ohio, categorised neighbourhoods based on their demographic characteristics and calculated current disparities in tobacco retailer density. We next simulated the four main types of licensing-law strategies (capping-based, declustering-based, school-based and pharmacy-based), as well as strategy combinations. Finally, using statistical methods that account for residual spatial dependence, we evaluated how each strategy would impact density disparities.

Findings The most impactful licensing-law strategy depended on the type of community. School-based reductions were equitable for low-income, African–American and urban neighbourhoods (eg, eliminating retailers from 1000 feet of all schools produced a 9.2% reduction in the log retailer rate for neighbourhoods with a low prevalence of African–Americans and a 17.7% reduction for neighbourhoods with a high prevalence of African–Americans). Conversely, capping-based reductions were equitable for rural neighbourhoods. Pharmacy-based reductions demonstrated inequitable impacts.

Conclusion Licensing-law strategies could be a central tobacco control effort that benefits both the overall population and vulnerable communities. Policymakers will need to consider their community's characteristics when selecting licensing-law strategies to correct (rather than inadvertently widen) density disparities. But when matched with the appropriate strategy, high-risk communities could remove over 20% of their tobacco retailers.

INTRODUCTION

Within the USA, the burden of tobacco is not equal. Rather, low-income, racial/ethnic minority and rural populations exhibit some of the highest rates of tobacco use,[1 2] lowest rates of tobacco cessation[3 4] and highest rates of tobacco-related morbidity and mortality.[5] Although many factors contribute to these disparities, the tobacco retail environment plays a major role. Specifically, tobacco retailers are more densely located in neighbourhoods with low-income, racial/ethnic minority and rural populations.[6–8] For example, one study found the per capita number of retailers to be three times as high in low-income areas compared with high-income areas.[9] Research from other countries has documented similar disparities in tobacco retailer density.[10 11]

With greater retailer density, vulnerable populations experience easier access to tobacco products and greater exposure to marketing at the point of sale. Moreover, the amount of tobacco advertising at a given store is also greater within vulnerable communities.[12 13] This inundation of tobacco marketing is concerning because exposure to tobacco marketing can have powerful effects on promoting initiation and inhibiting cessation.[14–16] It is, therefore, no surprise that greater retailer density is associated with worse quit outcomes among adult smokers.[15 16] Likewise, a recent review concluded that there is evidence of a positive association between tobacco outlet density and youth smoking.[17]

A new and promising approach for addressing retailer density is adding and modifying tobacco licensing laws. The most basic form of licensing laws requires stores to obtain a license to sell tobacco.[18] Importantly, language can be added to these laws that sets stipulations for granting a tobacco retail license. The objective of these stipulations is to reduce or restrict some aspect of the tobacco retailer landscape, such as the location of retailers or their proximity to each other. Currently, these types of licensing-law strategies have only been evaluated in the USA and New Zealand.[19] As reviewed in table 1, there are four main types of strategies that have been successfully implemented in US localities and are considered legally sound.[20] Strategies are also frequently used in combination, such as in Philadelphia, Pennsylvania, where both capping-based and school-based reductions are in place. Research suggests these strategies have the potential to substantially reduce retailer density.[21–27] Evaluations indicate capping-based restrictions may be the most effective (one study estimated it would reduce up to 22.1% of retailers) and that school-based and pharmacy-based reductions may have smaller impacts (reducing under 18% of retailers).[25] There is also emerging evidence linking licensing-law strategies with smoking reductions.[24 28]

Unfortunately, despite research on how licensing-law strategies could impact retailer density overall, very little work has examined their potential impact on density disparities. This is concerning because tobacco control approaches can sometimes exacerbate disparities when, despite reducing

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Table 1 Types of licensing-law strategies for tobacco retailer density reduction

Type name	Strategy for restriction/reduction
Capping-based	Cap the number of retailers in an area, generally based on population size (eg, 0.7 retailers per thousand people in a county)
Declustering-based	Prohibit retailers from being in close proximity to one another (eg, within 500 ft of other retailers)
School-based	Prohibit retailers from being close to schools (eg, within 500 ft)
Pharmacy-based	Prohibit the sale of tobacco in pharmacies

tobacco use at the population level, they fail to equitably benefit vulnerable groups.[29] In the case of licensing-law strategies, some approaches may be more beneficial for low-risk communities than vulnerable communities. For example, due to the distribution of retailer types, banning tobacco sales in pharmacies may be more beneficial to affluent areas.[23] Likewise, restricting tobacco retailers from 500 feet (ft) of schools may not benefit rural neighbourhoods, where the location of tobacco retailers can be more spread out.[30] Those few studies that have modelled the impact of licensing laws on disparities indicate some equity benefits from school-based reductions[31 32] and mixed effects for declustering-based reductions.[32 33] Yet, this previous work examined just one or two licensing laws,[31 33] focused only on urban areas[31 32 34] or used agent-based models rather than real-world retailer distributions.[32 33] There is a need for more comprehensive evaluations with real-world tobacco retailer distributions.

The purpose of this study was to assess the four main types of licensing-law strategies (capping-based, declustering-based, school-based and pharmacy-based) in terms of the equity of their impacts for low-income, racial/ethnic minority and rural neighbourhoods. In addition, we explored the impact of combined strategies (eg, school-based and pharmacy-based restrictions together). We sought to model these strategies for the state of Ohio, as this state has a varied sociodemographic profile with good representation of our groups of interest and none of the four major licensing-law strategies has yet been implemented. Analyses used spatial statistical methods to account for the tendency for retailers to cluster together in neighbourhoods.

METHODS

Measures

Tobacco retailers

A more detailed description of our process for identifying and geocoding tobacco retailers is provided elsewhere.[35] Names and addresses of all retailers with active cigarette licenses (gas stations, grocery stores, tobacco shops, etc) were obtained from Ohio's county auditor offices in the fall of 2017. To collect information on other types of tobacco retailers not requiring a cigarette license—namely, hookah cafés and vape shops—we employed methods described by Kates *et al*[36] for searching internet directories (eg, Yelp, Yellowpages.com). Our final list contained 11 392 tobacco retailers in Ohio (11 065 cigarette licenses and 327 vape/hookah stores), which we then geocoded.

Schools and pharmacies

We obtained a list of all 4317 primary and secondary public, non-public, community and vocational schools (adult and night schools excluded) in Ohio in spring of 2018 from the Ohio Department of Education. From the State of Ohio Board of Pharmacy, we obtained a list of all licensed pharmacies in Ohio with brick-and-mortar locations in fall of 2017. This list was matched with our list of tobacco retailers and identified 1139 tobacco retailers as being pharmacies. All school and pharmacy addresses were geocoded.

Demographic characteristics

For all Ohio census tracts, we obtained information about race/ethnicity, poverty, age and population size from the 2016 American Community Survey 5-year estimates. Cut-offs distinguishing 'high' and 'low' groups were selected a priori and justified elsewhere.[35] Tracts were coded as having a high (vs low) prevalence of African–Americans (or Hispanics) if 15% or more of the population was African–American (or Hispanic). Tracts were coded as having a high (vs low) prevalence of young people if 25% or more of the population was under age 18. Finally, tracts were coded as having a high (vs low) prevalence of poverty if more than 15.4% of the population was below the poverty level.

To determine whether a neighbourhood was urban, rural or suburban, we used the county-level classifications applied by the Ohio Family Health Survey (now the Ohio Medicaid Assessment Survey).[37] This system classifies all Ohio counties as metropolitan (urban), suburban, rural non-Appalachian or rural Appalachian. For analyses, we combined the two rural designations.

Analyses

Initial state of retailer density disparities

To understand the current distribution of retailers in Ohio, we calculated tobacco retailer density as the number of retailers per 1000 people in a census tract. To avoid fitting statistical models to census tracts with very low populations, we removed 14 tracts with populations of less than 500 people. This left 2937 tracts for analysis, after the removal of one further tract that was missing poverty information. These exclusions resulted in the loss of 3 tobacco retailers, leaving us with 11 389 retailers for analyses. TIGER shape files for the counties and census tracts for the state of Ohio came from the US Census Bureau (https://www.census.gov/cgi-bin/geo/shapefiles/index.php).

In analyses described in detail elsewhere,[35] we used negative binomial generalised linear models, adapted for residual spatial dependence, to model the retailer counts and assess association between the expected per capita tobacco retailer density and demographic characteristics. Results indicated that retailer density was greater in tracts with high (vs low) poverty, in tracts with high (vs low) prevalence of African–Americans or Hispanics and in rural (vs suburban or urban) areas.

Policy simulations

The following procedures were undertaken to simulate different licensing-law strategies. In instances where particular values were set (eg, stores per capita, distances in feet from other retailers), our selections were based on a review of what policies were already in place in US communities. All randomisations carried out in this paper are completely at random.

Capping-based reductions

Reductions based on the population of residents in an area vary in their level of strictness. We therefore ran two simulations, randomly removing retailers from each county in an iterative process until the density of retailers was (a) 1 retailer per thousand people and (b) 0.7 retailers per thousand people. The random nature of this operation leads to different counts by census tract each time a simulation is conducted. Therefore, for both capping values (1 and 0.7 per thousand), we repeated the random deletion of retailers 250 times to explore the potential variation (statistical uncertainty) of carrying out this strategy and present median values of these 250 simulations in the results.

Declustering-based reductions

Reductions based on the proximity of retailers to one another likewise vary in strictness. We therefore ran two simulations, randomly removing retailers from the data file so that no retailer was within (a) 200 ft and (b) 500 ft of any other retailer. For both distances (200 and 500 ft), we repeated this operation 250 times to explore statistical uncertainty.

School-based reductions

Reductions based on proximity to schools generally restrict based on a 500 ft or 1000 ft limit. We therefore constructed radial buffers around school addresses to approximate boundaries around schools (shapefiles on school property lines were not available) and removed all retailers identified as being within (a) 500 ft and then (b) 1000 ft of a school boundary. Since no randomisation was used in this strategy, we only carried out this operation once for each distance.

Pharmacy-based reductions

Current bans on tobacco in pharmacies include not only standalone pharmacies but also retailers that include pharmacies under their roof (eg, a grocery store that includes a pharmacy would not be allowed to sell tobacco anywhere on the property). Simulations therefore removed all retailers that contained a pharmacy from our data file. Since no randomisation was used in this strategy, we only carried out this operation once.

Combination policies

Most counties and municipalities enact a combination of licensing laws when restricting retailers. We therefore simulated two common licensing-law combinations. First, we looked at the combination of capping-based and school-based reductions. For this, we performed a capping-based reduction of 0.7 retailers per thousand people and then removed all remaining retailers within 1000 ft of a school boundary. Since the capping-based reduction policy is randomly implemented, we carried out this operation 250 times to assess uncertainty. For the second combination policy, we looked at pharmacy-based and school-based reductions. For this, we removed all retailers within 1000 ft of school and then removed the remaining retailers that were pharmacies.

Equity impact

Following the policy simulations, we conducted three sets of analyses to evaluate how the various licensing-law strategies would impact density disparities. Each set of analyses answered slightly different questions about the equity impact: whether the policy attenuated existing disparities, even if it did not eradicate them entirely (*reduction of disparities*); whether the density reduction was greatest for the more disadvantaged communities (*per cent reduction*) and whether the association we previously reported[35] between per capita tobacco retailer density and demographic characteristics attenuated after the policies (*weakened associations*).

For each strategy, we conducted evaluations at the census tract level to understand the impact across neighbourhood types. For all analyses, 'high-risk' census tracts were those with a high prevalence of African–Americans, Hispanics, poverty, populations under 18, urban individuals or rural individuals. Analyses used bivariate spatial models adapted from our previous methods[35] to account for the spatial association across the tracts and the dependence shared by the retailer rates before and after each policy implementation (here, spatial dependence is a nuisance factor accounted for by our statistical methods). For each of the three sets of analyses and each demographic characteristic, we adjusted for multiple comparisons over the nine licensing-law strategies using the Bonferroni method. Further details of these modelling methods are provided in the online supplementary materials.

Reduction of disparities

This analysis tested whether differences in the densities of high-risk versus low-risk tracts were attenuated following a policy. For each census tract, we calculated the log retailer density per thousand people (adding one to the retailer count to guard against taking the log of a zero count). This transformation also made the log retailer density closer to being normally distributed. We then calculated the difference in the mean log retailer rates between high-risk and low-risk census tracts. A positive difference score meant that greater density remained in high-risk tracts (a disparity). For pre–post policy comparisons, we also calculated prepolicy disparities, then calculated differences between prepolicy and postpolicy disparities using a z-test that adjusted for bivariate spatial dependence in the log retailer counts. When we rejected the null hypothesis for the z-test, we concluded that there was a significant difference between the prepolicy and postpolicy disparities. When the policy implementation was randomised and our simulations were conducted 250 times to assess uncertainty, we calculated a new disparity and z-test for each randomised policy operation. In our results, we presented the median disparity over the 250 replications.

Percent reduction

This analysis tested whether the per cent reduction in retailer density following a policy was significantly different for high-risk versus low-risk census tracts. Per cent reductions were calculated using the median retailer density per thousand people in each census tracts before and after each policy implementation. To determine whether the per cent reductions were significantly different, we use z-tests that compared the percentage reductions for high-risk and low-risk tracts, adjusting for bivariate spatial dependence before and after each policy implementation.

Weakened associations

This analysis tested whether the strength of the estimated relation between sociodemographic characteristics and tobacco retailer density significantly diminished following the policy. To answer this question, we fit negative binomial models to the retailer counts in each census tract before and after each policy implementation. In our negative binomial model, we included terms for a high/low prevalence of African–Americans and Hispanics, as well as a three-way interaction between poverty (high/low), urban/suburban/rural and the prevalence (high/low) of people aged under 18. By including an offset in the model, which is the log population in thousands, we were able to relate the expected retailer density to the covariates in the model. This model is based on our previous work,[35] but leaves out the Asian prevalence term as it was not significant in the original model.

RESULTS

Table 2 provides a summary of the overall impact of the various licensing-law strategies on retailer density. Findings indicated that a capping-based reduction of 0.7 retailers per thousand people and a declustering-based reduction on retailers within

Table 2 Summary of the expected overall impact of nine different licensing-law strategies on tobacco retailers in Ohio (prepolicy number of retailers=11 389)

Strategy	Number of retailers removed	Number of retailers remaining	% of retailers removed
Capping-based, 1 per thousand*	739	10 650	6.5
Capping-based, 0.7 per thousand*	3365	8024	29.6
Declustering-based, 200 ft*	[698, 709]	[10 680, 10 691]	[6.1, 6.2]
Declustering-based, 500 ft*	[2792, 2844]	[8545, 8597]	[24.5, 24.9]
School-based, 500 ft of a school	327	11 062	2.9
School-based, 1000 ft of a school	1470	9919	12.9
Pharmacy-based	1139	10 250	10.0
Capping-based and school-based*	[3464, 4458]	[6931, 7025]	[38.3, 39.1]
Pharmacy-based and school-based	2491	8898	21.9

[ ]Numbers in square brackets indicate, when needed, the range of potential values. While the capping-based policies are implemented at random, the final number of retailers removed does not vary over the randomizations.
*A policy that was implemented at random (250 times) to explore the potential variation (statistical uncertainty) of carrying out this policy.

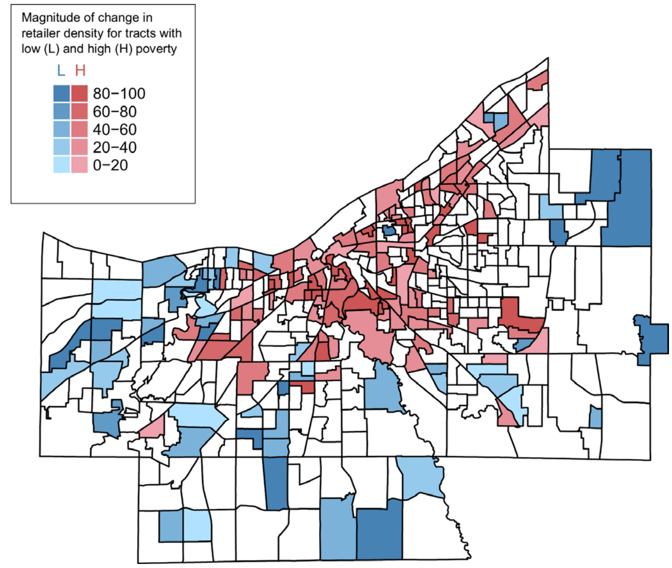

Figure 1 Illustration of the percentage reduction in retailer density following a 1000 ft school-based reduction in Cuyahoga county, Ohio (where Cleveland is located). Red regions indicate the magnitude of the decrease for high-prevalence (H) poverty tracts. Blue regions indicate the magnitude of the decrease for low-prevalence (L) poverty tracts. Non-shaded regions indicate where there was no change in retailer density relative to baseline. Overall, the school-based reduction removed 23.6% of retailers in the county.

1000 ft of another retailer are the single licensing-law strategies that would remove the greatest number of retailers. The combined school-based and capping-based reduction was estimated to have the largest impact on density, removing over 38% of tobacco retailers in Ohio. Unsurprisingly, in all cases where various versions of a strategy were tested, the weaker version produced a weaker effect (eg, a 1000 ft school-based reduction removed nearly 13% of retailers, whereas a 500 ft school-based reduction removed under 3% of retailers).

Reduction of disparities

Table 3 indicates, for each demographic characteristic, the extent of disparities between high-risk and low-risk census tracts (assessed in terms of difference in mean log retailer density); disparities are presented for both baseline and after each licensing-law strategy, with bolded values indicating when a disparity following a licensing-law strategy was significantly different from the disparity at baseline. For African–American tracts, a 500 ft declustering-based reduction, both school-based reductions, and the two combined strategies significantly reduced disparities. For example, the difference in mean log retailer density between high-prevalence versus low-prevalence African–American tracts was 0.33 before any policy but down to 0.23 after a 1000 ft school-based reduction. A similar but smaller effect occurred for high-prevalence and low-prevalence Hispanic tracts. Most strategies significantly reduced poverty-based disparities from a baseline 0.51 difference in high-poverty versus low-poverty tracts to values ranging from 0.38 to 0.50 (see figure 1 for an illustration in one county). Only the capping-based reduction to 1 per thousand in a county and

Table 3 Disparities in per capita tobacco retailer density in Ohio at baseline and following each licensing-law strategy

Licensing-law strategy	African–American	Hispanic	Poverty	Population under 18	Urban vs suburban	Rural vs urban
No strategy (baseline)	0.33	0.39	0.51	−0.07	−0.21	0.06
Capping-based, 1 per thousand*	**0.36**	0.41	0.50	−0.06	−0.21	**−0.07**
Capping-based, 0.7 per thousand*	0.35	0.35	**0.46**	−0.04	**−0.12**	**−0.10**
Declustering-based, 200 ft.*	0.33	0.39	0.50	−0.06	−0.20	0.06
Declustering-based, 500 ft*	**0.29**	0.35	**0.46**	−0.06	**−0.16**	**0.10**
School-based, 500 ft of a school	**0.31**	**0.36**	**0.50**	−0.08	**−0.19**	**0.07**
School-based, 1000 ft of a school	**0.23**	**0.27**	**0.43**	−0.10	**−0.14**	**0.13**
Pharmacy-based	**0.35**	0.41	**0.54**	**−0.05**	−0.21	0.08
Capping-based and school-based*	**0.26**	**0.25**	**0.38**	−0.06	**−0.06**	**−0.03**
Pharmacy-based and school-based	**0.24**	**0.28**	**0.45**	−0.08	**−0.14**	**0.15**

With the exception of urban/suburban/rural, for each demographic characteristic, disparities are calculated as the difference in mean log retailer density for high-prevalence versus low-prevalence census tracts. For urban/suburban/rural, comparisons are made relative to urban census tracts. Lower values from baseline indicate the disparity is reduced. Bold values indicate that the median value of the disparity in a given policy approach is significantly different from the baseline disparity.
*A policy that was implemented at random (250 times) to explore the potential variation (statistical uncertainty) of carrying out this strategy. The table provides the median value over the 250 randomizations.

Table 4 Percent reductions in tobacco retailer density disparities in Ohio following each licensing-law strategy

Licensing-law strategy	African–American	Hispanic	Poverty	Population under 18	Urban/ suburban/rural
Capping-based, 1 per thousand*	**L: 5.4** **H: 1.9**	L: 4.7 H: 3.0	L: 4.1 H: 5.2	L: 4.9 H: 3.9	**U: 1.4** S: 1.5 **R: 12.9**
Capping-based, 0.7 per thousand*	L: 23.3 H: 21.5	L: 22.8 H: 25.8	**L: 21.3** **H: 25.4**	L: 23.5 H: 21.3	**U: 20.4** **S: 13.4** **R: 32.0**
Declustering-based, 200 ft*	L: 4.0 H: 3.8	L: 3.9 H: 4.6	L: 3.5 H: 4.5	L: 4.1 H: 3.5	U: 4.1 S: 3.6 R: 4.0
Declustering-based, 500 ft*	**L: 16.5** **H: 19.2**	L: 17.2 H: 20.5	**L: 15.5** **H: 19.2**	L: 17.6 H: 16.5	**U: 18.6** **S: 14.4** **R: 15.1**
School-based, 500 ft of a school	**L: 2.1** **H: 3.7**	**L: 2.4** **H: 5.8**	**L: 1.7** **H: 3.6**	L: 2.3 H: 3.0	**U: 3.1** S: 1.8 **R: 1.7**
School-based, 1000 ft of a school	**L: 9.2** **H: 17.7**	**L: 11.2** **H: 21.7**	**L: 8.3** **H: 15.6**	L: 10.9 H: 13.3	**U: 14.3** **S: 8.0** **R: 7.7**
Pharmacy-based	**L: 7.6** **H: 5.7**	L: 7.1 H: 5.8	**L: 8.4** **H: 5.4**	**L: 7.7** **H: 5.6**	U: 7.5 S: 7.7 R: 5.7
Capping-based and school-based*	**L: 29.1** **H: 33.3**	**L: 30.4** **H: 39.8**	**L: 27.1** **H: 35.7**	L: 31.3 H: 30.9	**U: 30.5** **S: 19.9** **R: 36.2**
Pharmacy-based and school-based	**L: 15.7** **H: 22.3**	**L: 17.2** **H: 26.3**	**L: 15.6** **H: 20.1**	L: 17.5 H: 17.9	**U: 20.3** **S: 15.0** **R: 12.8**

For each level of the demographic characteristic, we calculated the percent reductions in median retailer density per thousand people in each census tract before versus after policy implementation.

Except for urban/suburban/rural, bold values indicate that the median percentage reductions for the low and high covariate values are significantly different. For 'urban/suburban/rural', bold values indicate when the median percentage reductions for suburban (S) or rural (R) tracts are significantly different from the median percentage reductions for the urban (U) tracts.

*A policy that was implemented at random (250 times) to explore the potential variation (statistical uncertainty) of carrying out this policy approach. The table provides the median value over the 250 randomizations.

the declustering-based reduction on retailers within 200 ft of another retailer were not significantly different from baseline; as with African–Americans, the pharmacy-based reduction increased disparities. The combined capping-based and school-based reduction led to the smallest disparity in poverty. In some cases, a strategy led to a worse disparity than under the baseline scenario. For example, capping retailer density to 1 retailer per thousand people in a county slightly inflated the African–American disparity. Whereas capping-based strategies improved rural (vs urban) disparities, declustering-based and school-based reductions seemed to worsen disparities for rural areas.

Percent reduction

Table 4 displays the percent reductions for different demographic characteristics and licensing-law strategies. Findings indicated that 1000 ft school-based reductions would have an equitable impact for high-poverty communities, as this strategy would reduce over 8% of the log tobacco retailer rate in low-poverty neighbourhoods and over 15% of the log tobacco retailer rate in high-poverty neighbourhoods. This policy also has an equitable impact for African–American and Hispanic tracts, as well as for urban (vs suburban) tracts. Restricting tobacco retailers from within 500 ft of a school had an equitable impact for high-poverty tracts, African–American and Hispanic tracts and urban (vs suburban) tracts. The combined capping-based and school-based reductions as well as the combined pharmacy-based and school-based reductions were equitable for high-prevalence African–American, Hispanic, and poverty tracts and urban (vs suburban) tracts. Pharmacy-based reductions were not equitable, as tracts with a high prevalence of African–Americans, poverty and people aged under 18 experienced less reductions compared with those with a low prevalence of those demographic characteristics. Capping retailer density to 1 retailer per thousand people in a county was also inequitable for African–Americans. However, both capping-based policies were equitable for rural (vs urban) tracts; urban (vs suburban) areas also benefited more from the 0.7 cap. For the more severe 500 ft declustering-based policy, and both school-based policies, relatively fewer retailers were removed from rural (vs urban) areas. The 500 ft declustering-based policy was also equitable for tracts with a high prevalence of African–Americans and poverty.

Weakened associations

Table 5 summarises the rate ratios obtained after fitting a negative binomial model to the retailer counts under each licensing-law strategy compared with the baseline log retailer counts. Findings indicate that the 1000 ft school-based reduction and the combined capping-based and school-based reduction led to a weakened association between density and high-prevalence African–American tracts (1.04 and 1.03, respectively, vs the baseline rate ratio of 1.12). The three-way interaction indicated that, for urban tracts, 1000 ft school-based reductions led to a weakened association between density and high-poverty tracts, regardless of whether tracts had a high or low prevalence of people aged under 18. For rural tracts, capping-based reductions led to a weakened association between density and high-poverty

Table 5 Strength of the estimated association between demographic characteristics and tobacco retailer density under each licensing-law strategy in Ohio

			Poverty					
			Low prevalence <18			High prevalence <18		
Licensing-law strategy	African–American	Hispanic	Urban	Suburban	Rural	Urban	Suburban	Rural
No strategy (baseline)	1.12	1.19	1.53	1.59	1.87	1.41	1.46	1.43
Capping-based, 1 per thousand*	1.12	1.19	1.53	1.59	**1.56**	1.41	1.41	**1.22**
Capping-based, 0.7 per thousand*	1.11	1.15	1.53	1.81	**1.50**	1.43	1.51	**1.20**
Declustering-based, 200 ft*	1.13	1.19	1.52	1.56	1.86	1.42	1.45	1.45
Declustering-based, 500 ft*	1.08	1.20	1.50	1.62	1.95	1.47	1.53	1.50
School-based, 500 ft of a school	1.11	1.17	1.50	1.60	1.89	1.38	1.42	1.42
School-based, 1000 ft of school	**1.04**	1.13	**1.44**	1.59	1.92	**1.31**	1.45	1.45
Pharmacy-based	1.13	1.19	**1.64**	1.64	**1.98**	**1.54**	**1.59**	**1.58**
Capping-based and school-based*	**1.03**	1.09	1.44	1.81	**1.55**	1.33	1.50	**1.22**
Pharmacy-based and school-based	1.05	1.13	1.54	1.63	**2.02**	1.44	1.59	**1.60**

For each demographic characteristic, retailer rate ratios were obtained by fitting a negative binomial model to the retailer counts.
Bold values indicate that the median values of the rate ratios in a given policy approach are significantly different from the baseline ratio, after accounting for the bivariate spatial dependence in the counts.
*A policy that was implemented at random (250 times) to explore the potential variation (statistical uncertainty) of carrying out this policy approach. The table provides the median value over the 250 randomizations.

tracts, regardless of whether tracts had a high or low prevalence of people aged under 18. In general, the pharmacy-based reduction demonstrated an inequitable impact, strengthening the association between density and high-poverty tracts.

DISCUSSION

The simulation-based modelling conducted for this study found that the most impactful licensing-law strategy for equitably reducing tobacco retailer density depended on the type of community. Based on our first benchmark for evaluating equity, we found that: high-poverty neighbourhoods benefit most from capping-based, declustering-based and school-based reductions; African–American neighbourhoods benefit most from declustering-based and school-based reductions; and rural (vs urban) neighbourhoods benefit most from capping-based reductions. Our next two benchmarks underscored the benefits of: (1) school-based reductions for neighbourhoods that are low income, African–American and urban and (2) capping-based reductions for neighbourhoods that are low income and rural. Another robust finding was that pharmacy-based reductions demonstrated an inequitable impact. This finding is consistent with another licensing-law evaluation in New York City.[23]

The fact that a licensing-law strategy's equity impact varies by community likely has to do with the type and distribution of tobacco retailers in different areas. For example, although rural areas have greater per capita tobacco retailer density, their distribution is more spread out; this means there are fewer retailers near schools, which renders school-based reductions less impactful. This finding is consistent with other work showing that rural youth pass by fewer tobacco retailers on their paths between home and school.[38] Similarly, whereas declustering-based (but not capping-based) reductions had a positive equity impact for African–American neighbourhoods, capping-based (but not declustering-based) reductions had a positive equity impact for rural neighbourhoods.

Results additionally identified two general rules for licensing-law strategies. The first was that more extreme versions of the policies are more impactful in their equity effect. Thus, eliminating retailers from 1000 ft (vs 500) of a school or 500 ft (vs 200) of another establishment was more powerful. The second rule was that combination strategies are somewhat stronger than a single type of licensing-law strategy on its own. This was particularly apparent in the case of combination capping-based and school-based reductions—both were equitable strategies independently, but implementing both together produced a greater equity impact. In the case of combination pharmacy-based and school-based reductions, the school-based reduction made up for the low equity impact of the pharmacy-based reduction.

Strengths, limitations and future directions

A major strength of this study was that we used bivariate spatial statistical methods. With tobacco retailer density, spatial dependence occurs as retailers tend to cluster together (eg, on a main thoroughfare), thereby violating underlying statistical assumptions of independence of observations and potentially leading to incorrect conclusions with hypothesis tests. We used a spatial modelling approach, which has been shown to sufficiently adjust for spatial dependence in retailer density research.[7 8 39] Using a bivariate spatial model accounted for the dependence in the retailer counts before and after policy approach. Another strength of this study is that we modelled licensing-law strategies over the entire state rather than just at a city or county level. This allowed a more thorough understanding of the distribution of tobacco retailers throughout a large area that varies widely in its demographic and geographic makeup.

There were, nevertheless, limitations to our approach. First, most policies implementing licensing-law strategies are forward-focused, such that existing retailers are not forced to stop selling tobacco—rather, only new retailers that would be in violation of the policy are refused a license to sell. The equity impacts observed in this study might, therefore, take years to fully show their effects in the real world. Our modelling also did not account for unlicensed tobacco sales or compensatory changes in the market postpolicy, such as when other stores replace pharmacies as tobacco retailers. Real-world observations will be needed to determine what types of compensatory changes occur (if any) as a result of particular licensing-law strategies. In addition, we used retailers per capita as our measure of density; there are other measures of density (eg, retailers per land area) and all are imperfect proxies for tobacco availability.[40] Finally, our modelling was based on the distribution of tobacco retailers in an area of the USA, and outcomes may not generalise to other states or countries. It is also worth noting that our study found few equity impacts for Hispanic neighbourhoods, which is likely due to the small prevalence of Hispanics in the state (3.6%).[41] Future studies conducted in other parts of the USA may be able to better identify the best licensing-law strategies for Hispanic communities.

Public health implications

Overall, this study's findings are important because they point to which licensing-law strategies are best suited for correcting which types of community's density disparities; conversely, findings also point to which licensing-law strategies could inadvertently widen inequalities. Our modelling results indicate that, when matched with the appropriate licensing-law strategy, high-risk communities could reduce their prevalence of tobacco retailers by over 20%. The magnitude of this impact is meaningful for public health, as previous work indicates that even seemingly moderate differences in tobacco retailer density (eg, zero vs >5 stores in a neighbourhood) can translate into real-world differences in smoking prevalence.[42] Licensing-law strategies are growing in popularity and there are numerous resources available for communities considering this approach.[20 43 44] Policymakers will need to be mindful of disparities when selecting the licensing-law strategies that are best for their communities. But if used thoughtfully, licensing-law strategies could be a central tobacco control effort that not only benefits public health at the population level but at the vulnerable population level as well.

What this paper adds

What is already known on this subject

- ► Greater tobacco retailer density is associated with increased likelihood of tobacco initiation and decreased likelihood of cessation.
- ► Greater tobacco retailer density is also greater in areas with a higher proportion of vulnerable populations.
- ► A growing body of literature demonstrates the effectiveness of licensing-law strategies for reducing/restricting overall tobacco retailer density.

What important gaps in knowledge exist on this topic

- ► Very little work has examined how licensing-law strategies would impact the disparities that are known to exist in retailer density.

What this paper adds

- ► The most equitable licensing-law strategy depends on the community: for example, school-based reductions are equitable for low-income, African–American and urban neighbourhoods, whereas capping-based reductions are equitable for low-income and rural neighbourhoods.
- ► Licensing-law strategies have the potential to equitably reduce the density of tobacco retailers, but policymakers must select the appropriate strategies for their communities.

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