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Sociodemographic Disparities in the Tobacco Retail Environment in Washington, DC: A Spatial Perspective

Andrew Anesetti-Rothermel, PhD, MPH[1]; Peter Herman, MA[2]; Morgane Bennett, MPH[1]; Ned English, MS[2]; Jennifer Cantrell, DrPH[3]; Barbara Schillo, PhD[1]; Elizabeth C. Hair, PhD[1,4]; Donna M. Vallone, PhD[1,3,4]

Objective: Studies assessing sociodemographic disparities in the tobacco retail environment have relied heavily on non-spatial analytical techniques, resulting in potentially misleading conclusions. We utilized a spatial analytical framework to evaluate neighborhood sociodemographic disparities in the tobacco retail environment in Washington, DC (DC) and the DC metropolitan statistical area (DC MSA).

Methods: Retail tobacco availability for DC (n=177) and DC MSA (n=1,428) census tract was assessed using adaptive-bandwidth kernel density estimation. Density surfaces were constructed from DC (n=743) and DC MSA (n=4,539) geocoded tobacco retailers. Sociodemographics were obtained from the 2011-2015 American Community Survey. Spearman's correlations between sociodemographics and retail density were computed to account for spatial autocorrelation. Bivariate and multivariate spatial lag models were fit to predict retail density.

Results: DC and DC MSA neighborhoods with a higher percentage of Hispanics were positively correlated with retail density (rho = .3392, P = .0001 and rho = .1191, P = .0000, respectively). DC neighborhoods with a higher percentage of African Americans were negatively correlated with retail density (rho = -.3774, P = .0000). This pattern was not significant in DC MSA neighborhoods. Bivariate and multivariate spatial lag models found a significant inverse relationship between the percentage of African Americans and retail density (Beta = -.0133, P = .0181 and Beta = -.0165, P = .0307, respectively).

Conclusions: Associations between neighborhood sociodemographics and retail density were significant, although findings regarding African Americans are inconsistent with previous findings. Future studies should analyze other geographic areas, and account for spatial autocorrelation within their analytic framework. *Ethn Dis.* 2020;30(3):479-488; doi:10.18865/ed.30.3.479

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[1] Schroeder Institute at Truth Initiative, Washington, DC

[2] NORC at the University of Chicago, Chicago, IL

[3] School of Global Public Health, New York University, New York, NY

[4] Department of Health, Behavior and Society, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD

Address correspondence to Barbara Schillo, PhD; Truth Initiative Schroeder Institute; 900 G Street, NW, Fourth Floor, Washtingon, DC 20001; bschillo@truthinitiative.org

Introduction

Despite the declines in the prevalence of tobacco use over the past decades, tobacco use remains the leading preventable cause of morbidity and mortality in the United States.[1] Unfortunately, the burden of tobacco-related disease and death is not shared equally across all populations.[2] Low-income populations have greater rates of tobacco use, higher prevalence of tobacco-related diseases, and lower cessation rates compared with the general population.[2]

Researchers have hypothesized that disparities exist, in part, due to differing levels of exposure to tobacco retail outlets. Several studies have examined the density of tobacco outlets within defined geographic areas (eg, census tracts), finding density to be greater in areas with higher proportions of racial/ethnic minority and low-income residents. In their assessment of tobacco outlet density across the United States, Rodriguez et al found that greater tobacco outlet density, measured as the number of tobacco retailers per 1,000 people, was associated with greater proportions of African American, Hispanic, and low-income residents.[3] Others have found similar results when examining tobacco outlet density within specific US cities,[4-6] counties,[7-9] and states.[10-12]

Higher tobacco outlet density has been found to be associated with greater intentions to smoke among youth[13]; increased tobacco use among youth[13-16]; initiation of cigarette use among young adults[17]; heavier smoking patterns among adults[18]; and reduced quit attempts.[19] Several mechanisms have been posited to explain the relationship between tobacco outlet density and tobacco use behavior. Greater tobacco outlet density may result in increased exposure to tobacco marketing,[4] which has been found to be associated with smoking.[20] Additionally, greater exposure to tobacco marketing may promote more positive community norms around tobacco use.[3] Finally, greater tobacco outlet density may result in easier access to products, as well as lower prices due to increased retailer competition.[8-11]

Researchers have hypothesized that disparities exist, in part, due to differing levels of exposure to tobacco retail outlets.

Many of the studies assessing sociodemographic disparities in the tobacco retail environment use non-spatial analytic techniques.[3-5,7-9,11] These non-spatial approaches do not control for spatial autocorrelation, (ie, these approaches fail to account for the location and arrangement of neighborhood units within the underlying data), which can yield inaccurate parameter estimates and p-values.[21] Thus, failing to account for spatial autocorrelation when examining geographic data can lead to potentially misleading conclusions.

Additionally, many studies, even those that have employed a spatial analytical approach to examine sociodemographic disparities in the tobacco retail environment,[6,10,12,22] may fail to adequately capture the true availability of retail tobacco due to aggregation bias. Many of these studies commonly utilize a neighborhood-based approach to calculate tobacco retailer density, which ignores the modifiable areal unit problem (MAUP), a well-established challenge in geographical analysis.[23] The MAUP can significantly impact statistical results when geographic point-based measures are aggregated into arbitrary neighborhoods, such as the density of tobacco retail outlets. For this reason, the neighborhood's chosen spatial boundary (ie, shape and scale) can result in spatial misclassification, because tobacco retail outlets that happen to fall outside each defined neighborhood are effectively ignored in the neighborhood's estimate. Therefore, a neighborhood-based approach fails to appropriately capture the neighborhood's true availability of retail tobacco across the entire study area due to aggregation bias.

An alternative spatial-based approach that addresses aggregation bias is to model and analyze geographic point data by employing kernel density estimation (KDE). This approach addresses the MAUP found in neighborhood-based approaches.[24] Recent studies have used KDE techniques to examine whether higher tobacco retailer density is associated with neighborhood-level contextual factors (ie, race, ethnicity, and socioeconomic status).[3,25,26] These studies have used an adaptive-based KDE approach, which limits the influence of an individual tobacco retail outlet to a small geographic area when the population density is high. Conversely, the geographic area and the influence of an individual tobacco retail outlet will be larger where the population density is lower. Results from these studies have provided more reliable estimates of tobacco retailer density because they incorporate population density into their tobacco retailer density estimates--which can be a superior approach when examining variations in exposure in health disparities research.

Place-based disparity studies are also commonly limited by "edge-effects." These effects are a result of failing to account for tobacco retail outlets located in adjoining and nearby neighborhoods outside the defined study area. Employing a broader "fuzzy" boundary around the specified study area is an approach that addresses edge-effects. In this approach, tobacco retail outlets found in neighborhoods adjoining the study area are included in the analysis to improve the reliability of neighborhood estimates near the boundary of the defined study area.

This study addresses prior measurement limitations in applying a spatial analytical framework to: 1) assess the overall spatial availability of retail tobacco across the District of Colombia (DC) and the broader DC metropolitan statistical area (DC MSA); and 2) examine the extent of variation in neighborhood sociodemographic factors in relation to the tobacco retail environment across these two geographic areas. Comparing these nested study areas will highlight how geographic extant can lead to inconsistent conclusions in health disparities research. This spatial analytical framework provides a more robust approach when examining geographic relationships in health disparities research, which may offer expanded insights necessary to develop equitable health policies.

Methods

Tobacco Retailer Data

We identified tobacco retailers across DC and DC MSA using the North American Industry Classification System (NAICS). NAICS is the standard coding system used by federal statistical agencies to classify a business based on their primary activity. We obtained a national geocoded dataset from Dun and Bradstreet's Hoovers database (www.hoovers.com) for all businesses likely to sell tobacco products in 2015. Ten unique retail categories were identified as: beer, wine and liquor stores; supermarkets and other grocery stores; convenience stores; pharmacies and drug stores; gasoline stations with convenience stores; other gasoline stations; department stores; discount department stores; tobacco stores; and warehouse clubs and supercenters. Among all chain grocery stores, pharmacies, discount department stores, and department stores, those with policies banning the sale of tobacco products were excluded (eg, Whole Foods, CVS, and Target). Duplicate records (ie, retailers with the same Dun and Bradstreet identification (DUNS) number, address, and/or geographical coordinates) were identified and excluded based on a hierarchical cleaning model and manual review. To avoid edge-effects in boundary neighborhood density estimates, we included tobacco retail outlets that were located within a fuzzy boundary around each study area. The fuzzy boundary for DC and DC MSA was derived using a first-order queen's contiguity spatial weights matrix, which identified adjoining census tracts for each study area based on whether they shared a common border edge or corner with the boundary census tracts in each study area. The final sample included tobacco retail outlets in DC (n=743) and tobacco retail outlets in DC MSA (n=4,539).

Tobacco Retailer Density

A tobacco retailer density surface was produced for each study area using adaptive-bandwidth KDE, a nonparametric method of extrapolating spatially-distributed point location data over an area by calculating the density of the point locations using a specified bandwidth (ie, a circle of a given radius centered at the focal location).[24] In adaptive-bandwidth KDE, the influence of each tobacco retail outlet is limited to the surrounding population of 1,000 people. Thus, the resulting smooth, continuous tobacco retailer density surface accounts for the underlying population density. Given that the daytime population of DC increases by 79% during the work week, we first created a daytime population density surface based on the US Census Bureau's commuter-adjusted population estimates, which were derived using the 2011-2015 American Community Survey 5-year estimates geodatabase and 2015 Longitudinal Employer-Household Dynamics data. For each census tract in each of the study areas, the commuter adjusted-population estimate was calculated by adding the overall residential population with the total workers working in the area, and then subtracting out the total workers living in the area. The final daytime commuter-adjusted population density surface for each study area was then constructed using commuter-adjusted population weighted census tract centroids and the kernel density tool with the expected count option in ArcGIS. The resulting population density surface had a spatial resolution of 250 meters. Utilizing these population density surfaces, the final tobacco retailer density surfaces for DC and DC MSA were created. Both final tobacco retailer density surfaces had a spatial resolution of 250 meters. For each study area, census tract density estimates were calculated by averaging the densities estimates across the pixels contained within each census tract; each DC and DC MSA census tract had a resultant density estimate expressed in units of tobacco retailers per 1,000 population.

Sociodemographic Data

The 2011-2015 American Community Survey 5-year estimates geodatabase was also used to derive the percent of non-Hispanic, African American residents, percent of Hispanic residents, and percent of families living below the federal poverty line for each DC (n=179) and DC MSA (n=1,433) census tract. We included the total number of jobs per census tract as a covariate. Consistent with previous studies,[6,10] we also excluded census tracts that were sparsely populated (ie, daytime population < 500 people). Our final sample included 177 DC and 1,428 DC MSA census tracts.

Spatial Analysis

For each study area, we first examined the descriptive statistics for each study variable and visualized their spatial distributions for potential spatial patterning. Next, for each study area, Global Moran's I-test statistic assessed possible spatial autocorrelation for each study variable.[27] Like a correlation coefficient, a Moran's I's value range between -1 and +1, with zero representing complete spatial randomness. Negative spatial autocorrelation (negative Moran's I value) indicates that neighboring census tracts have dissimilar density values compared with the density value of the focal census tract, while positive spatial autocorrelation (positive Moran's I value) signifies that density values between neighboring census tracts and the local census tract are similar. Our Global Moran's I values for each study area were generated using a first-order queen's contiguity spatial weights matrix to define the neighborhood structure of each census tract. Monte Carlo simulation of 999 permutations assessed the statistical significance of the Global Moran's I value for each study variable.

For each study area, Spearman's correlations between sociodemographic variables and tobacco retail density were calculated with and without accounting for spatial autocorrelation (ie, accounting for the location and arrangement of the neighborhood units). Clifford-Richardson adjustment was used to account for spatial autocorrelation in our correlation structure, which is an effective sample size methodology.[28] Spatially adjusted significance was assessed using the first-order queen's contiguity spatial weights matrix and six spatial lags. Correlation coefficients and significance values were reported for each study area.

The tobacco retailer density estimates in each study area were highly skewed transformed via a natural logarithmic transformation. Log-linear bivariate and multivariate regression models (controlling for all sociodemographic variables) predicting tobacco retailer density were fit for each study area. For each study area, ordinary least squares (OLS) regression models were fit and results were examined for spatial autocorrelation using a first-order queen's spatial weights matrix and calculating a Global Moran's I-test statistic and a Lagrange Multiplier test.[21,29] If OLS results suggested the existence of spatial autocorrelation, spatial regression models were fit – a method that controlled for spatial autocorrelation. Our planned spatial regression approach for each study included fitting both the spatial error and spatial lag models. Akaike Information Criterion (AIC) was used to assess model goodness of fit between the OLS and spatial models, whereby a smaller AIC value indicated better model fit. All analyses were conducted in the R statistical program version 3.3.

Results

DC census tracts had a mean density of .15 tobacco retailers per 1,000 population (SD = .26; range: 0-1.61). DC MSA census tracts had a mean density of .03 tobacco retailers per 1,000 population (SD = .1; range 0-.89). Neighborhood sociodemographic factors varied greatly across DC census tracts. The percentage of non-Hispanic, African American residents (mean = 52.86%; SD = 35.09%) and Hispanic residents (mean = 8.78%; SD = 8.66%) ranged from .85% to 100% and 0% to 45.43%, respectively. The percentage of families living in poverty (mean = 14.29%; SD = 14.03%) ranged from 0% to 56.62% across DC neighborhoods. These sociodemographic variations were also seen in DC MSA census tracts. The percentage of non-Hispanic, African American residents (mean = 25.11%; SD = 27.7%) and Hispanic residents (mean = 13.49%; SD = 12.96%) ranged from 0% to 100% and 0% to 89.31%, respectively. The percentage of families living in poverty (mean = 6.29%; SD = 7.49%) ranged from 0% to 61.21% across DC MSA neighborhoods. The spatial distribution of each study variable in DC and DC MSA exhibited spatial patterning when visualized, and there was significant (P=.001) global spatial autocorrelation observed for each variable across each study area as well. The significant global spatial autocorrelation observed in DC tobacco retailer density (Global Moran's I = .41, P = .001) can be seen in the spatial pattern of their neighborhood estimates. (Figure 1) This spatial pattern was also seen in DC MSA tobacco retailer density (Global Moran's I = .54, P = .001) neighborhood estimates. (Figure *2*)

In DC and DC MSA neighborhoods, sociodemographic characteristics were significantly correlated with tobacco retailer density. (Table 1) The percent of Hispanic residents living in DC and DC MSA neighborhoods was positively correlated with tobacco retail density (r_s = .34, P = .00 and

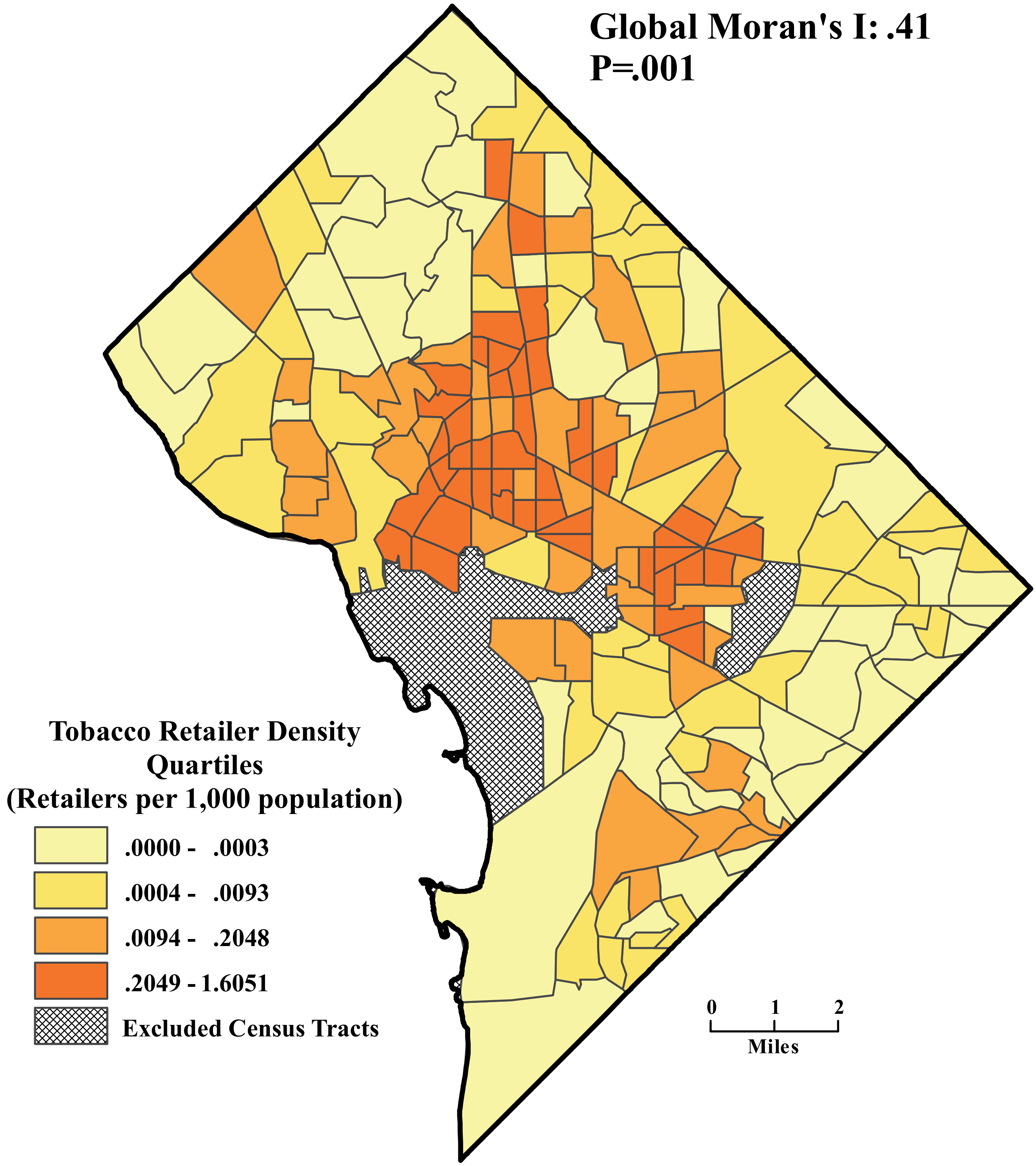

Figure 1. Spatial distribution of tobacco retailer density across DC neighborhoods

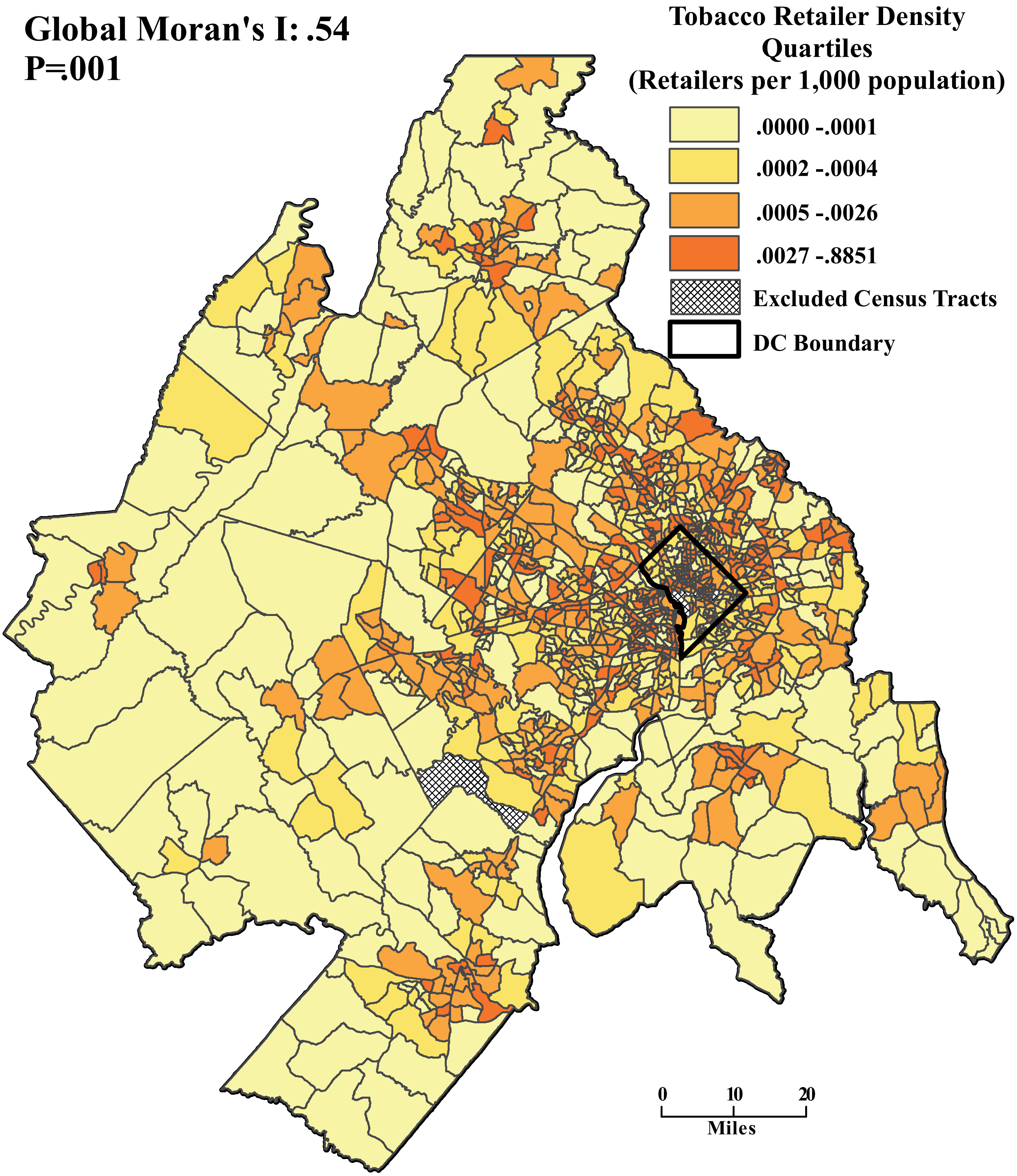

Figure 2. Spatial distribution of tobacco retailer density across DC MSA neighborhoods

r_s= .19, P = .00, respectively). In DC neighborhoods, the percentage of non-Hispanic, African American residents and families living in poverty was negatively correlated with tobacco retailer density (r_s = -.38, P = .00 and r_s = -.15, P = .04, respectively). However, in DC MSA neighborhoods, these patterns were reversed for non-Hispanic, African Americans residents (r_s = .10, P = .00) and families living in poverty (r_s = .11, P = .00). These patterns of associations were similar even after controlling for spatial autocorrelation; with the exception of the percentage of non-Hispanic, African American residents living in DC MSA neighborhoods, which was not significant.

For each study area, spatial regression approaches were used to predict tobacco retailer density, as the Global Moran's I-values and Lagrange multiplier terms were statistically significant (P<.05) across all bivariate and multivariate OLS models. Results for both study areas suggested that spatial lag models were the appropriate spatial regression approach. Compared to the OLS models and spatial error models for each study area, the spatial lag models' AIC values were lower. Bivariate and multivariate spatial lag models found a significant inverse relationship between the percentage of non-Hispanic, African American residents living in DC neighborhoods and tobacco retailer density: a 1% increase in the percentage of non-Hispanic, African-Americans living in DC neighborhoods was associated with a .01% and .02% decrease in tobacco retailer density, respectively. However, this relationship was not observed in DC MSA neighborhoods. A significant positive association was also observed in the bivariate relationship between the percentage of Hispanic residents living in DC neighborhoods and tobacco retailer density, such as a 1% increase in the percentage of Hispanic residents living in DC neighborhoods was associated with a .06% increase in tobacco retailer density. This association was close to significance (P=.056) in the multivariate spatial lag model. A similar positive association was also observed in the percentage of Hispanic residents living in DC MSA neighborhoods. This positive effect was observed in both the bivariate and multivariate DC MSA spatial lag models: a 1% increase in the percentage of Hispanic residents living in DC MSA neighborhoods was associated with a 1.72% and 1.66% increase in tobacco retailer density, respectively. The largest effect was observed between the percentage of families living in poverty in DC MSA neighborhoods and tobacco retailer density. Specifically, bivariate and multivariate spatial lag models found that every 1% increase in the proportion of families living in poverty in DC MSA neighborhoods was associated with a 3.51% and 2.82% increase in tobacco retailer density, respectively. (Table 2)

Discussion

Findings from this study provide evidence that the nature of sociodemographic disparities in the tobacco retail environment across DC and DC MSA neighborhoods may be more complex than other geographic areas. Although associations between neighborhood sociodemographic characteristics and tobacco retailer density were significant, retailer density was found to be lower among DC neighborhoods with a majority of non-Hispanic, African American residents, which is inconsistent with findings from prior studies.

Table 1. Spearman's correlations between sociodemographic factors and tobacco retailer density in DC and DC MSA

DC study area			
Sociodemographic characteristics	R_s	Conventional P	Spatially Adjusted P
Percent non-Hispanic, African American	-.38	.00	.00
Percent Hispanic	.34	.00	.00
Percent families living in poverty	-.15	.04	.02
Total number of jobs	.32	.00	.09
DC MSA study area			
Sociodemographic characteristics	R_s	Conventional P	Spatially Adjusted P
Percent non-Hispanic, African American	.10	.00	.12
Percent Hispanic	.19	.00	.00
Percent families living in poverty	.11	.00	.00
Total number of jobs	.29	.00	.00

Table 2. Association between sociodemographic factors and log of tobacco retailer density in DC and DC MSA[a]

DC study area		
Bivariate estimation	Coefficient (SE)	P
Percent non-Hispanic, African American	-.013 (.006)	.018
Percent Hispanic	.058 (.022)	.007
Percent of families living in poverty	-.012 (.013)	.367
Total number of jobs	.000 (.000)	.977
Multivariate estimation	Coefficient (SE)	P
Percent non-Hispanic, African American	-.016 (.008)	.031
Percent Hispanic	.047 (.022)	.056
Percent families living in poverty	.021 (.018)	.585
Total number of jobs	.000 (.000)	.252
DC MSA study area		
Bivariate estimation	Coefficient (SE)	P
Percent non-Hispanic, African-American	.334 (.29)	.25
Percent Hispanic	1.716 (.621)	.006
Percent of families living in poverty	3.513 (1.073)	.001
Total number of jobs	.407 (.08)	.000
Multivariate estimation	Coefficient (SE)	P
Percent non-Hispanic, African-American	.194 (.338)	.566
Percent Hispanic	1.656 (.637)	.009
Percent of families living in poverty	2.816 (1.258)	.025
Total number of jobs	.428 (.080)	.000

a. Spatial lag model estimation; SE, standard error.

However, this relationship shifts as the geographic study area increased, which reflects findings from previous studies and highlights how the geographic boundaries of a study area can influence findings. Variations between these study areas could reflect unobserved heterogeneity in the associations between sociodemographic factors and tobacco retailer density, such as the level of urbanicity of the neighborhoods found within each study area. For example, DC neighborhoods were predominantly urban, while DC MSA neighborhoods were mostly suburban. This pattern of association is similar to the differences observed in relationships between sociodemographic factors and tobacco retailer density by population density.[3] Findings highlight the need for a more detailed examination of how tobacco-related health disparities vary across areas with differing levels of urbanicity.

Findings may indicate that tobacco use in predominantly African American and low-income DC neighborhoods may not be influenced by the availability of retail tobacco, but rather the magnitude of marketing efforts of tobacco retailers located within these neighborhoods. For example, in major cities like DC, there are significantly more tobacco advertisements in socioeconomically disadvantaged areas than other neighborhoods.[30-32] A recent systematic review concluded that neighborhoods with a high proportion of African American and low-income residents was associated with tobacco retailers having more tobacco marketing generally and more menthol tobacco marketing, specifically.[33] Given the findings from the current study, tobacco control policies that aim to reduce the overall availability of retail tobacco in DC may not be sufficient to reduce tobacco use among some populations; additional policies should be considered, such as restricting the amount of tobacco marketing and advertising allowed within retail tobacco outlets.

The current study uses methodology that addresses the MAUP and edge-effect concerns. By accounting for tobacco retailers that fell outside of the defined areas of our tobacco retailer density areas, this approach helps mitigate any potential bias in the density estimates for neighborhoods along the DC and DC MSA boundaries. Future studies employing this method are needed to examine how and to what extent sociodemographic factors are associated with aspects of the tobacco retail environment in other geographic locations. Specifically, studies are needed to explore the tobacco retail environment across various geographic areas (eg, urban vs rural), and to consider how sociodemographic factors may vary by specific types of tobacco retailers and their promotional strategies.

Study Limitations

Several study limitations warrant discussion. First, the study relied on commercial business directory data to identify potential tobacco retailers. Relying on geocoded data from commercial sources could have produced some bias since the location data for tobacco retailers contain some level of positional errors related to the commercial geocoding process. However, validation studies of commercial business directories have found that between 80-90% of retail outlets are properly located within the correct census tract.[34,35] Since numerous studies have relied on commercial business directories to model the tobacco retail environment,[3,17,19,26] we expect any potential bias in our approach would not have impacted our findings. Next, daytime population estimates differ from the ACS residential data used in our analysis and may have contributed some error in our derived density estimates. We believe the daytime population provides a better reflection of the daily population in the area creating the demand for tobacco products and any potential error would not have altered our overall findings.

Findings may indicate that tobacco use in predominantly African American and low-income DC neighborhoods may not be influenced by the availability of retail tobacco, but rather the magnitude of marketing efforts of tobacco retailers located within these neighborhoods.

Lastly, the current study was restricted to one city and the surrounding metropolitan area; the results may not be generalizable to other study areas. DC is unique because of its large commuting population and federal government workforce. Moreover, DC neighborhoods with the highest concentrations of low-income and African American residents are also geographically isolated from most of the goods and services in DC by the Anacostia River. These physical and built environment characteristics demonstrate the need for a nuanced examination when examining geographic-related disparities in DC.

Conclusions

Findings revealed sociodemographic characteristics associated with tobacco retailer density in DC and DC MSA. However, findings related to the city of DC are inconsistent with previous studies. Future studies are needed to confirm whether vulnerable neighborhoods are more likely to contain a higher level of tobacco retailer density, especially in urban areas with heavy commuting populations, and must account for the underlying spatial autocorrelation. Determining how tobacco retail outlets are uniquely distributed geographically across an area and understanding their pattern in relationship to the built environment and neighborhood sociodemographics are important first steps when developing equitable tobacco retailer reduction policies.

Acknowledgments

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Availability of Data and Material

The data that support the findings of this study are available from Dun and Bradstreet but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of Dun and Bradstreet.

Conflict of Interest

No conflicts of interest to report.

Author Contributions

Research concept and design: Anesetti-Rothermel, English, Hair, Vallone; Acquisition of data: Anesetti-Rothermel, Herman, Vallone; Data analysis and interpretation: Anesetti-Rothermel, Herman, Bennett, English, Cantrell, Schillo, Hair; Manuscript draft: Anesetti-Rothermel, Herman, Bennett, Cantrell, Schillo, Hair, Vallone; Statistical expertise: Anesetti-Rothermel, Herman, Cantrell, Hair, Vallone; Administrative: Anesetti-Rothermel, Bennett, English, Hair, Vallone; Supervision: Anesetti-Rothermel, English, Schillo, Hair, Vallone

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