Student Column

DEMOGRAPHIC DISPARITIES IN THE TOBACCO RETAIL ENVIRONMENT IN BOSTON: A CITYWIDE SPATIAL ANALYSIS

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Tobacco use is recognized by global authoritative bodies, such as the Oxford Health Alliance, as a leading cause of preventable death in the world. Racial/ethnic minority groups (e.g., black and Hispanic people) as well as individuals of lower socioeconomic status (SES) (e.g., low-income individuals) experience disproportionately elevated rates of tobacco-related morbidity and mortality.[1] These disparities may be explained in part by differential geographic access to tobacco products.

Existing research has found that neighborhoods with high racial/ethnic minority concentrations and lower SES tend to have a higher density of tobacco retailers.[2–12] While informative, most of these studies ignore the spatial techniques that are often necessary when using spatial data, notwithstanding early tobacco retailer demographic disparities research explicitly noting the importance of accounting for spatial autocorrelation in future research.[4] Limited research has evaluated demographic disparities in the tobacco retail environment that employed a spatial analytic perspective.[2,10,12,13] Findings from some studies suggest that performing spatial regressions was necessary when analyzing demographic disparities in the tobacco retail environment.[2,13] Spatial regressions account for spatial autocorrelation explicitly by paying attention to the location and arrangement of neighborhood units, resulting in correct parameter estimates and *p*-values.[14–20] Additionally, most studies measure population composition as a continuous variable. However, there may be threshold effects, whereby categorizing population composition (e.g., >60% of a certain racial/ethnic minority group) might matter in the spatial distribution of tobacco retailers.

All of the existing research evaluating demographic disparities in the tobacco retail environment of which we are aware used older demographic data (e.g., from the 2000 U.S. Census). Additional studies are needed to monitor current potential demographic disparities in the tobacco retail environment. Indeed, it is important that studies about demographic disparities in the tobacco retailer environment are conducted frequently because the retail landscape may change constantly in certain geographies. In addition, while a study by Laws et al. gathered data on tobacco outlets from three neighborhoods in Boston, Massachusetts, to examine demographic disparities in the tobacco retail environment,[3] the results of the study may not be generalizable to other areas.

We evaluated racial/ethnic and socioeconomic disparities in the tobacco retail environment across neighborhoods in Boston, considering threshold effects of neighborhood demographics and employing a spatial analytic perspective with current demographic data.

METHODS

Geographic area

The geographic area of investigation for this study, Boston, is 89.63 square miles, including 48.43 square miles (or 54.03%) of land. Based on calculations using the 2010 U.S. Census, Boston has a population of more than 600,000 people.

Tobacco retailer geographic data

We obtained and geocoded geographic data on tobacco-selling retail outlets from the Cigarette and Tobacco Excise Unit of the Commonwealth of Massachusetts' Department of Revenue. The tobacco retailer data had various information including the business name and address for all tobacco retailers in Massachusetts from October 1, 2010, to September 30, 2012. These data included retailers that had tobacco licenses in Massachusetts during this specified time period and were restricted to the city of Boston for the current study. There were 1,025 licensed tobacco retailers in Boston during the 2010–2012 time period.

Using ArcGIS® version 10.1,[18] we calculated tobacco retail density (i.e., tobacco retailers per square kilometer) for census tracts in Boston. Previous research on demographic disparities in the tobacco retail environment used census tracts as the geographic unit of investigation.[2,4,5,7–11,13] We used 2010 U.S. Census tract boundaries in this study.

Census tract demographic data

Sociodemographic data at the census tract level for minority neighborhood racial/ethnic composition (i.e., percentage of non-Hispanic black residents and percentage of Hispanic residents) came from the 2010 U.S. Census data. These variables were measured as continuous and categorical variables (census tracts with >60% black [20 of the 167 tracts analyzed in this study] and Hispanic [five of the 167 tracts] populations were considered as predominantly black and Hispanic neighborhoods, respectively).[21–23] Census tract data on socioeconomic conditions were not collected in the 2010 U.S. Census; therefore, census tract data on socioeconomic disadvantage (i.e., percentage of families below the federal poverty level) came from the 2006–2010 American Community Survey (ACS). Census tract poverty was operationalized as both a continuous and a categorical variable, where high-poverty neighborhoods were defined as those having at least 20% of families living in poverty (51 of the 167 tracts).[24–26] Census tract data on population density (i.e., the total population per square kilometer) also came from the 2010 U.S. Census.

Spatial analysis

This study employed an explicit spatial approach to study demographic disparities in the tobacco retail environment. The initial analytic sample included contiguous 2010 Boston census tracts (n=179). Consistent with previously published neighborhood research in Boston, we excluded the sparsely populated Harbor Islands[27–29] and a census tract that includes only the Massachusetts Bay. Also consistent with previous demographic disparities research,[29,30] our analysis was restricted to census tracts with >500 people (final n=167), which ensured that census tracts with very small populations would not bias the results and remove missing or withheld ACS data due to small populations. Generally, the ACS does not release data for populations of <500 people at this scale to preserve anonymity.

After examining descriptive statistics for tobacco retail density (e.g., mean and range), we used geovisualization to explore potential spatial patterning. We then evaluated spatial autocorrelation via the Global Moran's *I*-test statistic.[16,17,31] Our previous research with the 167 census tracts found significant spatial autocorrelation in census tract demographics in Boston (e.g., census tract percent black),[29,32] so we did not evaluate spatial patterning in these variables in this study. The Moran's calculation for spatial patterning in the tobacco retail density was based on a row-standardized binary first-order Queen's contiguity spatial weights matrix. Moran's *I*-values fall between −1 (negative spatial autocorrelation) and +1 (positive spatial autocorrelation), with a zero value indicating no spatial autocorrelation. We determined statistical significance of the Global Moran's *I*-value via a Monte Carlo simulation of 999 random replications.

We computed Spearman's correlations between the demographic characteristics and tobacco retail density. Then, we computed Spearman's correlations accounting for spatial autocorrelation because existing spatial autocorrelation violates the independent observations assumption; thus, it can result in incorrect estimation of significance of effects in the conventional correlation tests of the significance.[33–35] The method used to account for spatial autocorrelation in a correlation framework is an effective sample size methodology.[33,34] Spatially adjusted significance of correlations also used the row-standardized binary first-order Queen's contiguity spatial weights matrix and six spatial lags. Correlation coefficients (r_S-values) and significance values are reported.

After computing a natural logarithm transformation on tobacco retail density, with a transformation offset of 0.001 because tobacco retail density was highly skewed, log-linear bivariate and multivariate regression models were fit predicting tobacco retail density. Multivariate models controlled for all demographics assessed in the study as well as census tract population density. Multivariate analyses including all neighborhood sociodemographic characteristics were also conducted due to potential suppressor and/or interactive effects. Our regression approach began with the conventional ordinary least squares (OLS) regressions, followed by spatial regressions (which control for spatial autocorrelation) if the OLS regression residuals exhibited significant spatial autocorrelation.[14–18] If we detected spatial autocorrelation in the OLS regression residuals, we planned to fit the spatial error model and the spatial lag model (as appropriate), in part because previous demographic disparities research has implemented both spatial models.[36] The Global Moran's *I*-test statistic and the Lagrange Multiplier test for both spatial regression modeling approaches were used to evaluate the fitted OLS regression residuals for spatial autocorrelation with the row-standardized first-order Queen's spatial weights matrix.[14,18,19,37,38] If the spatial error model or the spatial lag model was appropriate, we compared the OLS and spatial models using the Akaike Information Criterion (AIC).[39] A smaller AIC shows a better model goodness of fit. Lastly, if spatial error models were computed, we conducted the spatial Hausman test to compare the magnitude of the OLS and spatial error model parameter estimates based on the null hypothesis of correct specification.[14,40]

We used the R statistical program version 2.15 with the *spdep* package for all calculations.[41] For all analyses, we evaluated statistical significance at p<0.05.

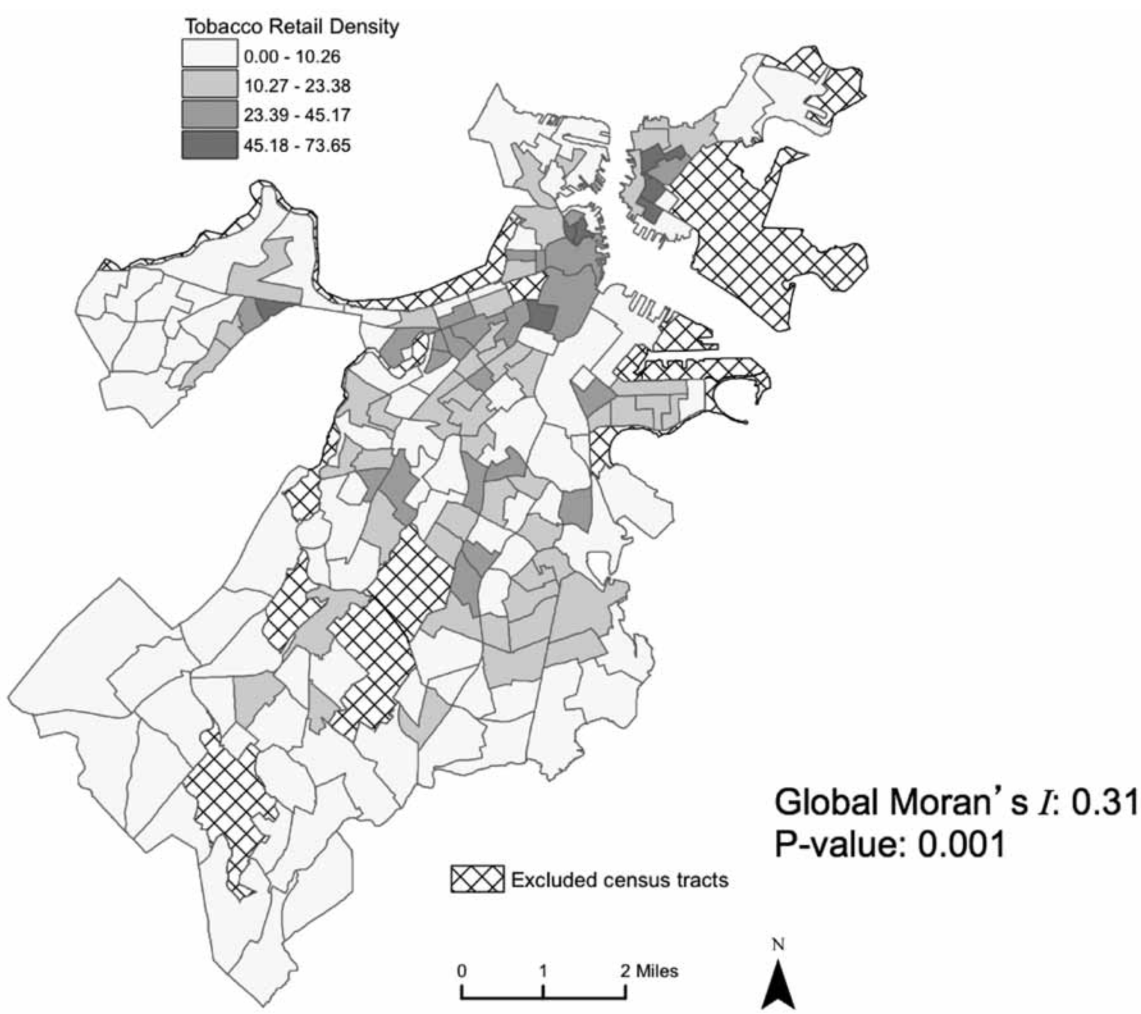
RESULTS

For the analytic sample of 167 census tracts, the mean number of tobacco retailers was 5.92 (standard deviation [SD] = 5.72; range: 0–48). The mean tobacco retailer density was 14.24 per square kilometer (SD=14.20, range: 0–73.65) for the analytic sample of 167 census tracts. Geovisualization revealed spatial patterns in tobacco retailers across Boston census tracts, and there was significant global spatial autocorrelation in tobacco retailer density (Global Moran's I=0.3139, p=0.001) (Figure).

Only one neighborhood demographic characteristic was significantly correlated with tobacco retailer density (Table 1): predominantly Hispanic census tracts (r_S=0.2005, p=0.0094).

Results suggested the need for spatial regression modeling approaches when predicting the log of tobacco retailer density. Across all bivariate and multivariate OLS models, the Global Moran's I-values for spatial autocorrelation were statistically significant, as were the Lagrange multiplier terms for spatial models in most models, suggesting the appropriateness of the spatial lag model ($p<0.05$). The AIC values were lower in the spatial lag models compared with the OLS models. No significant demographic relationships between log of tobacco retailer density were detected in the bivariate spatial lag models (Table 2). Similarly,

Figure. Spatial distribution of tobacco retailers at the census tract level:[a] Boston, Massachusetts, October 1, 2010–September 30, 2012



[a]Data culled from the Cigarette and Tobacco Excise Unit of the Commonwealth of the Massachusetts Department of Revenue (http://www.mass.gov/dor).

Table 1. Spearman's correlation between neighborhood-level demographics and tobacco retailer density in Boston

Demographic characteristic	R_S	*Conventional p-value*	*Spatially adjusted p-value*
Percent non-Hispanic black	−0.1050	0.1770	0.4512
Percent Hispanic	0.0312	0.6889	0.8018
Percent families in poverty	0.1322	0.0884	0.2048
Predominantly non-Hispanic black	−0.0562	0.4703	0.6232
Predominantly Hispanic	0.2005	0.0094	NA[a]
Predominantly families in poverty	−0.1279	0.0995	0.1377

[a]Due to the small sample size of predominantly Hispanic neighborhoods, the spatially adjusted correlation between neighborhood predominantly Hispanic and tobacco retailer density could not be computed.

NA = not applicable

in multivariate spatial regression analyses, no demographic characteristics were associated with tobacco retailer density.

DISCUSSION

Previous research has found racial/ethnic minority and socioeconomic disparities in geographic access to tobacco retailers,[2–13] including a study that analyzed three selected Boston neighborhoods.[3] In contrast with previous studies, we found no demographic disparities in the tobacco retailer environment across Boston neighborhoods. Specifically, although Spearman's correlations found a positive association between predominantly Hispanic census tracts and tobacco retailer density, the multivariate spatial regression analyses showed no associations between demographic characteristics and tobacco retailer density.

With 36 colleges and universities, Boston is an atypical city in that it has a very large student population that is often concentrated in non-racial/ethnic minority and non-poor neighborhoods. This feature might account for the lack of patterning of tobacco retail stores by racial/ethnic and socioeconomic composition of neighborhoods. In addition to tobacco retailers placing themselves in racial/ethnic minority and poor neighborhoods, tobacco retailers may choose to be in places with high concentrations of students (for profit maximization).

Our study extends previous research in several ways. For example, this study employed a spatial perspective and considered threshold effects (both of which few

Table 2. Association between neighborhood demographics and log of tobacco retailer density in Boston: spatial lag model estimation

Bivariate estimation	*Coefficient (SE)*	P-*value*	*Bivariate estimation*	*Coefficient (SE)*	P-*value*
Percent non-Hispanic black	0.003 (0.007)	0.640	Predominantly non-Hispanic black	0.203 (0.527)	0.701
Percent Hispanic	0.009 (0.012)	0.432	Predominantly Hispanic	1.270 (1.007)	0.207
Percent families in poverty	0.002 (0.012)	0.841	Predominantly families in poverty	0.213 (0.371)	0.566
Multivariate estimation[a]	*Coefficient (SE)*	P-*value*	*Multivariate estimation*	*Coefficient (SE)*	P-*value*
Percent non-Hispanic black	0.008 (0.008)	0.368	Predominantly non-Hispanic black	0.309 (0.536)	0.565
Percent Hispanic	0.010 (0.013)	0.433	Predominantly Hispanic	1.228 (1.016)	0.227
Percent families in poverty	−0.006 (0.014)	0.677	Predominantly families in poverty	0.270 (0.377)	0.474

Note: In the spatial lag model, which was estimated via maximum likelihood, there was evidence of remaining spatial autocorrelation and heteroskedasticity in some models. However, findings overall did not change when more advanced spatial models were implemented, including a combination spatial model where spatial effects were accounted for, including a spatial lag of the dependent variable and a spatial lag of the error term (sometimes referred to as spatial autoregressive model with autoregressive disturbances [SARAR]) and a two-stage least-squares model for the spatial lag model with heteroskedasticity and autocorrelation consistent SEs. The spatial lag model estimated via maximum likelihood is presented because it is the most parsimonious, but appropriate, spatial model. For instance, the Akaike Information Criterion value is lower in the maximum likelihood spatial lag model compared with the SARAR model.

[a]Multivariate models are controlled for population density and other neighborhood sociodemographics.

SE = standard error

studies have done). Mapping in ArcGIS suggested spatial patterning in tobacco retailers. Visually, there seem to be more tobacco retailers in certain neighborhoods of Boston, including Allston and East Boston. Using quantitative spatial analyses, we found spatial autocorrelation in tobacco retailer density and also found spatial autocorrelation in the OLS regression residuals when predicting the log of tobacco retail density. A previous study found no spatial autocorrelation in tobacco retailers, which likely would indicate no need for spatial regressions.[12] However, results from other research, which examined demographic disparities in the tobacco retailer environment, similarly suggest the need for spatial regressions.[2,13]

Future studies examining demographic disparities in the tobacco retail environment are needed (including in other geographic locations and using various neighborhood definitions). These studies could potentially examine demographic disparities by specific types of tobacco retailers (e.g., convenience stores). Additionally, future studies can use price data from tobacco retailers on tobacco products to further examine demographic disparities in the price as well as type and quantity of tobacco products. In this study, given the structure of the business data, we were unable to account for the type of tobacco products potentially sold, which could influence the findings. It is known that a majority of non-Hispanic black people smoke menthol cigarettes; thus, knowing what tobacco products are sold and where could be useful in future investigations. Furthermore, future research should examine the potential demographic disparities in in-store tobacco advertising across neighborhoods in Boston and other locations. The proposed future research can inform whether and where policies are needed. If demographic disparities are found in tobacco retailers, zoning restrictions might be implemented to remedy any disparities.[42,43]

Limitations

This study was subject to several limitations. For one, we note that using GIS data to measure store location, including tobacco retailers (e.g., GIS data on tobacco-licensing locations and business code GIS data on potential tobacco retailers), can have some positional errors. However, in this study, we analyzed tobacco-licensing data, which are better than proxy data, on the tobacco retail environment, including using business codes to define the tobacco retail environment, which some studies have done.[11,44,45] A validation study using North American Industry Classification System codes for operationalizing the tobacco retailer environment found that commercial datasets may underestimate the number of tobacco outlets, and there is likely some misclassification when using this method (e.g., not all grocery and convenience stores may sell tobacco products, such as cigarettes).[11]

Some other limitations pertain to the geographic area and unit investigated in this study. Because this study was conducted in one city (i.e., Boston), the results may not be generalizable to other geographies, including those that are non-urban. In this study, the definition of neighborhood selected was the U.S. census tract. We specifically used the census tract in this research because it is a frequently used neighborhood definition, including in previous demographic disparities in tobacco environment research[2,4,5,7–11,13] and in Boston-based neighborhood research in general.[24,29,46–48] Other neighborhood definitions in Boston exist (including based on the Boston Public Health Commission[28] and the Boston Redevelopment Authority).[49,50] However, these other neighborhood definitions are much larger than census tracts, so the sample size would be reduced, and using these definitions would increase the likelihood of less variation among the units being measured due to spatial aggregation at coarser scales.[51]

The modifiable areal unit problem was a concern in this study and all other geographic research.[52–54] The fact that residents in census tracts that are adjacent to areas outside of Boston might have easy access to a high tobacco retailer density outside the city was not accounted for in this analysis, highlighting the potential for existing "edge effects" (i.e., ignoring interdependent or close-by geographies outside of the study area), which may influence associations. Additionally, there are different approaches to operationalize predominantly minority racial/ethnic and high-poverty neighborhoods. For example, predominantly minority neighborhoods could be operationalized as 50% and high-poverty neighborhoods could be operationalized as ≥30% of the population living in poverty. While our categorizations were based on previously published research, the categorizations chosen may have influenced our study findings.

CONCLUSION

Contrary to existing research, results from this study suggest that there are no demographic disparities in the tobacco retailer environment in Boston. Replication studies in Boston and other areas using census tracts and other neighborhood definitions should be conducted in addition to examining policies that may promote an equitable distribution of tobacco retailers across neighborhoods in Boston (yet to be examined).

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