



Characterizing the spatial relationship between smoking status and tobacco retail exposure: Implications for policy development and evaluation

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ABSTRACT

Tobacco retail density and smoking prevalence remain elevated in marginalized communities, underscoring the need for strategies to address these place-based disparities. The spatial variation of smokers and tobacco retailers is often measured by aggregating them to area-level units (e.g., census tracts), but spatial statistical methods that use point-level data, such as spatial intensity and K-functions, can better describe their geographic patterns. We applied these methods to a case study in New Castle County, DE to characterize the cross-sectional spatial relationship between tobacco retailers and smokers, finding that current smokers experience greater tobacco retail exposure and clustering relative to former smokers. We discuss how analysis at different geographic scales can provide complementary insights for tobacco control policy.

1. Introduction

Adult cigarette smoking rates have decreased from a peak of over 40% in 1964, when the U.S. Surgeon General issued the first report on smoking and health, to approximately 14% more than 50 years later (Creamer et al., 2019; U.S. Department of Health and Human Services, 2014). Nevertheless, smoking remains the leading cause of preventable morbidity and mortality in the U.S., with more than 34 million current smokers (Creamer et al., 2019). In contrast to the 1960s when smoking was widely accepted, current smoking rates are significantly higher among groups with low socioeconomic status (SES) (Drope et al., 2018). These differences in smoking rates, in turn, contribute to tobacco-related health disparities (Frisco et al., 2019; Ho and Elo, 2013; Lortet-Tieulent et al., 2016). Thus, despite the overall successes of the last 50+ years, tobacco control measures have been less effective for low-SES groups (U.S. National Cancer Institute, 2017).

An underlying reason for the limited effectiveness of tobacco control measures for low-SES groups is that the tobacco industry adapted to broadcast and other mass-media bans on cigarette advertising by shifting marketing to the point-of-sale in retail locations where there are fewer restrictions (Lee et al., 2015; Ribisl et al., 2017). Importantly, research has shown that across the U.S., tobacco retailers tend to be more abundant in low-SES urban areas with larger proportions of

racial/ethnic minorities (Lawman et al., 2020; Lee et al., 2017; Rodriguez et al., 2013), though there can be heterogeneity in this general trend (Rodriguez et al., 2014). Furthermore, of the \$8.5 billion the tobacco industry spends annually on cigarette advertising and promotion, 66% (\$6.8 billion) is allocated to retailer price discounts (Trade Commission, 2015), counteracting the effect of taxation. As a consequence, given widespread geographic segregation along socioeconomic and racial/ethnic lines, greater exposure to tobacco retailers in disadvantaged areas contributes to spatial patterns in smoking prevalence. This has motivated the development of new policies aimed at reducing the numbers of tobacco retailers in low-SES communities (Lawman et al., 2020; Vyas et al., 2020). The evidence is mixed, however, as to whether these policies actually reduce tobacco retailer counts in marginalized communities (Giovenco et al., 2019) and ultimately impact smoking rates (Glasser and Roberts, 2021).

In order to improve the potential impact of tobacco retailer regulations, the development and evaluation of these policies should be informed by spatial methods that account for localized variation in the tobacco retail environment. While community boundaries define jurisdictions in which tobacco control policy may be applied, they can mask spatial variation in smoking behavior and tobacco retail exposure within and across communities – information that can be used to tailor these policies. Commonly used spatial measures of tobacco retailers that

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aggregate to census tracts or other administrative units, such as tobacco retailer density, can obscure trends when census tracts do not correspond to meaningful spatial boundaries (Vyas et al., 2020). For example, tobacco retailers are frequently located on major roadways, which are often used in defining census tract boundaries (U.S. Census Bureau, 1994). The allocation of tobacco retailers to a tract can depend, somewhat arbitrarily, on which side of the street the retailer is located. Spatial statistical methods that use point-level data can overcome these limitations. Furthermore, when evaluating the spatial relationship between tobacco retailers and smoking behavior, it is also advantageous to utilize point-level data over aggregated data structures. Data from representative population-based cohorts derived from panel studies (Chaiton et al., 2018), patient registries (Clemens et al., 2020), or electronic health records (EHR) (Siegel et al., 2019) offer the advantage of including point-level address data, which allow for the detection of clustering between smokers and tobacco retailers.

Tobacco retailer reduction policies are typically implemented at the local level and will require tailored approaches for evaluation. Therefore, as an initial step toward developing a robust evaluation framework that can be customized to local settings, we conducted a case study by joining publicly available point-level tobacco retail license data with an EHR-derived population of current and former smokers from a Mid-Atlantic health system. We examined spatial variation in the locations of current smokers relative to former smokers, since our EHR-based sample prevents us from estimating smoking prevalence or cessation rates in the general population. Smoking cessation was operationalized using the ratio of current to former smokers, measured at different geographic scales across the study region. We utilized tools from the field of spatial statistics to characterize the cross-sectional spatial relationship between tobacco retailers and smoking cessation, using data at both the point level and aggregated to area-level units. We illustrate how point-level and aggregated units of spatial analysis offer complementary interpretations of this relationship that can inform where and how tobacco control policies are implemented.

2. Methods

2.1. Setting

The Christiana Care Health System is a not-for-profit teaching health system headquartered in Wilmington, DE. The system's two primary

hospitals, Newark Hospital and Wilmington Hospital, are located in New Castle County, DE and provide 88% of all adult non-veteran acute care in New Castle County (Delaware Health Statistics Center. No Title. Market Share, n.d.). This study was reviewed and approved by the Christiana Care Health System Institutional Review Board.

2.2. Study sample

The study included 10,117 adult residents of New Castle County, DE with a history of smoking who were admitted to Newark and Wilmington Hospitals between July 1, 2018 and June 30, 2019. Smoking status was assessed through a standardized, nurse-administered interview at time of admission and documented as one of eight categories in the EHR. These categories were recoded for the current study as follows: current smoker ("current everyday smoker", "current some day smoker", "heavy tobacco smoker", "light tobacco smoker") and former smoker ("former smoker"). Smoking status was determined for 93% of in-patients during the study period and those with unknown smoking status were excluded. Patients' address information and demographic and clinical characteristics were extracted from the EHR. The last known smoking status and home address were used for patients with multiple admissions. Patients' addresses were manually cleaned and geocoded using ArcGIS 10.6 (match rate = 98%, 10,117/10,350) (Fig. 1, box A). Of the 233 unmatched patients (non-geocodes), 208 had no address information and 25 had addresses that were not able to be located. Descriptive statistics and appropriate bivariate tests (chi-square and Mann-Whitney U tests) were used to compare the populations of current and former smokers, as well as geocoded and non-geocoded patients.

We examined differential geocode match rates by smoking status and demographic characteristics. Compared to geocoded patients, non-geocoded patients were younger (mean age 58.2 vs. 63.0, respectively) ($p < 0.001$) and included more males (63.9% vs. 51.4% male, respectively) ($p < 0.001$) and more current smokers (54.5% vs. 37.1%, respectively) ($p < 0.001$). While we observed these disparities in geocode match rates, the non-geocodes comprise such a small fraction of the total sample (2%) that their exclusion would not bias our analysis to characterizing the spatial relationship between smoking cessation and tobacco retail exposure.

A public state business license database was used to create a directory of establishments with a tobacco retail license that sell directly to consumers (i.e., excluding cigarette affixing agents, wholesalers,

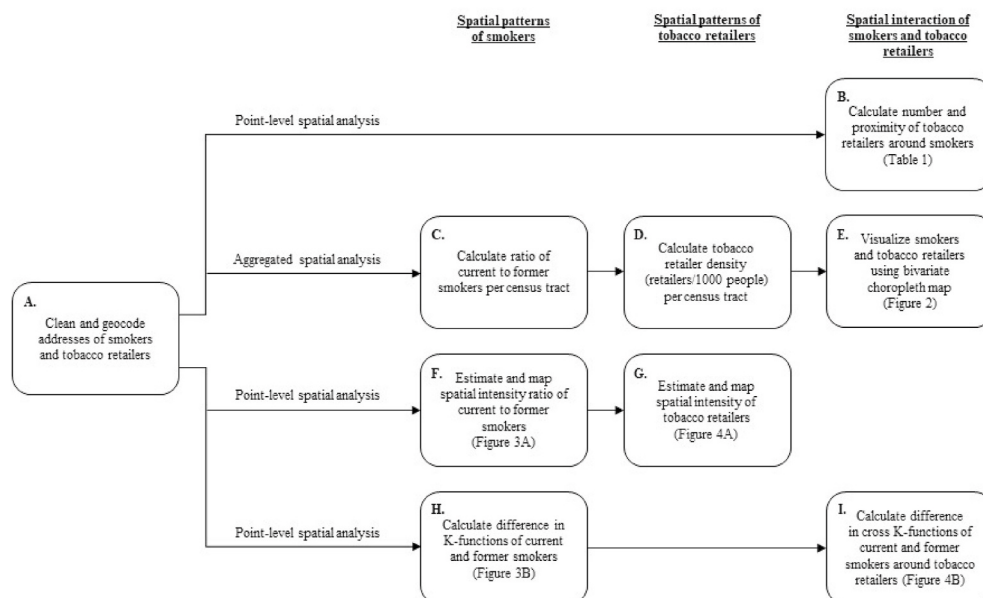


Fig. 1. Spatial analysis steps for smoker and tobacco retailer data.

internet retailers, and tobacco manufacturers). This database included all establishments with a tobacco retail license issued by Delaware's Division of Revenue as of April 17, 2019 (Delaware Division of Revenue, 2019). The database was reviewed to remove duplicates and update records where the address corresponded to the business owner's home rather than the storefront. Retailers were geocoded using ArcGIS 10.6 (match rate = 100%, $N = 642$) (Fig. 1, box A). These data were used to calculate measures of tobacco retail exposure for each patient. These included the number of tobacco retailers within a half-mile (0.8 km) of each person's home address, and each person's proximity in miles (and kilometers) to their nearest tobacco retailer (Fig. 1, box B). Both measures were calculated using Euclidean (straight-line) distance.

To provide context around the broader population and geographies in which our patient population resides, census tract-level data for age, sex, race, ethnicity, and poverty status were obtained from the American Community Survey's 2015–2018 five-year estimates and used to describe the sociodemographic characteristics of New Castle County's general population (U.S. Census Bureau, 2018). Previous work has shown that the Christiana Care Health System patient population of current and former smokers differ by these characteristics, as well as by whether or not they reside within the City of Wilmington, the county's largest and most populous city (Siegel et al., 2019). For this reason the American Community Survey data were stratified by the general populations living inside and outside of Wilmington. Descriptive statistics and two-tailed two-proportion z-tests were used to compare the characteristics of Wilmington versus non-Wilmington residents.

2.3. Aggregated spatial analysis

We begin with area-level spatial analyses at the census tract unit to demonstrate common practice for describing trends in where smokers and tobacco retailers are located. Current and former smokers were aggregated to their respective New Castle County census tracts and used to calculate a ratio of current to former smokers, aiding identification of areas in which current smokers represent a disproportionate share of inpatients with history of smoking (Fig. 1, box C). The aggregated unit of exposure was tobacco retail density, calculated as the number of tobacco retailers per 1000 people by census tract (Fig. 1, box D). The association between these measures was depicted using a bivariate choropleth map, which visualizes two numerical values for the same location by showing variation in the combination of values using color and saturation (Fig. 1, box E). The ratio of current/former smokers and tobacco retail density values were each sorted into three quantiles and combined to create a 3×3 classification system of low, medium, and high current/former smoker ratios and tobacco retail density. Each of the resulting nine values represents a combination of current/former smoker ratio and tobacco retail density values, ranging from low in both to high in both.

3. Point-level spatial analysis

Tools from the field of spatial statistics, spatial intensity and K-function analysis, were used to characterize the point-level distribution of smoking status (current and former), tobacco retailers, and the spatial interaction between smoking status and tobacco retailers. These methods focus on describing the mapped pattern of events, with events taken generically to refer to the mapped pattern of current smokers, former smokers, or tobacco retailers. Spatial intensity describes larger-scale variation in where events are located, while the K-function describes smaller-scale variation between events (clustering of events). These methods allow analysis based on the available spatial point-level information (geocoded addresses) rather than counts aggregated to administrative boundaries such as census tracts. Spatial intensity, defined as the expected number (concentration) of events per unit area, represents the continuous spatial distribution of events and is often displayed using a "heat map." Intensity was estimated using the kernel density approach for both the current and former smoker home address

locations (Diggle, 1985). This begins by overlaying the study region with a fine grid of generic locations. Then for each location the method counts the number of events (e.g., smokers) within a circular window weighted by their distance to the window center (the generic location where intensity is being estimated), thereby accounting for any local clustering of events. Once intensity is estimated at each location on the fine grid, the results are mapped and smoothed to represent spatial variation in the concentration of events, providing a spatially continuous alternative to the aggregated approach of counting of events per distinct administrative unit. The size of the window used in the kernel density approach (referred to as the bandwidth) was set at 3000 m based on exploratory analyses to obtain spatially smooth estimates of their respective patterns of events (Waller and Gotway, 2004).

Following established methods for estimating spatially varying risk in case control applications (Kelsall & Diggle, 1995a, 1995b), the ratio of the current to former smoker spatial intensities was generated as a measure of spatial odds and mapped to display spatial variation in the concentration of current smokers relative to former smokers (Fig. 1, box F). Spatial intensity was also estimated and mapped for the pattern of tobacco retailers using the same fixed bandwidth set at 3000 m (Fig. 1, box G).

The K-function, defined as the expected number of other events within distances of each event and scaled by an estimate of constant intensity, measures the level of spatial clustering (Ripley, 1976). Constant intensity is simply estimated by the total number of events in the study region divided by the study area, so that clustering characterized by the K-function accounts for both the total number of events and the size of the study region. The K-function plotted as a function of distance provides an interpretation of spatial clustering (spatial compactness) of a point pattern of events at a range of distances. Because current and former smokers are not spatially random but tend to be located within population centers, the difference in their respective K-functions, $K(\text{current}) - K(\text{former})$, was calculated to assess if one pattern clustered more than the other (Fig. 1, box H). The Monte Carlo procedure based on random labelling (permuting of the current and former smoker locations) provides the mechanism to assess significance in the K-function difference (Besag and Diggle, 1977). The mapped ratio of spatial intensity of current to former smokers and the difference in their respective K-functions provide separate but complementary assessments of the spatial distribution of current and former smokers.

The final analysis compared the extent to which current and former smokers cluster around tobacco retailers. Two point patterns (e.g., current smokers and tobacco retailers) are said to spatially interact if the level of clustering of one around the other is more so than what would be expected if the two patterns were spatially independent. The cross K-function, defined as the expected number of type 1 events within distances of type 2 events, scaled by the product of their constant intensities, measures the level of spatial interaction between the event locations of two types (Lotwick and Silverman, 1982). In this application we fix the type 2 events to be tobacco retailers and consider the difference in cross K-functions, $K_{\text{cross}}(\text{current}, \text{tobacco}) - K_{\text{cross}}(\text{former}, \text{tobacco})$ to assess if current smokers cluster around tobacco retailers more so than former smokers (in which case the cross K-function difference would be positive) (Fig. 1, box I). The Monte Carlo random labelling approach was used to assess significance.

ArcGIS 10.6 (ESRI, 2018) was used for spatial data management, geocoding, and final map preparations. All statistical and spatial statistical analysis was performed in the R Statistical Computing Environment (R Core Team, 2019) and R Studio with a suite of specific R packages for spatial analysis (Baddeley et al., 2015; Davies et al., 2018; Hijmans, 2020; Pebesma, 2018; Ribeiro and Diggle, 2020; Rowlingson and Diggle, 2017).

4. Results

Of the 10,117 adult county residents with a history of smoking who

were admitted to Newark or Wilmington Hospitals, 3749 (37%) were identified as current smokers and 6368 (63%) as former smokers. Table 1 shows that current smokers compared to former smokers were significantly younger and include more males, people of Black/African American race and Hispanic/Latino/a ethnicity, and those with Medicaid as their primary insurance. Current smokers also had significantly greater tobacco retail exposure as measured by proximity to their nearest tobacco retailer (0.26 miles vs. 0.37 miles for former smokers, $p < 0.001$) and the number of tobacco retailers within a half-mile of their home (4 retailers vs. 2 for former smokers, $p < 0.001$). Some of these trends are better understood when comparing the county-level socio-demographic context of current and former smokers as measured using American Community Survey data. Nearly a quarter (24%) of current smokers reside in the City of Wilmington, compared to 12% of former smokers. Wilmington's general population, compared to the rest of New Castle County, has significantly greater proportions of Black/African American residents (58% vs. 20%, respectively, $p < 0.001$) and those living below poverty level (25% vs. 9%, respectively, $p < 0.001$) (Table 2).

The relevance of Wilmington is made apparent in the Fig. 2 bivariate choropleth map, which shows New Castle County census tracts by their combinations of current/former smoker ratios and tobacco retail density, ranging from low in both, high in one of these values, or high in both. Areas with greater ratios of current to former smokers (areas depicted in darker shades of blue) are found primarily in northeastern New Castle County, with some pockets at the southern end of the county. Moderate to high concentrations of tobacco retailers (depicted in shades of pink and red) are seen mostly in northern New Castle County. Most notable are the areas highlighted in dark purple, representing high concentrations of both tobacco retailers and current smokers relative to former smokers. These areas are concentrated in the City of Wilmington, extending south through the northeastern part of the county. Smaller census tracts with both high tobacco retail density and current/former smoker ratios are also seen in the upper northeastern edge of the county.

Table 1

Characteristics of New Castle County, DE adults with a history of smoking who were admitted to Christiana Care Health System hospitals between July 1, 2018 and June 30, 2019.

	Current Smokers (N = 3,749)	Former Smokers (N = 6,368)	Total (N = 10,117)
Sociodemographic characteristics			
Age, median*	55	71	65
Male, n (%)	2,005 (53.5)	3,197 (50.2)	5,202 (51.4)
Race, n (%)			
White	2,426 (64.7)	4,847 (76.1)	7,273 (71.9)
Black/African American	1,167 (31.1)	1,314 (20.6)	2,481 (24.5)
Other Race	156 (4.2)	207 (3.3)	363 (3.6)
Hispanic/Latino/a, n (%)	172 (4.6)	198 (3.1)	370 (3.7)
Payor, n (%)			
Commercial	927 (24.7)	1,331 (20.9)	2,258 (22.3)
Medicaid	1,474 (39.3)	585 (9.2)	2,059 (20.4)
Medicare	1,307 (34.9)	4,430 (69.6)	5,737 (56.7)
Self-Pay	41 (1.1)	22 (0.3)	63 (0.6)
Residence in City of Wilmington, n (%)	906 (24.2)	788 (12.4)	1,694 (16.7)
Tobacco retail exposure characteristics			
Miles to nearest tobacco retailer, median*	0.26 (0.42 km)	0.37 (0.60 km)	0.33 (0.53 km)
Tobacco retailers within half mile (0.8 km) of home, median*	4	2	3

*p-value ≤ 0.001 .

Table 2

Sociodemographic characteristics and tobacco retail exposure of the New Castle County, DE general population according to residence in the City of Wilmington.

	Wilmington (N = 70,904)	Non-Wilmington (N = 484,229)	New Castle County (Total) (N = 555,133)
Sociodemographic characteristics^a			
Age groups, n (%)			
Under 18	16,424 (23.2)	104,760 (21.6)	121,184 (21.8)
18-34	18,291 (25.8)	115,326 (23.8)	133,617 (24.1)
35-54	18,148 (25.6)	127,623 (26.4)	145,771 (26.3)
55-74	14,399 (20.3)	106,103 (21.9)	120,502 (21.7)
75 and older	3,642 (5.1)	30,417 (6.3)	34,059 (6.1)
Male, n (%)	33,365 (47.1)	235,505 (48.6)	268,870 (48.4)
Race, n (%)			
White	24,902 (35.1)	333,281 (68.8)	358,183 (64.5)
Black/African American	41,359 (58.3)	97,249 (20.1)	138,608 (25.0)
Other Race	2,409 (3.4)	9,877 (2.0)	12,286 (2.2)
Hispanic/Latino/a, n (%)	7,257 (10.2)	46,814 (9.7)	54,071 (9.7)
Living below poverty level, n (%) ^b	17,138 (25.1)	44,392 (9.4)	61,530 (11.4)
Tobacco retail exposure characteristics			
Tobacco retailers, n	167	475	642
Tobacco retailers per 1000 people*	2.36	0.98	1.16

*p-value < 0.001 .

^a Sociodemographic data from U.S. Census Bureau, American Community Survey 2014–2018 estimates.

^b Counts and percentages reflect poverty status for the civilian non-institutionalized population, not the total population.

Tables 1 and 2 further confirm these trends. A disproportionate share of current smokers reside in Wilmington, and the city contains more than twice as many tobacco retailers per 1000 people compared to the rest of the county.

The ratio of the spatial intensity of current smokers relative to former smokers is mapped in Fig. 3a. Higher concentrations of current smokers relative to former smokers (intensity ratios above 1.0) are evident in northeastern New Castle County around the city of Wilmington stretching southward including parts of central New Castle County. Other areas of the county show lower concentrations of current to former smokers. Areas identified along the central and southern borders of New Castle County, along the central east coast and in the far southern edge of the county with elevated concentrations of current to former smokers are likely due to small sample sizes and thus interpreted accordingly. Fig. 3b shows the difference in K-functions for current and former smokers, $K(\text{current}) - K(\text{former})$, to be above zero, indicating that the point pattern of current smokers clusters more than the point pattern of former smokers and significantly more up to about a distance of 12 km (7.5 miles) since the difference extends outside the minimum/maximum confidence bands derived from Monte Carlo random labeling.

Interpretation of both results in Fig. 3 reveals that the concentration of current to former smokers varies spatially across the county and that current smokers are more spatially compact (closer together) than former smokers. To provide further insight into these descriptions of the spatial distribution of current and former smokers we consider the locations of tobacco retailers. The spatial variation in the concentration of tobacco retailers, spatial intensity mapped in Fig. 4a, visually matches that shown for the intensity ratio of current to former smokers in Fig. 3a; areas of higher concentration of current to former smokers spatially coincide with areas of higher concentration of tobacco retailers. This may help explain why current smokers cluster more than former smokers (Fig. 3b). Fig. 4b provides additional evidence for this relationship. It shows the difference in cross K-functions, $K_{\text{cross}}(\text{current, tobacco}) - K_{\text{cross}}(\text{former, tobacco})$, revealing that current smokers cluster around tobacco retailers significantly more than former smokers.

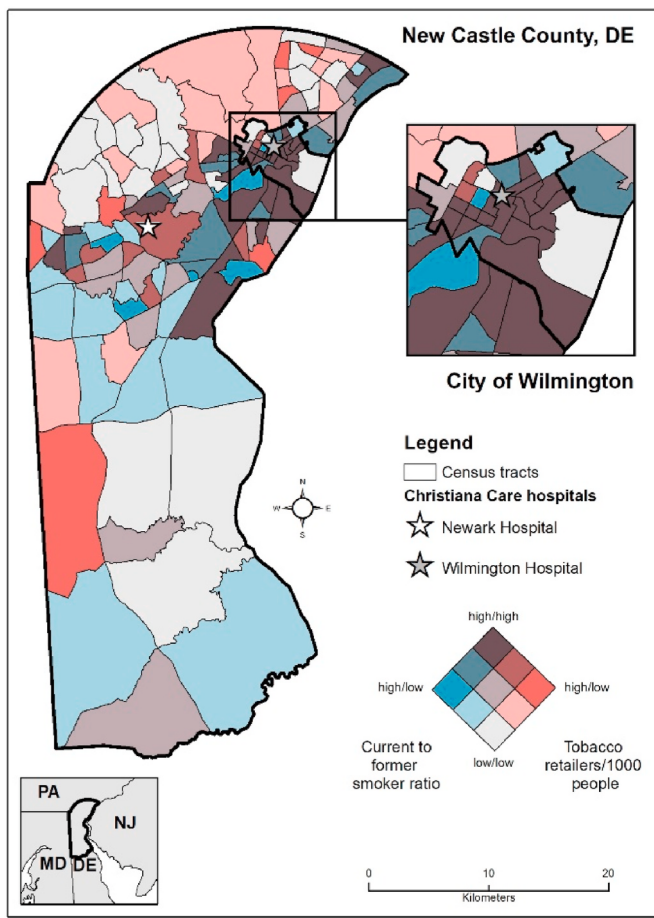


Fig. 2. This map depicts the aggregated ratio of adult current to former smokers from a hospital-based population and tobacco retailers per 1000 people (tobacco retail density) at the census tract level in New Castle County, DE. Tracts in darker shades of blue represent higher ratios of current to former smokers, while tracts in darker shades of red and pink represent higher tobacco retail density. Tracts in dark purple represent areas with both high current to former smoker ratios and high tobacco retail density.

The clustering is significant within 12 km (7.5 miles) of a tobacco retailer where the cross K-function difference is above zero and above the Monte Carlo confidence bands. In other words, current smokers compared to former smokers are significantly more clustered around tobacco retailers, within up to 12 km of any retailer.

5. Discussion

This study demonstrates how under-utilized spatial statistical methods may be used to elucidate patterns of smoking cessation and tobacco retail exposure. Concurrent analysis of these patterns at different geographic scales can provide novel insights on where and how to focus tobacco control efforts. We observed a higher burden of tobacco retail exposure among current smokers relative to former smokers, a finding that is robust across different methods of spatial analysis. The bivariate choropleth and spatial intensity maps depict similar large-scale geographic trends in the overlap of smoking and tobacco retailers. These findings are substantiated by the difference in K-function analyses, which show similarly greater small-scale clustering (spatial compactness) of current smokers relative to former smokers. The difference in cross K-functions provides evidence that current smokers are significantly more likely to cluster around tobacco retailers than former smokers. Current smokers and tobacco retailers are concentrated in the City of Wilmington, which has disproportionately more Black/African American residents and those living in poverty compared to the rest of the county. These findings are consistent with industry efforts to deliberately target racial/ethnic minorities and people of low SES with tobacco marketing at the point of sale (Cruz et al., 2019). Taken together, these findings reveal demographic and socioeconomic inequities in tobacco retail exposure at the individual and ecological levels.

Aggregated and point-level spatial analyses provide complementary applications to tobacco control policy while balancing the limitations of each approach. Area-level measures that aggregate to city or other administrative boundaries, as seen in Fig. 2, are relatively easy to calculate and offer two “real-world” advantages. First, these boundaries delineate areas that fall within the jurisdiction of a local governmental authority and accordingly align the processes of policy design, implementation, enforcement, and evaluation. Additionally, high tobacco retail exposure within city limits may suggest policy-relevant influences such as zoning regulations. Second, sociodemographic variables are typically measured within these units and can therefore facilitate the evaluation of potential inequities Duncan et al., 2018. When using

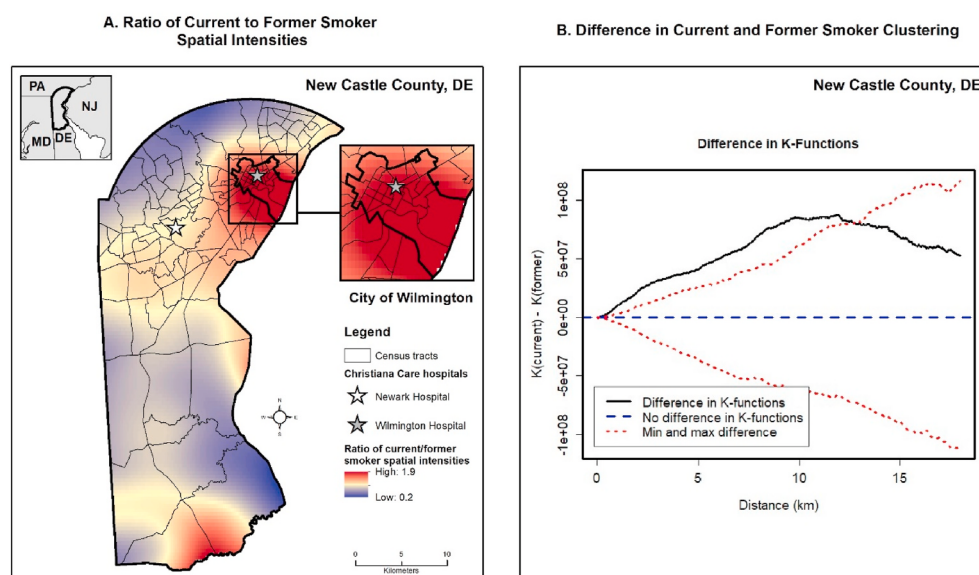


Fig. 3. Fig. 3 describes the spatial distribution of New Castle County, DE adults with a history of smoking who were admitted to Christiana Care Health System hospitals between July 1, 2018 and June 30, 2019. Fig. 3a depicts the ratio of the spatial intensities of current and former smokers, showing spatial variation in smoking cessation across the county. Fig. 3b depicts the difference in K-functions between current and former smokers, along with the minimum/maximum confidence bands derived from the Monte Carlo random labeling.

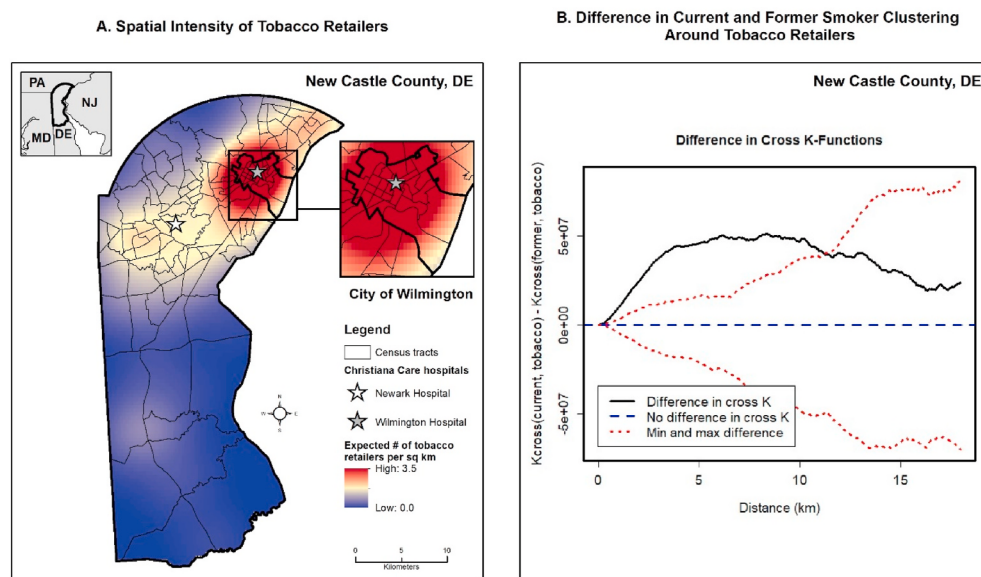


Fig. 4. Fig. 4 describes the spatial distribution of licensed tobacco retailers in New Castle County, DE and their spatial interaction with adult current and former smokers who were admitted to Christiana Care Health System hospitals between July 1, 2018 and June 30, 2019. Fig. 4a depicts the spatial intensity of licensed tobacco retailers across the county. Fig. 4b depicts the difference in cross-K functions between current and former smokers, along with the minimum/maximum confidence bands derived from the Monte Carlo random labeling.

sociodemographic variables to compare the distribution of smoking status and population characteristics across the county, Wilmington has greater proportions of Black/African American residents and those living below poverty level, two groups disproportionately targeted by tobacco industry marketing (Lee et al., 2015).

The main benefit of spatial intensity, a point-level approach for depicting geographic trends, is that it does not constrain its pattern of events to administrative boundaries. This addresses a major limitation of aggregated approaches – their tendency to mask within-unit (within-boundary) variation, which can falsely convey that people and their exposures are confined to these units. Aggregated approaches display the count or density of events per area unit and disregard information on any within-unit clustering of events or the borrowing/sharing of information across neighboring units. Proximity to and surrounding density of tobacco retailers have been shown to influence smoking status and have accordingly different regulatory strategies (Siegel et al., 2019; Reitzel et al., 2011). Tobacco retail density may be regulated through retailer caps, while retailer proximity may be regulated through minimum distance restrictions from other retailers and places such as schools (ChangeLab Solutions, 2019). Because spatial intensity estimation considers retailer density on a more spatially continuous scale, it can highlight areas which may benefit from one or both of these regulatory strategies. While spatial intensity does not convey where larger populations account for more tobacco retailers, Macdonald et al. (2018) argue that higher counts of these retailers in population-dense areas correspond to more population-level exposure and therefore deserve policy attention (Macdonald et al., 2018).

For all these reasons, spatial intensity can be employed as a useful precursor to specifying aggregated approaches because it can be used to identify disparate distributions of exposures (tobacco retailers) or populations (current smokers) regardless of boundaries. It may then inform the selection of boundaries in which tobacco control policies are warranted. Thus, spatial intensity can be used to identify where to focus tobacco regulatory policy based on greatest exposure, while aggregated measures permit linkage to data that specify the affected populations and the source of governmental authority for instituting tobacco regulations. In this case study, both the bivariate choropleth and spatial intensity maps identified the City of Wilmington as a clear “container” or geographic unit for concentrations of current smokers and tobacco retailers. While the bivariate choropleth map identified other parts of the county with elevated tobacco retail density and current/former smoker ratios, the spatial intensity maps convey the localization of both

phenomena in Wilmington and the need for city-specific policies. The use of both measures in tandem can help policymakers implement a pro-equity approach to tobacco regulation by focusing on reducing geographically-based inequities.

Policy applications that use spatial intensity to track large-scale variation in smoking status and tobacco retail environment are complemented by K-function analyses, which measure small-scale variation and can serve as a population-level measure of proximity to tobacco retailers. They quantitatively assess the strength and distance at which smokers and tobacco retailers cluster together, while spatial intensity maps show where any clustering occurs. K-function analyses can inform both the development and evaluation of tobacco control policies. First, K-functions may be stratified by retailer type (e.g., convenience stores, smoke shops, pharmacies, etc.) or by smoker subpopulations (e.g., by race or SES) to identify if either are associated with greater clustering patterns irrespective of spatial boundaries. These distinctions may be used to target specific retailers through density and proximity regulations or to target cessation resources to subpopulations that exhibit greater clustering around tobacco retailers. Second, K-function analyses can be applied longitudinally to evaluate whether tobacco control policies reduce the clustering of tobacco retailers, and of current smokers around these retailers, at a population level.

The K-function analyses presented here show significant clustering of current smokers around themselves and tobacco retailers relative to former smokers, raising questions about the extent to which retailers create or maintain a spatially proximal market for smoking. We cannot infer whether retailers precede current smokers because this study was not designed to address temporality. At a minimum, point-of-sale marketing has been shown to increase smoking susceptibility among never smokers (Robertson et al., 2015) and impede cessation among current smokers (Siahpush et al., 2016), which may explain the clustering of current smokers around these retailers. Longitudinal studies conducted in the U.S. have supported drawing causal inferences between tobacco retailer exposure and a decreased likelihood of smoking cessation (Cantrell et al., 2015; Reitzel et al., 2011; Siahpush et al., 2016), though similar studies conducted in Canada (Fleischer et al., 2019) and England (Han et al., 2014) produced contradictory findings.

Strengths of our study include the use of a large hospital-based sample and state tobacco license data, which provide point-level address data used to calculate measures of smoking status and tobacco retail exposure. The point-level data also accommodated the use of more advanced spatial statistical methods, assessing variation between and

among individuals' smoking status and their tobacco retail exposure, without the limitations from analysis of data aggregated to administrative units. Our study has several limitations. First, our sample is derived from the EHR rather than the general population and may therefore over-represent current and former smokers due to the negative health sequelae of smoking. However, the health system from which the sample is drawn provides the majority of adult acute care in the county, and this sample was found to be spatially representative of the general population of smokers in the City of Wilmington (Siegel et al., 2020), suggesting that these findings generalize beyond the hospital-based population. Second, this is not a national or multi-site study and the county of interest includes few rural areas. Our findings do, however, align with other national studies which have found associations between tobacco retail exposure and smoking status at the individual (Kirchner et al., 2017) and county (Golden et al., 2020) levels. Our work is intended as case study in applying under-utilized spatial methods to inform tobacco control policy. Replication is needed at different geographic levels, such as within cities or across states. Third, the analyses presented here do not consider the activity space of current and former smokers, which are unknown but influence their tobacco retail exposure beyond what is measured within their census tract or a certain distance of their home (Shareck et al., 2016). This reflects the uncertain geographic context problem, or the inability to know the precise spatial and temporal units of influence on a given behavior such as smoking (Kwan, 2012). Similarly, the half-mile buffer-based measures of individual tobacco retail density do not reflect travel distance or time associated with reaching tobacco retailers. This is especially relevant for our patients who live in urban Wilmington, where they are more likely to travel by foot or public transportation and have an accordingly smaller activity space more influenced by local exposures. Finally, this study did not consider spatial determinants of smoking status beyond exposure to tobacco retailers. Access to smoking cessation medications and behavioral treatments via the state quitline and Medicaid, the differential enforcement of smoke-free laws, and the local anti-smoking campaigns represent unmeasured covariates that have been shown to differentially impact low-SES and racial groups (Dahne et al., 2017). Despite our inability to account for each person's activity space, road-based travel, or exposure to other spatial determinants of smoking, the substantial overlap between tobacco retailers and smokers' home locations suggests that their residence is a meaningful source of tobacco exposure.

6. Conclusion

This study demonstrates how concurrent use of aggregated and point-level spatial methods can assess disparities in tobacco retail exposure and inform the development and evaluation of policies to mitigate these disparities. Used in combination with area-level visualizations, spatial intensity can identify where to focus tobacco control policy while K-function analyses can be used to tailor and measure the impact of such policies. Furthermore, the use of point-level data for smokers and tobacco retailers can refine measurement of their spatial patterning and provide evidence of the mechanisms by which tobacco retail exposure may impede smoking cessation. Future research is needed to extend these approaches to other geographic settings and longitudinal evaluations, as well as measuring the impact of tobacco retailer reduction policies on smoking cessation rates, further demonstrating their applicability and value to local tobacco control policies.

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Declaration of competing interest

None.

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