

ASSOCIATIONS OF TOBACCO RETAILER DENSITY WITH NEIGHBORHOOD
SOCIODEMOGRAPHICS, INDIVIDUAL SMOKING BEHAVIORS, & COPD HOSPITAL
DISCHARGE RATES: A SPATIAL HEALTH APPROACH

Amanda Y. Kong

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Approved by:

Shelley D. Golden

Christopher D. Baggett

Paul L. Delamater

Nisha C. Gottfredson

Kurt M. Ribisl

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ABSTRACT

Amanda Y. Kong: Associations of tobacco retailer density with neighborhood demographics, individual smoking behaviors, & COPD hospital discharge rates: A spatial health approach
(Under the direction of Shelley D. Golden)

Background. Tobacco retailer density (TRD) is a measure of the availability of tobacco retailers in an area. Although some studies indicate that TRD is not equitably distributed across neighborhoods, they are limited by inconsistent TRD measures and do not account for the sociodemographics of surrounding areas. Even fewer studies consider the impact of TRD on smoking behaviors or associated health outcomes at the national level. This dissertation encompasses four 2014 cross-sectional studies to investigate these gaps.

Methods. Study 1 investigated associations of TRD with census tract-level sociodemographic characteristics in the contiguous U.S., comparing associations across four commonly used density measures. Study 2 used spatial econometric modeling to determine whether the sociodemographics of neighboring census tracts additionally impact a focal tract's TRD. Study 3 used multilevel modeling to investigate whether county-level TRD is associated with an individual's likelihood of smoking and making a quit attempt in a national sample. Finally, Study 4 examined associations between county-level TRD and chronic obstructive pulmonary disease (COPD) related hospital discharge outcomes in 1510 counties.

Results. In Study 1, tracts with a greater proportion of residents living below 150% of the federal poverty level (FPL) had higher TRD. Disparities between TRD and percent non-Hispanic Black,

Hispanic or Latino, and vacant housing units, however, were sensitive to the TRD measure operationalized. In Study 2, a tract that was surrounded by neighboring tracts with a higher proportion of individuals living below 150% FPL, non-Hispanic Black residents, and Hispanic or Latino residents, was associated with greater TRD. In Studies 3 and 4, higher county-level TRD was associated with a greater likelihood of every-day smoking and higher county-level COPD-related discharges, hospital stays, and financial costs.

Conclusion. In 2014, there were racial, ethnic, and socioeconomic disparities in TRD, and both the neighboring attributes of census tracts and the TRD measures used may impact observed disparities. County-level TRD is also associated with daily smoking and greater hospital discharges rates and costs: longitudinal studies are needed to better disentangle the mechanisms driving these associations. Integrated tobacco control policies that include retailer reduction strategies may help ameliorate smoking behaviors and related disease burdens.

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TABLE OF CONTENTS

LIST OF TABLES	xiii
LIST OF FIGURES	xv
LIST OF ABBREVIATIONS AND SYMBOLS	xvi
CHAPTER 1. OVERVIEW AND SPECIFIC AIMS	1
CHAPTER 2. THEORETICAL & LITERATURE REVIEW	6
THEORETICAL REVIEW	6
OVERVIEW OF PROJECT CONCEPTUAL MODEL & LITERATURE REVIEW	10
Aim 1: Neighborhood Composition & Tobacco Retailer Density.....	11
Local Studies.....	11
National Studies	12
Aim 2: Spatial Econometrics – Do Your Neighbors Matter?.....	14
Aim 3: Tobacco Retailer Density & Adult Smoking and Cessation Behaviors	16
Aim 4: Tobacco Retailer Density & COPD Hospital Discharge Rates and Costs	19
CHAPTER 3. ASSESSING NEIGHBORHOOD SOCIODEMOGRAPHIC DISPARITIES IN TOBACCO RETAILER DENSITY AND THE DISTRIBUTION OF PHARMACIES AND TOBACCO SHOPS, UNITED STATES, 2014 (STUDY 1).....	22
INTRODUCTION	22
MATERIALS & METHODS	24
Neighborhood Sociodemographics.....	24
Tobacco Retailer Density.....	24
Analytic Sample.....	26
Analysis.....	26

RESULTS	27
DISCUSSION	34
CONCLUSIONS.....	38
 CHAPTER 4. NEIGHBORHOOD SOCIODEMOGRAPHIC DISPARITIES IN TOBACCO RETAILER DENSITY: DO YOUR NEIGHBORS MATTER? (STUDY 2)	
INTRODUCTION	40
METHODS	42
Neighborhood Sociodemographics.....	42
Tobacco Retailer Density.....	43
Spatial Econometric Modeling	44
Analytic Sample.....	45
RESULTS	46
DISCUSSION	49
CONCLUSIONS.....	52
 CHAPTER 5. ASSOCIATIONS OF COUNTY TOBACCO REATILER DENSITY WITH ADULT SMOKING STATUS AND CESSATION BEHAVIORS, UNITED STATES, 2014-2015 (STUDY 3).....	
INTRODUCTION	53
METHODS	55
Tobacco Use Supplement (TUS)	55
Smoking Status (Self- and Proxy- Respondents).....	56
Quit Attempt in Last 12 Months among Current Smokers (Self-Respondents)	56
Quit Length for Current Smokers Reporting Quit Attempt of One Day or Longer (Self-Respondents)	57
County-Level Tobacco Retailer Density	57
Analysis.....	59
RESULTS	59

Analytic Sample Characteristics	59
Smoking Status	62
Quit Attempts and Quit Length.....	64
Sensitivity Analyses.....	66
DISCUSSION.....	66
CHAPTER 6. ASSOCIATIONS OF TOBACCO RETAILER DENSITY WITH COPD-RELATED HOSPITAL OUTCOMES, UNITED STATES, 2014 (STUDY 4).....	70
INTRODUCTION	70
MATERIALS & METHODS	72
Data Sources and Measures	72
Tobacco Retailer Density.....	72
COPD-Related Hospital Discharge Data	74
Control Variables	76
Analysis.....	77
Negative Binomial Regression Models	77
RESULTS	78
Negative Binomial Regression Results.....	80
DISCUSSION.....	84
CONCLUSION.....	87
CHAPTER 7. DISCUSSION AND CONCLUSION	88
OVERVIEW AND THEORETICAL FOUNDATION.....	88
IMPLICATIONS FOR HEALTH AND HEALTH EQUITY	88
IMPLICATIONS FOR FUTURE RESEARCH.....	90
IMPLICATIONS FOR POLICY	91
STRENGTHS AND LIMITATIONS	93

CONCLUSION.....	94
APPENDIX A: 2010 RURAL-URBAN COMMUTING AREA CODES (RUCA).....	96
APPENDIX B: REFERENCEUSA NATIONAL TOBACCO RETAILER LIST METHODOLOGY	98
APPENDIX C: CHRONIC OBSTRUCTIVE PULMONARY (COPD) RELATED CLINICAL CLASSIFICATION SOFTWARE (CCS) CODES, UNITED STATES, 2014.....	111
APPENDIX D: 2013 RURAL-URBAN CONTINUUM CODES (RUCC).....	112
REFERENCES	113

LIST OF TABLES

Table 3.1. Sociodemographic and Tobacco Retailer Availability Characteristics of Census Tract Neighborhoods, Contiguous United States and DC, 2014 (N=71,084) 27

Table 3.2. Unadjusted Analyses Testing Tract-Level Associations of Percent Sociodemographics with Measures of Tobacco Retailer Density, Contiguous United States and DC, 2014 (N=71,084)..... 29

Table 3.3. Adjusted Analyses Testing Tract-Level Associations of Percent Sociodemographics with Measures of Tobacco Retailer Availability, Contiguous United States and DC, 2014 (N=71,084)..... 31

Table 3.4. Analyses Testing Tract-Level Associations of Percent Sociodemographics with Number of Pharmacies and Tobacco Shops, Contiguous United States and DC, 2014 (N=71,084)..... 33

Table 4.1. Sociodemographic and Tobacco Retailer Density Characteristics of Census Tract Neighborhoods, Contiguous United States and DC, 2014 (N=71,074)..... 46

Table 4.2. Spatial Durbin Error Model Analyses Testing Tract-Level Associations of Sociodemographics with Tobacco Retailer Density, Contiguous United States and DC, 2014 (N=71,074)..... 48

Table 5.1. Descriptive Sample Characteristics for Analytic Samples, 2014-2015 Tobacco Use Supplement, United States..... 61

Table 5.2. Associations of Tobacco Retailer Density with Individual Smoking Status, 2014-2015 Tobacco Use Supplement, United States (N=88,850)..... 63

Table 5.3. Standardized Associations of Tobacco Retailer Density with Individual Smoking Status, 2014-2015 Tobacco Use Supplement, United States (N=88,850) 64

Table 5.4. Associations of County Tobacco Retailer Density with Individual Quit Attempt in the Last 12 Months (N=7332) and Quit Length (N=2915), 2014-2015 Tobacco Use Supplement, United States..... 65

Table 6.1. 2014 HCUP Sample Characteristics, County-Level, United States..... 79

Table 6.2. Associations of Tobacco Retailer Availability (Retailers per 1000 people) and COPD-Related Hospital Outcomes, United States, 2014 (N=1510) 81

Table 6.3. Model-Predicted Average COPD-Related Hospital Outcome Rates for Quartiles of Tobacco Retailer Density, United States, 2014 (N=1510)..... 83

Table B.1. NAICS Codes of Probable Tobacco Retailers.....	98
Table B.2. Additional SIC Codes to be Omitted from Eligible Sample	101
Table B.3. Final RefUSA Store Type Categories and Inclusion and Exclusion Criteria.....	101
Table B.4. Frequency of RefUSA Latitude/Longitude Location Matches	107

LIST OF FIGURES

Figure 2.1. Dissertation Conceptual Model	10
Figure 4.1. Focal Tract and 10 Adjacent Neighboring Tracts	41
Figure 4.2. Focal (Direct) and Neighboring (Indirect) Effects of Spatial Durbin Error Model (SDEM)	45
Figure 5.1. Counties of Individual Respondents, 2014-2015 Tobacco Use Supplement, United States (N=368)	56
Figure 6.1. Counties in Publicly Available Healthcare Utilization Project State Inpatient Database (HCUP-SID), United States, 2014 (N=1501)	75
Figure B.1. 2014 RefUSA Tobacco Retailer Sampling Methodology (N=359,253).....	100

LIST OF ABBREVIATIONS AND SYMBOLS

ACS	American Community Survey
aOR	Adjusted Odds Ratio
AQI	Air Quality Index
AQS	Air Quality System
CCS	Clinical Classification Software
CI	Confidence Interval
COPD	Chronic Obstructive Pulmonary Disease
DC	District of Columbia
FPL	Federal Poverty Level
HCUP	Healthcare Cost and Utilization Project
ICD	International Classification of Diseases
IRR	Incidence Rate Ratio
NAICS	North American Industry Classification System
OR	Odds Ratio
RefUSA	ReferenceUSA
RUCA	Rural-Urban Commuting Area
SD	Standard Deviation
SDEM	Spatial Durbin Error Model
SE	Standard Error
SES	Socioeconomic Status
SIC	Standard Industrial Classification

SID	State Inpatient Database
TRD	Tobacco Retailer Density
TUS	Tobacco Use Supplement
U.S.	United States
UA	Urbanized Area
UC	Urban Cluster
$W\lambda_u$	Spatially lagged error term
β	The average effect of a focal tract's sociodemographics on its own tobacco retailer density
ε	Random error
θ	The average effect of neighboring sociodemographics on a focal tract's tobacco retailer density

CHAPTER 1. OVERVIEW AND SPECIFIC AIMS

Tobacco use is the leading cause of preventable death in the United States (U.S.), estimated to cause more than 480,000 deaths annually.¹ Although smoking rates have declined over the past decade, nearly 14 of every 100 adults still smoke,² increasing the risk for premature death and/or disability. Furthermore, some demographic groups are at a much higher risk of cigarette use, including adults with lower education and income.² The health consequences of smoking are well documented, contributing to cardiovascular disease, chronic obstructive pulmonary disease (COPD), and one third of all cancer deaths, including lung, mouth, lip, stomach, uterus, cervix, and colon cancers.^{1,3} In the U.S., smoking causes as many as 8 out of 10 COPD-related deaths,¹ and the association between long term tobacco use and COPD is 1.5-3 times greater for people of lower socioeconomic status.⁴ Furthermore, the health and financial costs due to smoking are enormous, amounting to over \$170 billion each year.⁵

The World Health Organization recognizes the importance of the built environment on health.⁶ The availability of tobacco retailers near where people live may influence smoking behaviors. In places with a high availability of tobacco retailers, there may be decreased travel costs to purchase tobacco products⁷ and greater product advertising and marketing,^{8,9} which could cue smokers to use^{10,11} and purchase products.^{10,12,13} Tobacco retailer density (TRD) is a measure of the concentration of tobacco retailers in an area. Research to date indicates that in places with higher TRD, individuals have greater smoking intentions,¹⁴ higher prevalence of smoking, initiation or maintenance,¹⁵⁻²¹ and reduced smoking cessation.¹⁶ Recently, some cities

and counties, such as San Francisco, Philadelphia,²² Rock County (Minnesota), and Rockland, Albany, and Erie counties (New York)²³ have recognized the likely relationship between TRD and smoking and implemented various tobacco retailer reduction policies to reduce smoking behaviors and demographic disparities in tobacco retailer exposure. Assessing the evidence in support of such strategies, however, is hindered by a wide variety of measures of TRD used in the literature (with no gold standard), and limited comparison of research results across different measures.

TRD may vary for individuals or neighborhoods. Numerous studies have documented higher tobacco retailer concentration in lower income neighborhoods and in those with a higher proportion of non-White residents. For example, a study in New Jersey found that lower income census tracts and those with a higher percentage of Black or Latino residents had a significantly higher TRD per 10 kilometers of roadway.²⁴ A national study using 2000 Census Bureau neighborhood demographic estimates of census tracts found that a 1% increase in proportion Hispanic ethnicity was associated with a 0.91% increase in TRD per 1000 people; a 1% increase in families living below the federal poverty level (FPL) was associated with a 0.83% increase in TRD; and a 1% increase in proportion Black was associated with a 0.43% increase in TRD (all significant, $p < 0.0001$).²⁵ Additionally, researchers found that urban census tracts were associated with a 32% increase in TRD.²⁵ Studies of disparities in TRD face a challenge common to most place-based research: identifying a salient measure of a “neighborhood.”²⁶⁻²⁸ Current U.S. studies usually use governmentally defined boundaries (e.g., census tracts) as neighborhoods without considering the potential effects of surrounding neighborhoods.²⁶

Urban areas may be particularly important places in which to investigate the role of TRD on smoking behavior. Individuals living in urban areas travel less distance per day²⁹ and may

also have a higher TRD.^{7,25} The 2010 Census estimated that 80.7% of the population lives in urban areas,³⁰ and by 2050, this is expected to rise to 87.4%.³¹ TRD²⁵ and some retailer reduction policies may most impact urban areas,⁷ warranting further need to assess how these associations may differ by neighborhood characteristics in the national urban setting.

Finally, very few studies have assessed associations of retailer concentration with health outcomes. Two studies found that a higher number of retailers in California zip codes was positively associated with COPD hospitalizations^{32,33} while an Australian study found that the odds of heart disease diagnosis/hospital admission was greater for smokers with more tobacco retailers within a mile around their home.³⁴ A recent Baltimore City study found that TRD per 10,000 population was significantly associated with a lower life expectancy ($b=-0.10$, $p<0.001$), greater age-adjusted mortality ($b=0.67$, $p<0.001$), and greater rates of death from chronic lower respiratory disease ($b=0.40$, $p<0.03$).³⁵ Future work studying the impact of retailer concentration on health outcomes is needed to provide scientific evidence about whether altering the tobacco retailer built environment is likely to reduce smoking-related disease.

The overall objectives of this dissertation were to examine associations of TRD with 1) neighborhood sociodemographics, 2) individual-level smoking behaviors, and 3) county COPD-related hospital discharge rates. This dissertation included four Specific Aims. Aims 1 and 2 used data that encompassed the entire U.S. while Aims 3 and 4 used data from a national sample of U.S. residents and participating hospitals.

Aim 1. Using four common measures of tobacco retailer density, investigate census tract-level racial, ethnic, and sociodemographic disparities in tobacco retailer density and the number of tobacco shops and pharmacies.

Aim 2. Using spatial econometrics, identify whether sociodemographic compositions of census tracts surrounding a focal tract are associated with tobacco retailer density.

Aim 3. Examine associations of county-level tobacco retailer density with individual-level smoking and cessation behaviors.

Aim 4. Examine associations of county-level tobacco retailer density with county-level COPD-related hospital discharge rates and costs.

Results from this dissertation may inform current research on TRD and ongoing policy debates about regulating the tobacco retail environment. First, this dissertation contributes to the overall literature on neighborhoods and health and will additionally increase understanding of measuring place-based health disparities. In Study 1, we extend findings from local studies and describe tract-level disparities by race, ethnicity, and socioeconomic status in a near census of tracts. As previous literature has used a variety of measures of TRD, we compare observed associations of disparities with four commonly used measures of TRD.

In Study 2, we used spatial econometric modeling to determine whether the TRD and sociodemographics of neighboring census tracts impact a focal tract's TRD. Assessments of disparities in TRD have been used to justify policy interventions in the retail environment: results from this study may help provide insight on the "definition" and "size" of neighborhood that might be most appropriate to use when assessing sociodemographic disparities in TRD.

In Study 3, we used multilevel modeling to investigate associations of county-level TRD on multiple smoking behaviors, including smoking status (every-day, some-day, non-smoker) and cessation behaviors (quit attempt, quit length). Tobacco retailer reduction policies have been implemented at the county level, and documenting whether and how county retailer density

impacts individual smoking behaviors may provide policymakers with evidence to design and implement retailer reduction policies in their local communities.

Finally, Study 4 contributes to the sparse literature assessing whether TRD is associated with actual health outcomes (vs. health behavior). Understanding whether TRD is associated with area COPD hospital discharge rates is the one of the first steps in helping researchers unravel if the built environment is associated with community health outcomes, in addition to health behaviors. Furthermore, understanding the long-term health implications related to TRD can help policymakers plan and anticipate future burdens and costs on the healthcare system. This evidence may guide urban communities in prioritizing built environment health actions and policies that may reduce smoking-related disease.

CHAPTER 2. THEORETICAL & LITERATURE REVIEW

THEORETICAL REVIEW

The proposed project is primarily grounded in Diez Roux & Mair's *Neighborhoods and Health* theoretical framework that posits, "neighborhood physical and social environments could contribute to health and health inequalities."²⁷ In other words, features or characteristics of the neighborhood may influence health behaviors and subsequently health outcomes.²⁷

The *Neighborhoods and Health* theoretical framework posits that processes such as discrimination and residential segregation by race, ethnicity, or socioeconomic status (SES) will result in the unequal distribution of resources across space.²⁷ This is in line with *Social Dominance Theory*, which aims to understand how processes and systems are used to develop and sustain discriminatory "group-based hierarchy."³⁶ *Social Dominance Theory* describes three systems of group-based hierarchy: age, gender, and arbitrary-set.³⁶ An arbitrary-set system groups people that are "defined by social distinctions meaningfully related to power" such as race, ethnicity or class.³⁶ In their paper on the theoretical conceptualization of a neighborhood, Bernard and colleagues also discuss how "spatially patterned health inequities are rooted in the unequal distribution of resources"³⁷ and that this distribution is often influenced by higher institutions, such as governmental policymakers in power. Taken together, these theoretical frameworks all recognize that discrimination by social distinction results in the spatial stratification³⁸ of individuals, resulting in social groups having differential access to both material and social resources.^{27,36,37} This unequal distribution of resources influences both the

physical environments (e.g., built environment, environmental exposures) and the *social* environments (e.g., social norms) where people live. For example, areas with high residential segregation often have less access to medical care, grocery stores, safe places to exercise, high quality education, high paying employment, and affordable and safe housing, but have more access to things like fast food restaurants and alcohol and tobacco marketing.³⁹⁻⁴⁴

Urban health researchers have also argued that sociodemographic compositions of communities can be linked to urban land-use patterns and structural aspects of a neighborhood, including vacancy rates and deterioration of the physical built environment.^{45,46} Residential turnover may be associated with this infrastructure deterioration, which may then lead to social disorganization, ultimately affecting health.^{45,47} Originally applied to explaining urban neighborhood crime rates, *Social Disorganization Theory* posits that structural factors related to neighborhood stability may lead to social disorganization among community members.⁴⁸⁻⁵⁰ For example, residential stability may be measured by rates of home ownership.⁵¹ A lack of residential stability may reflect low attachment to a community, potentially leading to fewer opportunities for social cohesion and collective efficacy among its residents to empower a healthy community,^{48-50,52} such as organizing to prohibit tobacco retailers near schools.

A key tenant of the *Neighborhoods and Health* framework and *Social Cognitive Theory* is that individuals interact with their environments.^{27,53,54} An individual's economic and psychosocial resources, as well as their biological attributes (e.g., sex, age) may influence how they experience their neighborhoods: these interactions may then ultimately shape people's health behaviors and health outcomes.^{27,53,54} Indeed, inequities in health behaviors and health outcomes associated with residential segregation (a structural factor) include less physical activity, less healthy eating, and higher rates of obesity, cardiovascular disease, and cancer

risk/late cancer diagnosis.^{41,43,55-59} At the population-level, individuals' collective aggregated exposure to these differing environments and the resulting health behaviors and health outcomes, especially over a life course, may explain some observed population-level health disparities.

Over the last several years, there has been increased recognition of the tobacco retailer environment as an aspect of the built environment that may influence smoking behaviors. Neighborhoods with high TRD provide easily accessible *physical* options for purchasing tobacco. Increased TRD is associated with greater tobacco marketing,⁸ which studies have found to be associated with an increase in tobacco product purchases and smoking.^{10,12,13} Furthermore, in places with a high concentration of retailers, there may be lower travel costs to obtain tobacco products,⁷ which may increase smoking behaviors, especially for some price responsive smokers⁶⁰ (e.g., lower income). High TRD might also result in a *social* environment where smoking is more accepted and normative.^{18,35,61} Furthermore, consistent with *Social Cognitive Theory*,⁵⁴ health behaviors may be influenced through constructs of observational learning and social support enabled by high TRD: seeing a “dominant norm” of community members using and purchasing tobacco may increase the likelihood of an individual to comply with this social norm, especially if there is social support for this behavior. This pro-smoking social environment may then put more people at risk of smoking-related disease, such as COPD, due to an increase in smoking and secondhand smoke.

TRD environments also vary by race, ethnicity and SES,²⁵ partially attributable to inequalities in resource distribution and tobacco industry targeting efforts.^{62,63} The *Social Stress Theory* argues that racism is a structural stressor, in which structures or institutions create conditions that impact disadvantaged groups, such as Black individuals.⁶⁴ For example, after the Great Depression, the racist federal Home Owners' Loan Corporation systematically created

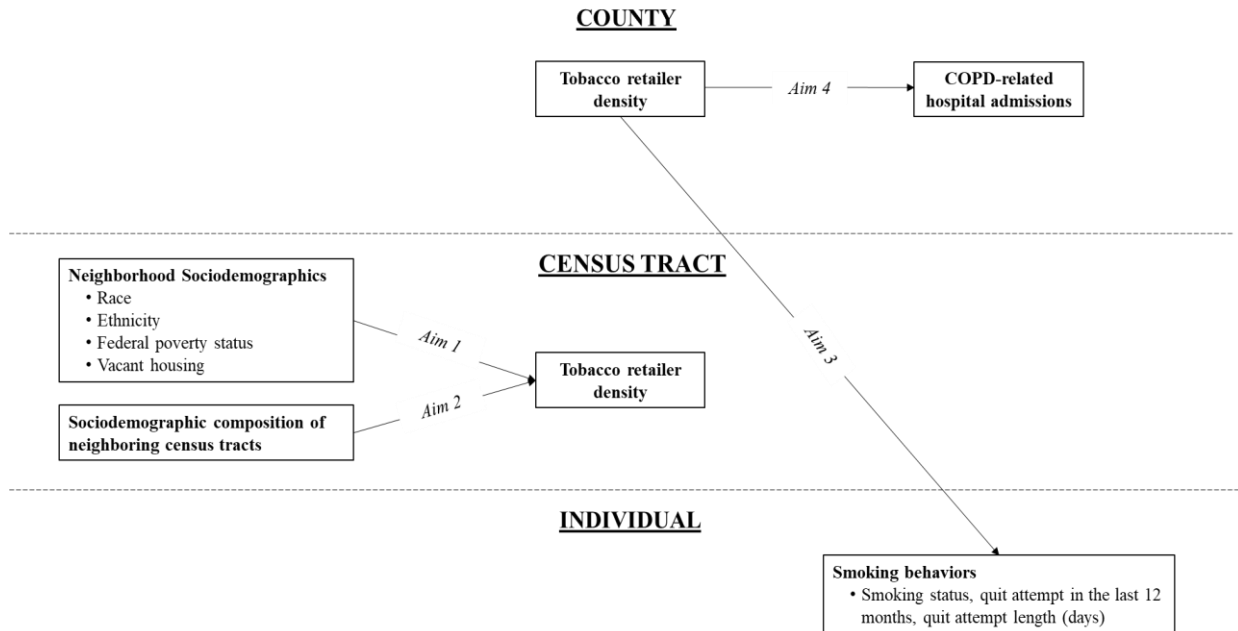
racially segregated neighborhoods, potentially allowing the tobacco industry to more easily target the Black community with menthol advertising, promotions, and products.⁶² Gee et al., expands upon the *Social Stress Theory* by also applying a *life course perspective*: repeated exposure to racism and the structures that racism produces (such as residential segregation) produce stressors and the proliferation of stressors that may then further add indirect stress on others in one's network.⁶⁵ This repeated exposure to stressors related to directly experienced (experiential stress) and structural/institutionalized racism may be associated with poorer health outcomes.^{64,65} For example, a racially segregated neighborhood may lead to less interpersonal racism against Black people within a primarily Black neighborhood. However, in this same neighborhood, the lack of health-promoting resources due to institutionalized racism (e.g., high quality education, jobs, fair policing) coupled with the repeated and targeted exposure to cigarette advertisements may lead some to start smoking as a coping mechanism.⁶⁶ And, because menthol cigarettes have been systematically targeted to the Black community^{62,63,67} and are potentially more addictive,⁶⁸ this could lead to sustained smoking among Black smokers as they try to cope with repeated stress proliferation in their communities.

In summary, several health behavior theories and theoretical frameworks recognize how neighborhoods provide places in which the inequitable distribution of resources and stress exposure brought about by discriminatory systems manifest, both physically and socially. Evidence to date indicates that the tobacco retail environment may influence smoking behaviors; however, the concentration of retailers may not be distributed equitably in all neighborhoods, potentially leaving some communities to bear a larger burden of tobacco-related disease.

OVERVIEW OF PROJECT CONCEPTUAL MODEL & LITERATURE REVIEW

Figure 2.2, below, is the conceptual model for the proposed study, developed based on the previously described theoretical literature, as well as current empirical research.

Figure 1.1. Dissertation Conceptual Model



By using PubMed, Scopus, Web of Science, Google Scholar, Tobacco Control (peer-reviewed journal), and Nicotine & Tobacco Research (peer-reviewed journal), I conducted a narrative literature review of peer-reviewed tobacco retailer accessibility articles published between January 1, 1990 and December 1, 2018. After an initial abstract review of search results, I reviewed 108 articles focused on tobacco retailer availability or accessibility. The following literature review is largely focused on those manuscripts (n=64) that were not specifically youth-oriented (e.g., only measuring the retail environment around schools or youth smoking behaviors) and that utilized measures of tobacco retailer availability or accessibility as primary variables.

Aim 1: Neighborhood Composition & Tobacco Retailer Density

Local Studies

To date, several cross-sectional studies have documented higher TRD in lower income neighborhoods and neighborhoods with higher proportions of Black and Hispanic or Latino residents. Most of these studies have been conducted with samples of neighborhoods in select states or regions. In 2003, Hyland and colleagues conducted the first study assessing sociodemographic disparities in tobacco outlet density in Erie County, New York.⁶⁹ Researchers tested associations of census tract TRD per 10 kilometers of roadway with 1990 Census population sociodemographics. Both lower median household income quartiles and higher percentage African American quartiles had a significantly ($p < 0.05$) higher TRD.⁶⁹ This preliminary study concluded that implementing zoning restrictions may serve as a policy tool to decrease access to retailers, especially for more price-sensitive smokers living in neighborhoods with a higher proportion of lower income and African American residents.⁶⁹ Studies in the Midwest have also documented demographic disparities in TRD. Within Polk County (Iowa), census tracts with the lowest median household income quartile had two times the number of tobacco retailers per 10 kilometers of roadway than those in the highest median household income quartiles ($p < 0.05$).⁷⁰ Additionally, tracts with the highest proportion African Americans and Latino ethnicity had more than twice the TRD ($p < 0.05$).⁷⁰ A similar Iowa study was conducted using counties as the unit of analysis and found that counties with a higher proportion of African Americans also had a significantly higher TRD per 50 kilometers of roadway and cigarette smoking prevalence.⁷¹ In Ontario (Canada), TRD per 1000 people (15 years and older) was significantly greater in areas with higher neighborhood deprivation, and this was consistent in both urban and rural providences.⁷² Recognizing that both income and race are associated with

TRD, Fakunle et al. conducted a study comparing associations of average TRD per 1000 people with 2010/2011 census tract sociodemographics in Baltimore City (household income=\$43,571; percent Black = 65.3%) and Prince George's County (household income = \$77,190; percent Black = 67.5%), Maryland.⁷³ Researchers found that Prince George County had a significantly lower TRD than Baltimore City (3.94 vs. 7.95, $p < 0.01$), and models controlling for spatial dependence indicated that as tract income increased, TRD also significantly decreased.

National Studies

While local studies are more common in the literature to date, there are a few national studies assessing neighborhood demographic disparities in TRD. Operationalizing the census tract as a neighborhood, Rodriguez et al. calculated average kernel TRD per 1000 people, which incorporated the spatial distribution of people across geographic boundaries.²⁵ Researchers then assessed the association of this measure with several 2000 census tract sociodemographic estimates and the urban/rural nature of a tract. Multivariable regression indicated that (log) proportion Hispanic ($b=0.91$), Black ($b=0.43$), families living in poverty ($b=0.83$), women without a high school diploma ($b=0.34$), and urbanicity ($b=0.32$) were significantly and positively associated with TRD (all $p < 0.0001$). More recently, Lee and colleagues assessed associations of TRD per 1000 people with 2010 tract level demographic disparities in a sample of national census tract neighborhoods across 97 U.S. counties.^{74,75} Unadjusted univariate models indicated that TRD was significantly ($p < 0.05$) and positively associated with tract proportion of Black residents ($b=0.05$) and negatively associated with tract proportion of Asian/Pacific Islander ($b=-0.04$) and White ($b=-0.24$) residents, as well as median household income ($b=-0.24$).⁷⁵ Adjusted multivariable models showed that the percent of vacant housing units and

percent of those that were not owner occupied was also positively associated with TRD ($b=0.22$ and $b=0.12$, respectively).⁷⁵

Finally, while most studies find disparities in TRD by socioeconomic status (usually operationalized by median household income or federal poverty level), very few studies have expanded beyond these economic measures to measure neighborhood disadvantage. According to several theoretical frameworks on place-based health and urban health researchers (discussed above), measures of neighborhood stability (e.g., proportion of a population that rents) and physical infrastructure deterioration (e.g., proportion of vacant dwellings) may lead to social disorganization of community members, eventually affecting health behaviors and outcomes.⁴⁵ Lee et al. was the first to investigate this and found significant positive associations between TRD per 1000 people and proportions of vacant housing and rental units.⁷⁵ Li and colleagues included measures of vacant housing, owner-occupied housing, and racial diversity as contributing factors in their small area estimates of smoking prevalence in Massachusetts.⁷⁶ Finally, Fakunle et al. also found significant positive associations between tract TRD per 1000 people and the count of vacant houses.⁷⁷ **This 2014 national study updates the only previous national study to examine racial, ethnic, and socioeconomic disparities in tobacco retailer density in a near census of tracts across the U.S. While previous studies have only used a single measure of tobacco retailer density, this study compares the magnitude and significance of results across four of common measures of retailer density. Identifying these relationships may help communities better track disparities in tobacco retailer availability and use this information to design pro-equity tobacco control policies.**

Aim 2: Spatial Econometrics – Do Your Neighbors Matter?

According to Tobler’s first law of geography, “Everything is related to everything else, but near things are more related than distant things.”⁷⁸ Spatial dependence, or spatial autocorrelation describes the phenomena that the values at one location depend on values at other nearby locations (and vice versa), such as proximal surrounding neighbors.⁷⁹⁻⁸¹ TRD in one location may be spatially correlated with TRD in another location, possibly due to similar consumer demand, place-based industry targeting, or zoning ordinances dictating where retailers may be located. Spatial econometric modeling is an extension of conventional regression models and is designed to test and model this spatial dependence among geographic areas.⁸² Ignoring this spatial dependence may result in biased or inaccurate results, similar to multilevel studies that do not account for nesting of individuals within neighborhoods;⁸¹⁻⁸³ however, only a few studies on TRD have appropriately tested for evidence of and accounted for spatial autocorrelation.^{75,77,84,85}

Assessing associations of tract TRD in New Jersey, researchers found significant spatial autocorrelation in TRD and conducted spatial regression models to account for this dependence.⁸⁴ The authors state that though results were similar to ordinary least squares models that do *not* account for dependence, their spatial regression models demonstrated better model fit and generated less biased results. Consistent with other literature, researchers found that median household income was significantly and negatively associated with TRD, and the proportion of African American and Hispanic residents was positively associated with TRD.⁸⁴ Other researchers have indicated statistically significant spatial dependence of TRD in several places, including community districts in New York City,⁸⁶ a national sample of census tracts in 97 U.S. counties,^{74,75} and tracts in Baltimore, Prince George county (Maryland),⁷³ Boston,⁸⁷ and Rhode

Island.⁸⁵ However, others note that counties may be a large enough geography that spatial autocorrelation in TRD is not significantly present.⁶⁹ In 2003, Hyland and colleagues noted in the very first article assessing sociodemographic disparities in TRD the need for additional studies to investigate and account for spatial autocorrelation of TRD⁶⁹ in an effort to yield less biased results; however, very few have to date.

While these few studies have tested and modeled spatial dependence of the dependent variable, a focal tract's outcome (dependent variable) may also be influenced by characteristics of its neighboring tracts (independent variables).^{81,88} This may be partially due to how the boundaries of neighborhoods are drawn, as the overall study area may represent one larger neighborhood that has been partitioned into smaller neighborhood tracts.⁸⁹ Given established neighborhood sociodemographic disparities in TRD, the *sociodemographics of surrounding neighborhoods* of a focal tract may be predictive of a *focal tract's TRD*. Residential segregation by race, ethnicity, and SES may have resulted in tracts with similar characteristics being next to one another; therefore, some focal tracts (e.g., lower income, higher TRD)^{25,70} may also be surrounded by lower income tracts with higher TRD, potentially inflating the TRD in the focal tract due to supply and demand and industry targeting. Though the tobacco industry has a legacy of targeting lower income and non-White neighborhoods,^{62,63} researchers do not know how the tobacco industry defines neighborhoods when placing tobacco retailers. It is plausible that the tobacco industry examines the distribution and connectivity of neighborhood characteristics across several adjacent neighborhoods, such as census tracts that share borders with one another. For example, neighboring lower income tracts (associated with higher TRD) may have a detrimental effect, increasing a focal tract's TRD.

In November 2018, Faulkunkle et al. conducted the first study that included average sociodemographic effects of neighbors as predictor variables of a focal neighborhood's TRD.⁷⁷ While tract median household income (per \$10,000) was significantly associated with a lower odds of TRD per 1000 people (OR=0.90, p<0.001), the average income of *adjacent neighboring tracts* was also significantly associated with a lower TRD (OR=0.87, p<0.001), above and beyond the focal tract's impact. Research needs to investigate if and how surrounding neighborhood characteristics may impact the tobacco retailer environment that one lives in.⁹⁰⁻⁹²

This 2014 national study contributes to existing theoretical and methodological discussions on how the size of a neighborhood, as well as its potential interactions with surrounding neighborhoods, might influence our current understanding of place-based tobacco-related health disparities.

Aim 3: Tobacco Retailer Density & Adult Smoking and Cessation Behaviors

The first study (2003) assessing TRD on smoking behavior was conducted among 11 randomly sampled towns in Illinois.⁹³ Pokorny et al. calculated TRD as the number of tobacco retailers per youth population (i.e. 10-17 years old) within each community. Multilevel model results indicated that higher TRD was significantly associated with youth smoking initiation (OR=1.49, 95% CI 1.20-1.84).⁹³ Following this publication, several studies have been conducted with adult populations. Researchers in Scotland recently conducted a 2000-2015 longitudinal study linking maternal birth records to self-reported smoking behavior and neighborhood kernel TRD (per 800 meter buffer).⁹⁴ The study sample included mothers who had more than one pregnancy and who had changed their smoking status at least once during the time period. Models controlled for several variables including year of delivery, area income deprivation, urban/rural residential location, mother's age, and neighborhood maternal smoking prevalence.

Researchers found that those living in areas with high TRD (compared to areas with no TRD) had a significantly higher odds of smoking during pregnancy. For example, those in the highest TRD group had a 39% excess risk of being a smoker during pregnancy (OR=1.39; 95% CI 1.17-1.66).⁹⁴ Another Scottish study found that higher postcode kernel TRD (per 800 meter buffer) was significantly associated with a 3-7% increased chance of being a current smoker, even after controlling for individual sex, age, race, education, income, and area urbanicity.¹⁷ A California study using 1979-1990 data from the Stanford Heart Disease Prevention Program found that even after controlling for individual sociodemographic characteristics, high (vs. low) convenience store TRD was significantly associated with a 0.174 ($p<0.05$) increase in number of cigarettes smoked per day.⁹⁵ Based on 1999-2005 Massachusetts Behavioral Risk Factor Surveillance System data, an increase in TRD per community neighborhood was associated with 1.13 (95% CI 1.00-1.27) times the adjusted odds of being a smoker.⁷⁶ Two related ecological studies conducted in Iowa found similar results. A 2000 cross-sectional study found that Iowa counties could be classified into two clusters: low TRD (per 50 kilometers of roadway) and smoking prevalence vs. high TRD and smoking prevalence.⁹⁶ After accounting for neighborhood proportion of African American residents, TRD explained an additional 6% of the variance in area smoking prevalence.⁹⁷

Research has also documented significant associations between TRD and adult cessation attitudes and behaviors. A 2012 study of a national sample of converted non-daily smokers (i.e. those that used to smoke daily) and native non-daily smokers (i.e. those that never smoked daily) assessed associations of average zip code kernel TRD (per 5 mile buffer) with cigarette use patterns, quit attempts in the last year, readiness to quit, and purchase behaviors.¹⁶ Converted non-daily smokers (compared to native non-daily) were significantly ($p<0.001$) more likely to

live in areas with greater TRD and to always purchase (vs. borrow) their cigarettes, and this behavior was also associated with higher TRD and a failed quit attempt in the last year. Converted non-daily smokers that lived in areas with high TRD were also more likely to report that cigarette price impacted their decision to smoke less. Among native non-daily smokers, living in areas with high TRD was significantly associated with decreased intentions to quit smoking in the next 6 months.¹⁶ A national longitudinal cohort study of adult smokers found that residential TRD per 500 meters of roadway was associated with reduced 30-day abstinence (OR = 0.94, 95% CI 0.90-0.98) and lower pro-cessation attitudes ($b=-0.07$, 95% CI: -0.10 to -0.03), but only in high poverty areas.⁹⁸ Interestingly, in low poverty areas, higher TRD was associated with greater pro-cessation attitudes, indicating a *protective* effect. In Toronto (Canada), after adjusting for individual sociodemographics, adult smokers (who were receiving treatment at a nicotine dependence clinic) with at least one tobacco retailer within 250 meters of their home smoked 3.4 more cigarettes per day, were less likely to be abstinent (more than 24 hours), and had a shorter time until their first cigarette.⁷² A study in Ontario (Canada) found that an increase in TRD per 500 meters of roadway was significantly associated with a reduced adjusted odds in an individual having a quit attempt (OR=0.54, 95% CI 0.35-0.85) if they lived in a high (vs. low) income neighborhood.⁹⁹

In contrast to these studies, Reitzel et al. found that TRD per roadway (i.e. 500 meters; 1 and 3 kilometers) was not a significant predictor of cigarette smoking abstinence (26 weeks after quit date) in a longitudinal sample of adult smokers in Houston, Texas; however, researchers did find that proximity to the nearest tobacco retailer had an significant inverse relationship with smoking abstinence.¹⁹ In a separate study, TRD per meters (i.e. 250, 500, 1000, 3000) of

roadway was also not predictive of smoking abstinence at 6 months in a sample of adult smokers from two English cities.¹⁰⁰

Additional research assessing the impact of TRD on both adult smoking and cessation behaviors is needed, especially as some studies have found conflicting results. To the best of my knowledge, there are only two studies on TRD that use a *national* U.S. sample of adult participants, and these studies were limited to understanding cessation behaviors among a sub-sample of smokers. **This 2014-2015 multi-level study examines associations of TRD with multiple smoking behaviors (i.e. smoking status, quit attempt, quit length) in a national sample of adults in metropolitan counties. Tobacco retailer reduction policies have been implemented at the county level, and documenting whether and how county retailer density is associated with individual smoking behaviors across the nation may provide policymakers with information that may be useful for designing and implementing retailer reduction policies in their communities.**

Aim 4: Tobacco Retailer Density & COPD Hospital Discharge Rates and Costs

While there are several studies assessing neighborhood disparities in TRD and a growing number that are evaluating its impact on smoking behaviors, very few studies have assessed associations of tobacco retailer concentration with actual health *outcomes*. The health consequences of smoking are well documented, contributing to cardiovascular disease, chronic obstructive pulmonary disease (COPD), and one third of all cancer deaths, including lung, mouth, lip, stomach, uterus, cervix, and colon cancers.^{1,3}

A recent cross-sectional ecological study conducted in Baltimore found that TRD (per 10,000 population) was significantly associated with a lower life expectancy ($b=-0.10$, $p<0.001$), greater age-adjusted mortality ($b=0.67$, $p<0.001$), and greater rates of death from chronic lower

respiratory disease ($b=0.40$, $p<0.03$).³⁵ An Australian study found significant positive associations of TRD with individual-level heart disease diagnosis and hospital admission.³⁴ Using spatial regression models that accounted for the spatial correlation of outcomes of interest, a 1999 study found that a higher count of tobacco retailers in California zip codes was significantly and positively associated ($b=0.227$) with COPD hospitalization counts.³² The authors of this study also examined correlates of COPD hospitalization charges in California in 1993 and 1999. In both years, tobacco outlets per area were significantly and positively associated with COPD hospitalization charges.³³

COPD is a pulmonary disease that includes emphysema and chronic bronchitis and can obstruct normal breathing.^{101,102} Smoking is the main cause and risk factor of COPD development, but exposure to second-hand smoke and air pollution may also contribute to its development or exacerbation.¹⁰² In the U.S., smoking causes as many as 8 out of 10 COPD-related deaths,¹ and the association between long term tobacco use and COPD is 1.5-3 times greater for people of lower socioeconomic status.⁴ Between 2014-2015, more than 15.9 million adults reported that they had been medically diagnosed with COPD; however, variation exists across states (Hawaii: 3.7% vs. West Virginia: 12.0%).¹⁰² In 2010, the economic costs due to COPD were \$32.1 billion and projected to reach \$49 billion by 2020,¹⁰³ averaging to over \$4000/year per COPD patient.¹⁰² Smoking can exacerbate COPD, leading to hospital admissions,¹⁰⁴ which account for the greatest cost of COPD-related care.^{102,105} As the burden of COPD is estimated to increase substantially over the next 15 years (by 182% from 2010-2030),¹⁰⁵ there is an urgent need for interventions that may ameliorate this burden.

Smoking cessation is the most important modifiable determinant in COPD management.¹⁰² Smoking cessation is significantly associated with a 40% reduced risk of COPD

hospital admission;¹⁰⁶ however, TRD has been shown to impair smoking cessation.¹⁶ **This 2014 study provides a rationale for future longitudinal research investigating associations of TRD with long-term health outcomes that may experience a time lag (e.g., cancer development). Furthermore, this study provides evidence that could aid policymakers and public health practitioners in gaining traction to implement retailer reduction policies or target smoking cessation funding in areas with high TRD.**

CHAPTER 3. ASSESSING NEIGHBORHOOD SOCIODEMOGRAPHIC DISPARITIES IN TOBACCO RETAILER DENSITY AND THE DISTRIBUTION OF PHARMACIES AND TOBACCO SHOPS, UNITED STATES, 2014 (STUDY 1)

INTRODUCTION

Tobacco retailer density is a measure of the availability of tobacco retailers in a geographic area. Research indicates that in places with higher tobacco retailer density, individuals have greater smoking intentions,¹⁴ a greater likelihood of smoking initiation,¹⁵ being a current smoker,¹⁷ smoking more cigarettes,⁹⁵ and reduced smoking cessation.⁹⁸ In places with a high availability of tobacco retailers, there may be decreased travel costs to purchase tobacco products⁷ and greater product advertising and marketing.^{8,9}

Several cross-sectional studies in the United States (U.S.) have documented higher tobacco retailer density in lower income neighborhoods and in those with higher proportions of non-White residents, potentially putting residents of these neighborhoods at a higher risk of smoking. Studies of local areas like Erie County (New York),¹⁰⁷ Omaha (Nebraska),⁸ or states like Iowa,^{70,96} have documented greater tobacco retailer density in places with lower median household, or more African American or Hispanic residents. While regional studies are more common, there are a few national studies assessing neighborhood demographic disparities in tobacco retailer density. In the most recent national study, tract-level proportion of Hispanic residents, Black residents, families living in poverty, and urbanicity in 2000 were each uniquely and positively associated with the number of retailers per 1000 people in 2007.²⁵ In another study of a sample of tracts in 97 counties across the U.S., researchers documented inverse relationships

between 2012 retailer density per 1000 people and percent of non-Hispanic Black and Hispanic or Latino residents and positive associations for proportion of vacant housing units and units those that were not owner occupied.⁷⁵

This research, however, is limited in two ways. First, few studies have investigated the neighborhood availability of specific tobacco retailer types such as pharmacies and tobacco shops that are commonly the point of intervention for retailer-focused tobacco control policies, both domestically and internationally. For example, the Dutch Parliament is discussing a ban on sales of tobacco products in all store types, except for specialty tobacco shops.¹⁰⁸ Additionally, a pharmacy sales ban was implemented in New York City in 2018. Understanding whether there are sociodemographic disparities in the distribution of tobacco retailer types commonly targeted in retailer-focused policies may be important for informing the design and implementation of tobacco retailer reduction policies that may unintentionally exacerbate place-based and smoking-related disparities.

Second, there is substantial variation in how researchers and policymakers operationalize tobacco retailer density. Some of the most common measures are the number of tobacco retailers: per population,^{74,109} per land area,^{8,110} or per kilometers of roadway.^{70,110} There has been little comparison across measures both within and between studies.¹¹⁰ As a result, conclusions about area-level sociodemographic disparities may not be robust to different measures. Understanding whether national findings are similar across measures may be useful for past and future study comparison purposes. The purpose of this study is to assess and compare associations of four measures of tobacco retailer density in 2014 with tract-level sociodemographic characteristics in the contiguous U.S. in the same year. We also assess

patterns in the distribution of pharmacies and tobacco shops, by neighborhood sociodemographics.

MATERIALS & METHODS

Neighborhood Sociodemographics

In this study, we operationalize a neighborhood as a census tract. Census tracts are administrative boundaries that vary in size and population (1200-8000 residents) and are most often used in neighborhoods and health research.^{26,28,111} The American Community Survey (ACS) is a survey of a nationally representative sample of households, providing population demographic estimates at several geographic levels.^{112,113} The ACS releases 5-year estimates, which are the most reliable and stable and recommended for smaller geographic areas, such as census tracts.^{112,113} Independent variables of interest included 5-year 2010-2014 ACS estimates of percent of each tract population that is non-Hispanic Black, Hispanic or Latino ethnicity, living below 150% of the federal poverty level (FPL), as well as the percent of tract housing units that are vacant. In some analyses, we also incorporated a measure of tract-level urbanicity as a control variable, using U.S. Department of Agriculture Rural-Urban Commuting Area (RUCA) codes that take into account population density, urbanization, and commuting patterns (Appendix A).¹¹⁴ Each census tract was categorized as either urban, large rural city/town, or small and isolated rural town.

Tobacco Retailer Density

Consistent with common measures in the literature, we operationalized the outcome variable, tobacco retailer density, in four ways: 1) total count of tobacco retailers; 2) tobacco retailers per 1000 people; 3) tobacco retailers per land area (square mile), and 4) tobacco retailers per 10 kilometers (km) of roadway. To calculate these measures, we used a spatial join in

ArcMap 10.5 to assign each retailer to its respective census tract and then summed the total number tobacco retailers within each tract. We downloaded 5-year 2010-2014 ACS total population and land area data from Social Explorer^{112,115} and roadway data from the U.S. Census Bureau. We also calculated the total number of pharmacies and the total number of tobacco shops in a census tract.

There is no national tobacco retailer licensing system in the U.S., so we created a 2014 list of probable tobacco retailers based on store types, similar to other studies.^{25,116,117} The U.S. Census Bureau assigns store type North American Industry Classification System (NAICS) codes to all business establishments in the U.S. Using tobacco product sales data from the latest 2012 Economic U.S. Census, we identified ten NAICS codes (i.e. convenience stores; gasoline stations; gasoline stations with convenience stores; warehouse clubs and supercenters; tobacco stores; supermarkets and other grocery stores; pharmacies and drug stores; beer, wine and liquor stores; other general merchandise stores; discount department stores) that account for approximately 99% of all retail tobacco product sales.¹¹⁸ We used ReferenceUSA (RefUSA),¹¹⁹ a database of business establishments that contains NAICS codes and geographic indicators to build the retailer list. Retailer sub-types (e.g., specialty food markets, compounding pharmacies, marine services stations, independent pharmacies) and retailers known to not sell tobacco products (e.g., Target, Whole Foods, Trader Joes) were omitted. Appendix B describes this methodology in further detail. Although CVS stopped selling tobacco products in all its stores in September, 2014, we kept all CVS stores in the sample as they were present as tobacco retailers in the census tracts for the majority of the year. Though there has not been national validation of commercial lists, like RefUSA, two local studies have indicated good validation when compared

to ground-truthed retailer locations in three counties in North Carolina¹¹⁶ and to tract-level retail density using a Washington state licensing list.²⁵

Analytic Sample

In 2014, there were 72,404 census tracts in the U.S. and District of Columbia (DC) with a population of at least one person. We employed several decision rules to yield our final analytic sample of 71,084 tracts. All ratio measures of retailer density are sensitive to low denominator values. We assessed the distribution of calculated values of density and omitted 28 extreme outliers (e.g., 3000 retailers per 1000 people). We focus on the contiguous U.S., and excluded Alaska and Hawaii from analysis (n=483), as well as those tracts with incomplete data (n=181). Finally, as tracts are intended to range from 1200-8000 people and our per capita retailer density measure is per 1000 people, we excluded those tracts with less than 1000 people (n=628). To determine the sensitivity of our analysis to these choices, we examined how our results would differ had the full sample been employed.

Analysis

All analyses were conducted using Stata 15. To investigate associations between the four measures of tobacco retailer density and neighborhood sociodemographics, we fit unadjusted and adjusted multivariable regression models that controlled for the other tract-level sociodemographic variables and area urbanicity. We then fit unadjusted and adjusted models to assess relationships between neighborhood sociodemographics and the total number of pharmacies and tobacco shops. We did not find evidence of collinearity in multivariable models (average variance inflation factor was 1.39). To aid in interpretability, each sociodemographic variable was scaled to tens (e.g., 13% = 1.3) so that 1-unit difference in a demographic variable actually represents a 10-percentage point difference.

RESULTS

Characteristics of the analytic sample are shown in Table 3.1. The average number of tobacco retailers in a tract was 5, but this ranged widely from 0 to 75 retailers. Average retailer density per 1000 people was 1.25; per square mile was 6.06; and per 10km of roadway was 1.33. Overall, each tract had, on average, fewer than one pharmacy or tobacco shop. Comparing density measures, Pearson correlation coefficients were high for retailers per 10km roadway and per square mile ($r=0.96$), and for total count of retailers and retailers per 1000 people ($r=0.77$). Correlation was low to moderate for all other retailer density combinations (range: 0.21-0.32).

Table 3.1. Sociodemographic and Tobacco Retailer Availability Characteristics of Census Tract Neighborhoods, Contiguous United States and DC, 2014 (N=71,084)

	Mean/Percent (SD)	Range
Demographic Characteristics		
Percent non-Hispanic Black	13.5 (22.0)	0-100
Percent Hispanic or Latino	15.7 (21.2)	0-100
Percent living below 150% FPL	26.7 (16.9)	0-100
Percent of vacant housing units	12.0 (10.5)	0-100
Urbanicity		
Urban	82.9	-
Large rural city/town	8.6	-
Small and isolated rural town	8.5	-
Tobacco Retailer Density		
Total count of retailers	5.0 (4.3)	0-75
Retailers per 1000 people	1.25 (1.15)	0-24.0
Retailers per square mile	6.06 (15.8)	0-270.8
Retailers per 10 kilometers of roadway	1.33 (2.5)	0-43.7
Total count of pharmacies	0.48 (0.84)	0-15.0
Total count of tobacco shops	0.28 (0.68)	0-25.0

For all measures of retailer density, unadjusted analyses indicated positive and significant associations for percent Black and percent living below 150% FPL (Table 3.2). Percent Hispanic or Latino was positive and significant for all retailer density measures except per 1000 people. For percent vacant housing, effects were positive and significant for total count of retailers and

retailers per 1000 people, but negative for retailers per square mile and retailers per 10km of roadway.

Table 3.2. Unadjusted Analyses Testing Tract-Level Associations of Percent Sociodemographics with Measures of Tobacco Retailer Density, Contiguous United States and DC, 2014 (N=71,084)

	Total count of retailers		Retailers per 1000 people		Retailers per square mile		Retailers per 10 km of roadway	
	B (SE)		B (SE)		B (SE)		B (SE)	
Non-Hispanic Black	0.12 (0.01)	**	0.07 (0.00)	**	0.84 (0.03)	**	0.15 (0.00)	**
Hispanic or Latino	0.12 (0.01)	**	0.00 (0.00)		1.74 (0.03)	**	0.31 (0.00)	**
Living below 150% FPL	0.48 (0.01)	**	0.18 (0.00)	**	1.89 (0.03)	**	0.33 (0.01)	**
Vacant housing units	0.23 (0.02)	**	0.25 (0.00)	**	-0.34 (0.06)	**	-0.10 (0.01)	**

Note: All models control for tract-level urbanicity. Tract-level demographic variables were scaled to 10s (e.g., 10% is coded 1.0) so that estimates may be interpreted as the expected difference in tobacco retailer availability for a census tract that has a 10-percentage point greater value in the demographic variable.

FPL = Federal Poverty Level; km=kilometers

*p<0.01; **p<0.001

In multivariable adjusted models (Table 3.3), there were positive and significant associations between percent Black and all retailer density measures, except for the total count of retailers. When comparing two census tracts, one of which had a non-Hispanic Black composition that was 10 percentage points higher than the other (e.g., neighborhood with 10% non-Hispanic Black vs. neighborhood with 20% non-Hispanic Black residents), we would expect to have 0.01 more retailers per 1000 people ($p < 0.0001$), 0.52 more per square mile ($p < 0.0001$), and 0.09 more per 10km of roadway ($p < 0.0001$) in the tract with the higher proportion of non-Hispanic Black residents. A similar disparity was present for percent living below 150% FPL for all four measures of retailer density.

Percent Hispanic or Latino was positive and significant for all retailer density measures except per 1000 people, which had a negative significant effect ($B = -0.03$, $p < 0.0001$). Finally, a tract with a composition of vacant housing that was 10 percentage points higher than another would be expected to have 0.12 more retailers per 1000 people ($p < 0.0001$) but 0.13 fewer retailers ($p < 0.0001$), 0.22 fewer retailers per square mile ($p < 0.0001$), and 0.07 fewer retailers per 10km of roadway ($p < 0.0001$).

In a sensitivity test, we compared results from the full sample with no outliers removed to the analytic sample. The direction and significance of all estimates were the same, except in two cases. For retailer density per 1000 people, the adjusted effects of both percent non-Hispanic Black and Hispanic or Latino ethnicity were no longer significant (not shown).

Table 3.3. Adjusted Analyses Testing Tract-Level Associations of Percent Sociodemographics with Measures of Tobacco Retailer Availability, Contiguous United States and DC, 2014 (N=71,084)

	Total count of retailers		Retailers per 1000 people		Retailers per square mile		Retailers per 10 km of roadway	
	B (SE)		B (SE)		B (SE)		B (SE)	
Non-Hispanic Black	0.01 (0.01)		0.01 (0.00)	**	0.52 (0.03)	**	0.09 (0.00)	**
Hispanic or Latino	0.03 (0.01)	*	-0.03 (0.00)	**	1.33 (0.03)	**	0.23 (0.00)	**
Living below 150% FPL	0.46 (0.01)	**	0.16 (0.00)	**	1.14 (0.04)	**	0.21 (0.01)	**
Vacant housing units	-0.13 (0.02)	**	0.12 (0.01)	**	-0.22 (0.06)	**	-0.07 (0.01)	**

Note: All models control for tract-level urbanicity. Tract-level demographic variables were scaled to 10s (e.g., 10% is coded 1.0) so that estimates may be interpreted as the expected difference in tobacco retailer availability for a census tract that has a 10-percentage point greater value in the demographic variable.

FPL = Federal Poverty Level; km=kilometers

*p<0.01; **p<0.001

Finally, we investigated associations between neighborhood sociodemographics and the number of pharmacies and tobacco shops in a census tract. Adjusted results indicated that neighborhoods with a greater proportion of non-Hispanic Black residents and vacant housing units had fewer pharmacies and tobacco shops (Table 3.4). On the other hand, if the percent of residents living below 150% FPL in one census tract was 10 points higher than another, we would expect the former to have 0.05 more tobacco shops ($p < 0.0001$).

Table 3.4. Analyses Testing Tract-Level Associations of Percent Sociodemographics with Number of Pharmacies and Tobacco Shops, Contiguous United States and DC, 2014 (N=71,084)

	Pharmacies				Tobacco Shops			
	Unadjusted		Adjusted		Unadjusted		Adjusted	
	B (SE)		B (SE)		B (SE)		B (SE)	
Non-Hispanic Black	-0.01 (0.00)	**	-0.01 (0.00)	**	-0.02 (0.00)	**	-0.03 (0.00)	**
Hispanic or Latino	-0.02 (0.00)	**	-0.02 (0.00)		0.02 (0.00)	**	-0.00 (0.00)	**
Living below 150% FPL	-0.03 (0.00)	**	0.00 (0.00)	**	0.02 (0.00)	**	0.05 (0.00)	**
Vacant housing units	-0.06 (0.00)	**	-0.05 (0.00)	**	-0.02 (0.00)	**	-0.02 (0.00)	**

Note: All models control for tract-level urbanicity. Tract-level demographic variables were scaled to 10s (e.g., 10% is coded 1.0) so that estimates may be interpreted as the expected difference in the number of tobacco retailer type for a census tract that has a 10-percentage point greater value in the demographic variable.

FPL = Federal Poverty Level

*p<0.01; **p<0.001

DISCUSSION

In 2014, tobacco retailer density differed by area sociodemographic characteristics, but the extent and direction of these associations was sometimes sensitive to the density measure used. Neighborhoods with a greater proportion of residents living below 150% FPL were associated with higher tobacco retailer density in all models, regardless of the measure of retailer density used. These results are consistent with the only previous national study, which used sociodemographic data from 2000 and a single per capita measure of retailer density in 2007,²⁵ suggesting that this disparity has persisted across time. In our results, however, the direction and significance of associations between retailer density and percent non-Hispanic Black, Hispanic or Latino, and vacant housing units, however, were sensitive to the retailer density measure operationalized.

Several local and national studies have documented greater retailer density (using several measures across studies) in neighborhoods with a higher proportion of Black residents.^{25,71,107} Our unadjusted results replicate these findings for all retailer density measures. This disparity is also consistent in adjusted models except when measuring density as the total count of retailers; in this model, the association is no longer significant. We also find that a higher neighborhood proportion of Hispanic or Latino residents was associated with a greater total count of retailers, retailers per square mile, and retailers per 10km of roadway in unadjusted models. However, in adjusted models, we document a potential protective relationship when using retailers per 1000 people, in which a higher neighborhood proportion of Hispanic or Latino residents was associated with fewer retailers per 1000 people. This inverse association is consistent with a study limited to a sample of tracts within 97 counties across the U.S.⁷⁵ The tobacco industry has a long history of marketing tobacco products in the retail environment to historically

marginalized populations, including Black individuals and communities,^{63,120,121} young adults, and those with less educational attainment.¹²² That tobacco retailers may be more readily available in some neighborhoods that have a higher proportion of these individuals is a public health and social justice concern given that both greater tobacco retailer availability^{16,94,95} and tobacco product point-of-sale marketing¹²³⁻¹²⁵ are associated with increased smoking behaviors.

While most studies document disparities in tobacco retailer density by socioeconomic status (usually operationalized by median household income or FPL), very few studies have expanded beyond these economic measures. Consistent with two studies that found a positive association between vacant housing and tobacco retailer density per 1000 people,^{75,77} we find that for tracts with a 10-percentage point difference in vacant housing, the model-estimated density difference is 0.12 tobacco retailers per 1000 people, almost 10% of the average density in the sample. However, for all other measures of retailer density, we document inverse associations. Though this study is cross-sectional and we cannot infer about changes in retailer density or demographics over time, we posit one reason for these conflicting findings. Vacant housing may reflect a relatively low population count in a place that historically housed more people, and may therefore be both physically large enough and structurally equipped with enough roads to accommodate more people. In places with a high proportion of vacant dwellings, retailers may not have a desire to invest in neighborhoods where there may be little demand. Fewer retailers in the same sized space with the same number of roads would produce a reduction in land area or roadway-based density measures over time. Yet a drop in retailers that also corresponds with a population decrease may not alter population-based density measures, and could actually increase them depending on the relative drop in each. Longitudinal research

assessing changes over time are needed to further shed light onto some of these potential processes.

In this study, we use different measures of retailer density to help increase comparability of findings to past and future studies assessing disparities in tobacco retailer density. Taken together, our findings indicate that while there are neighborhood sociodemographic differences in the availability of tobacco retailers, these differences vary based on the measure of retailer density used. This may be particularly critical for local jurisdictions, who are currently using different measures of retailer density in policies designed to reduce retailer disparities (e.g., total count in San Francisco; retailers per 1000 people in Philadelphia).²² Although statistical criteria can indicate which measure may best fit specific models, these analyses may not be generalizable to other data. Future research is therefore needed to better understand which measures best capture the aspects of the built and social environment most tied to consumer attitudes and behavior, and to determine which measures are most predictive of community-level tobacco use patterns. Per capita measures may reflect different levels of consumer demand for retailers, land area measures may also describe proximity of consumers to retailers, and roadway measures may further indicate the ease with which consumers can access retailers via existing infrastructure. Which of these measures might most influence consumer marketing exposure, purchasing behavior, and tobacco use, however, requires greater research on how people move and interact within their activity spaces.

Given that policies regulating the sale of tobacco products in both pharmacies and tobacco shops have been discussed in the literature and implemented in several jurisdictions, we investigated whether neighborhood demographics were associated with the number of pharmacies or tobacco shops in 2014. We found fewer pharmacies in neighborhoods with a

greater proportion of non-Hispanic Black residents, suggesting that policies that restrict the sales of tobacco products in pharmacies may not decrease the number of tobacco retailers equitably in neighborhoods with a greater proportion of non-Hispanic Black residents. These findings are consistent with a few studies that have investigated the impact of a pharmacy ban on disparities in overall tobacco retailer density. In the state of Rhode Island, retailer density remained higher in tracts with a higher proportion of Black residents, even after CVS stopped selling tobacco products.⁸⁵ In New York City, an evaluation of implementing a pharmacy ban indicated that the policy had the largest beneficial impact in neighborhoods with greater income, more educational attainment, and a higher proportion of non-Hispanic White residents – groups that have lower smoking prevalence.¹²⁶ While the policy focus to date has been on restricting sales of tobacco products in pharmacies, one New Zealand modeling study considered the impact of only *permitting* sales of tobacco products in pharmacies (which could be paired with cessation services from the pharmacy).¹²⁷ Our results indicate that this type of policy may result in less tobacco availability in neighborhoods with a higher proportion of non-Hispanic Black residents.

We also find that tobacco shops were less likely to be in neighborhoods with a greater proportion of non-Hispanic Black residents, but were significantly more likely to be in areas with a greater proportion of residents living below 150% FPL. Some jurisdictions have implemented policies that only allow flavored tobacco products to be sold in adult-only tobacco shops.¹²⁸ If flavored tobacco products, or possibly any tobacco products, are only permitted to be sold in tobacco shops, people living in neighborhoods with a greater proportion of non-Hispanic Black residents may have less tobacco product availability, yet those in neighborhoods with a greater proportion of residents living below 150% FPL may have more. Policymakers may want to consider the distribution of certain tobacco retailer types in their local communities when

implementing retailer reduction and/or product availability regulations, as these regulations may have a differential impact on tobacco product availability and subsequent marketing in certain neighborhoods.

Several considerations should be made when interpreting the results of this study. First, we created a probable list of tobacco retailers using the best available data, but this list does not represent stores with verified tobacco product sales. It is possible that our list contained retailers that do not sell tobacco, or there could be tobacco retailers missing from this list. We have no reason to believe that this potential error is systematic, however. Second, as our analytic sample represents a near census of all tracts in the contiguous U.S., we have high power to detect small effects, and caution should be taken when interpreting small effect sizes. On the other hand, because this is a near census of tracts, associations observed may be more likely to represent the ‘true’ population parameter. Of importance is that we conceptualized the neighborhood as a census tract, but other neighborhood scales (e.g., block groups, districts) may be appropriate. Additionally, there may be other important neighborhood characteristics that may contribute to the associations observed (e.g., commercial land use, zoning)¹²⁹ that deserve future investigation. Finally, this study is cross-sectional and temporality cannot be established. Regardless of temporality, tobacco products are not a health-promoting neighborhood commodity, and it is a public health concern if they are readily available in the neighborhoods that the tobacco industry has targeted, especially as this availability could influence smoking behaviors.^{15-18,20,21}

CONCLUSIONS

In this national study, we use several common measures of tobacco retailer density to investigate associations with tract-level sociodemographic characteristics. While we document disparities in retailer density by area race, ethnicity, poverty level, and vacant housing, these

relationships were not consistent across all measures. Researchers and policymakers should consider how various measures of tobacco retailer density may capture aspects of and population-level interactions with the tobacco retailer environment differently in their local communities. Furthermore, attention to how certain tobacco retailer types may be distributed by neighborhood sociodemographics may be important when considering the varying impact of some retailer reduction policies. Overall, identifying the relationships between neighborhood sociodemographic characteristics and tobacco retailer availability may help communities better track place-based tobacco retailer disparities and design impactful pro-equity retailer-focused strategies

CHAPTER 4. NEIGHBORHOOD SOCIODEMOGRAPHIC DISPARITIES IN TOBACCO RETAILER DENSITY: DO YOUR NEIGHBORS MATTER? (STUDY 2)

INTRODUCTION

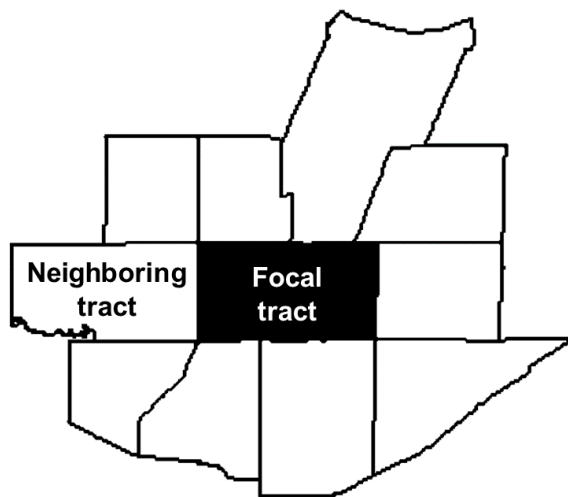
In the United States (U.S) tobacco use causes more than 480,000 deaths annually,¹ and 13.7% of adults smoke.² Tobacco retailer density is a measure of the availability of tobacco retailers in a geographic area. In 2012, U.S. counties with the highest tobacco retailer density had a 0.86% higher adult cigarette smoking prevalence compared to those with the smallest tobacco retailer density.¹³⁰ Studies indicate that individuals living in places with higher tobacco retailer density have a greater likelihood of being a current smoker¹⁷ and smoking more cigarettes,⁹⁵ and are less likely to have quit smoking.⁹⁸

Several studies have documented disparities in tobacco retailer density. In a sample of census tracts in 97 counties across the U.S., a higher neighborhood proportion of Black residents was associated with greater tobacco retailer density; however, in models that adjusted for other neighborhood demographics, this association was reversed.⁷⁵ Adjusted models also indicated an inverse relationship for neighborhood proportion of Hispanic or Latino residents and median household income.⁷⁵ Finally, in the only national-level study conducted to date, researchers found that 2007 census tract-level tobacco retailer density was positively associated with 2000 neighborhood proportion Hispanic, Black, families living in poverty, women without a high school diploma, and urbanicity.²⁵ That the distribution of tobacco retailer density is not equitable across neighborhoods may partially be due to historical tobacco industry efforts to segment consumers and target marketing by shared social characteristics (e.g., demographics, consumer

behaviors and lifestyles, and geographic areas).¹³¹ For example, Philip Morris used a 1997 Integrated Retail Demographic Database Micro-Marketing Tool¹³² to create ‘trade areas’ based on several factors of a geographic area, such as area demographic data, smoker profile demographics, and consumer preference for certain tobacco products.

The studies described above have focused on associations between area demographics and tobacco retailer density *within* the same census tract. However, maps reveal the industry’s use of geodemographics¹³³ to spatially target multiple connecting administrative units that share certain sociodemographic characteristics.¹³² Therefore, the characteristics of the places surrounding any given census tract could also be relevant to the experiences, behaviors, and health of people living in that unit. A neighborhood, as defined by people who live there, includes the spaces where daily social interaction and commerce transactions occur,^{28,134,135} and therefore could be comprised of multiple neighboring administrative units, rather than just a single focal one (Figure 4.1).

Figure 4.1. Focal Tract and 10 Adjacent Neighboring Tracts



As a result, tobacco retailer density in one tract may be correlated with tobacco retailer density in a nearby location, possibly due to similar consumer demand, place-based industry targeting,⁶³ or local land use ordinances.¹²⁹ To the best of our knowledge, only one research study has specifically investigated the potential impact of the sociodemographic characteristics of neighboring tracts on a focal tract's retailer density. Faulkner et al. found that the average income of adjacent neighboring tracts was also significantly associated with a lower tobacco retailer density in the focal tract in a sample of counties in Maryland.⁷⁷

This study determines whether the racial, ethnic, and socioeconomic characteristics of neighboring census tracts impact a focal tract's 2014 tobacco retailer density, using nearly all of the census tracts in the contiguous U.S. We contribute to theoretical and methodological discussions on how characteristics of places are related to each other in space. This study also provides insight on the "definition" and "size" of neighborhood that might be appropriate to consider when assessing neighborhood-level disparities in the tobacco retailer environment.

METHODS

Neighborhood Sociodemographics

The American Community Survey (ACS) is a nationally representative survey of households, providing population area-level demographic estimates.¹¹² The U.S. Census Bureau recommends using 5-year ACS estimates for smaller geographic areas, such as census tracts, as these are the most stable population estimates.^{112,113} We used 5-year 2010-2014 ACS tract-level estimates of percent non-Hispanic Black, Hispanic or Latino ethnicity, and living below 150% of the federal poverty level (FPL) as independent variables (downloaded from Social Explorer).^{112,115} To control for tract-level urbanicity, we also used U.S. Department of

Agriculture Rural-Urban Commuting Area (RUCA) codes that take into account population density, urbanization, and commuting patterns (Appendix A).¹¹⁴

Tobacco Retailer Density

As no national tobacco retailer licensing system in the U.S. exists, we created a 2014 list of probable tobacco retailers based on store types, similar to previous work.^{25,116,117} The U.S. Census Bureau assigns North American Industry Classification System (NAICS) codes to all retail establishments, which indicate a retailer type. Using tobacco product sales data from the latest 2012 Economic U.S. Census, we identified a total of ten NAICS codes (i.e. convenience stores; gasoline stations; gasoline stations with convenience stores; warehouse clubs and supercenters; tobacco stores; supermarkets and other grocery stores; pharmacies and drug stores; beer, wine and liquor stores; other general merchandise stores; discount department stores) that account for approximately 99% of all tobacco product sales in the retail setting.¹¹⁸ Using these codes, we identified likely tobacco retailers in ReferenceUSA (RefUSA),¹¹⁹ a database of business establishments that assigns NAICS codes and geographic indicators to each retailer. Retailer sub-types (e.g., specialty food markets, independent pharmacies) and certain retailers known to not sell tobacco products (e.g., Target, Whole Foods, Trader Joes) were omitted from the sample. Appendix B describes this methodology in further detail. Though no researchers have validated a national commercial list, two analyses have implicated good validation when compared to ground-truthed retailer locations in three counties in North Carolina¹¹⁶ and to aggregate tract-level retail density values using a state licensing list (Washington).²⁵

We used a spatial join in ArcMap 10.5 to assign each retailer to its respective census tract and then summed the total number tobacco retailers within each tract. Using total population and land area data from the 5-year 2010-2014 ACS (in Social Explorer),^{112,115} we calculated two

measures of tobacco retailer density commonly analyzed in the literature: 1) tobacco retailers per 1000 people and 2) tobacco retailers per land area (square mile).

Spatial Econometric Modeling

A Spatial Durbin Error Model (SDEM) can be used to model local effects,¹³⁶ or how characteristics of the adjacent neighbors of a focal tract may impact a focal tract. These models separate an association into a part that is attributable to focal tract characteristics (also called a direct effect) as well as a part attributable to neighboring characteristics (also called an indirect effect). As we are interested in examining the neighboring effect of sociodemographics on a focal tract retailer density (e.g., are neighbors' average proportion of residents living below 150% of the federal poverty level associated with a focal tract's tobacco retailer density), we used R and the `spatialreg` package¹³⁷ to fit several SDEMs, specified in Equation 1.¹³⁶

$$\begin{aligned} \mathbf{y} &= \mathbf{X}\boldsymbol{\beta} + \mathbf{WX}\boldsymbol{\theta} + \mathbf{u} && \text{[Equation 1]} \\ \mathbf{u} &= \mathbf{W}\boldsymbol{\lambda}\boldsymbol{\varepsilon} + \boldsymbol{\varepsilon} \end{aligned}$$

where

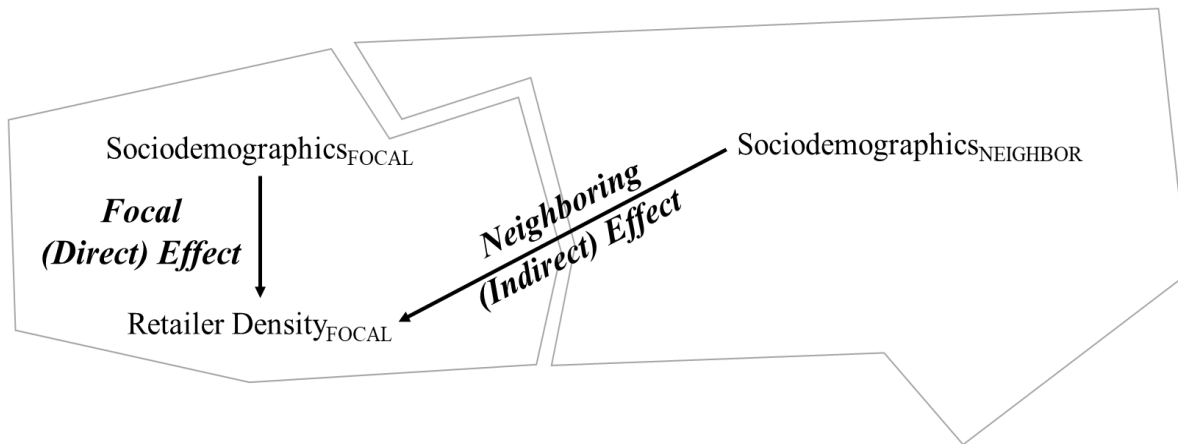
- \mathbf{y} represents a $N \times 1$ vector of tobacco retailer density values of a census tract
- $\boldsymbol{\beta}$ represents a $K \times 1$ vector of fixed parameters to be estimated for a matrix of sociodemographic characteristic values of the *focal* tract (\mathbf{X} , an $N \times K$ matrix)
- \mathbf{W} represents a $N \times N$ square matrix, and an area is assigned a zero if it is not an adjacent neighbor of a focal tract
- $\boldsymbol{\theta}$ represents a $K \times 1$ vector of fixed parameters to be estimated for a matrix of sociodemographic characteristic values of the *neighboring* tracts (\mathbf{WX})
- \mathbf{u} consists of a $N \times 1$ vector of random error ($\boldsymbol{\varepsilon}$) and spatially correlated error ($\mathbf{W}\boldsymbol{\lambda}\boldsymbol{\varepsilon}$)

LeSage and Pace recommend that researchers interpret at least three types of spatial effects.¹³⁸ The *direct effect*,¹³⁸ $\boldsymbol{\beta}$, is the average effect of a focal tract's sociodemographics on its own tobacco retailer density – this effect is similar to those produced in non-spatial regression models. The *indirect effect*,¹³⁸ $\boldsymbol{\theta}$, represents the average effect of neighboring sociodemographics on a focal tract's tobacco retailer density. Summing the direct effect and the indirect effect

results in the *total effect*,¹³⁸ representing the average effect attributable to the sociodemographics of both the focal tract *and* its adjacent neighbors. A SDEM also incorporates a spatially lagged error term ($\mathbf{W}\lambda\mathbf{u}$) that both reduces model bias due to spatial dependence of the error terms and accounts for omitted variables that are spatially dependent across geographic areas.¹³⁹

As a simplified demonstrative example, we illustrate the main spatial effects of interest (i.e. focal, neighboring) in Figure 4.2 for a focal tract with a single neighbor. We defined a focal tract’s “neighbors” as those that immediately touch any part of the focal tract. For each retailer density outcome, we fit models with just a single primary sociodemographic variable, as well as adjusted models that included all sociodemographic variables and the urbanicity control variable. There was no evidence of multicollinearity in adjusted models (average variance inflation factor was 1.39).

Figure 4.2. Focal (Direct) and Neighboring (Indirect) Effects of Spatial Durbin Error Model (SDEM)



Note: This figure is simplified demonstrative example to illustrate the focal and neighboring effects between a focal tract and a single adjacent neighbor. This figure does not illustrate all statistical correlations between terms, such as that between the sociodemographics of the focal and neighboring tract, or the error terms.

Analytic Sample

Our analytic sample included a total of 71,074 census tracts with complete sociodemographic data across the contiguous U.S. and the District of Columbia (DC). Ratio

measures are sensitive to small denominator values. We omitted 28 outliers that we thought were implausible (e.g., 3000 retailers per 1000 people) and tracts that had fewer than 1000 people (n=181). We additionally omitted those remaining tracts with no neighbors (n=10).

RESULTS

Tract-level sociodemographic and tobacco retailer density characteristics are summarized in Table 4.1. The average number of retailers per 1000 people was 1.25 while the average number of retailers per square mile was 6.07. Mean values for tract-level percent non-Hispanic Black, Hispanic or Latino, and living below 150% FPL were 13.4, 15.7 and 26.5, respectively. A focal tract had an average of 6.2 neighbors (i.e., adjacent census tracts), ranging from 1 to as many as 26 neighbors (not shown).

Table 4.1. Sociodemographic and Tobacco Retailer Density Characteristics of Census Tract Neighborhoods, Contiguous United States and DC, 2014 (N=71,074)

	Mean/Percent (SD)	Range
Demographic Characteristics		
Percent non-Hispanic Black	13.4 (21.8)	0-100
Percent Hispanic or Latino	15.7 (21.2)	0-100
Percent living below 150% FPL	26.5 (16.7)	0-100
Urbanicity		
Urban	82.9	-
Large rural city/town	8.6	-
Small and isolated rural town	8.5	-
Tobacco Retailer Density		
Retailers per 1000 people	1.25 (1.15)	0-24.0
Retailers per square mile	6.07 (15.8)	0-270.8

A SDEM simultaneously considers characteristics of both a focal tract and that of its neighbors in explaining variability in the tobacco retailer density of a focal tract. The results of the SDEMs are found in Table 4.2. We first discuss the results for retailers per 1000 people as the outcome (Models 1 and 2).

Although in the unadjusted model (Model 1), we found that the focal effect was positive for percent non-Hispanic Black (B=0.06, p<0.001), after further controlling for urbanicity and

other area sociodemographics (Model 2), this effect was negative. In other words, focal tracts with a higher percent non-Hispanic Black were associated with fewer ($B=-0.01$, $p<0.01$) tobacco retailers per 1000 people. The neighboring effect, however, indicated that a higher proportion of non-Hispanic Black residents in the adjacent tracts of a focal tract was associated with a greater tobacco retailer density per 1000 people (Model 2: $B=0.03$, $p<0.001$). The summed total effect, representing the expected difference in retailer density if both the focal and neighboring tracts had a higher proportion of non-Hispanic Black residents, was also positive (Model 2: $B=0.02$, $p<0.001$).

There was no significant focal effect for neighborhood proportion of Hispanic or Latino residents, but both the neighboring (Model 2: $B=-0.06$, $p<0.001$) and total effects (Model 2: $B=-0.05$, $p<0.001$) were inversely associated with the number of retailers per 1000 people.

The adjusted focal ($B=0.17$, $p<0.001$), neighboring ($B=0.01$, $p<0.001$), and total ($B=0.19$, $p<0.001$) effects for neighborhood proportion of residents living below 150% FPL were all significantly associated with greater tobacco retailer density (Model 2).

For the land area measure of tobacco retailer density, results were similar in terms of directionality and significance (Models 3 and 4). However, for percent Hispanic or Latino, all effects were significantly associated with more retailers per square mile.

Table 4.2. Spatial Durbin Error Model Analyses Testing Tract-Level Associations of Sociodemographics with Tobacco Retailer Density, Contiguous United States and DC, 2014 (N=71,074)

	Retailers per 1000 people				Retailers per square mile			
	Model 1		Model 2		Model 3		Model 4	
	B (SE)		B (SE)		B (SE)		B (SE)	
Non-Hispanic Black (Total: Focal & Neighboring)	0.07 (0.00)	***	0.02 (0.00)	***	0.13 (0.01)	***	0.06 (0.01)	***
Direct (Focal)	0.06 (0.00)	***	-0.01 (0.00)	**	0.05 (0.01)	***	-0.02 (0.01)	*
Indirect (Neighboring)	0.01 (0.01)	*	0.03 (0.01)	***	0.09 (0.01)	***	0.07 (0.01)	***
Hispanic or Latino (Total: Focal & Neighboring)	-0.02 (0.00)	***	-0.05 (0.00)	***	0.33 (0.01)	***	0.23 (0.01)	***
Direct (Focal)	0.09 (0.01)	***	0.01 (0.01)		0.24 (0.01)	***	0.15 (0.01)	***
Indirect (Neighboring)	-0.11 (0.01)	***	-0.06 (0.01)	***	0.09 (0.01)	***	0.08 (0.01)	***
Living below 150% FPL (Total: Focal & Neighboring)	0.18 (0.00)	***	0.19 (0.00)	***	0.40 (0.01)	***	0.27 (0.02)	***
Direct (Focal)	0.18 (0.00)	***	0.17 (0.00)	***	0.25 (0.01)	***	0.21 (0.01)	***
Indirect (Neighboring)	0.01 (0.01)		0.01 (0.01)	*	0.15 (0.01)	***	0.07 (0.02)	***

Note: Models 1 and 3 include the primary sociodemographic variable in focal and neighboring tracts while Models 2 and 4 additionally include the other listed sociodemographics and tract-level urbanicity. Tract-level demographic variables were scaled to 10s so that a 1-unit increase represents a 10-percentage point increase in the respective demographic variable.

FPL = Federal Poverty Level

* p<0.05, ** p<0.01; *** p<0.0001

DISCUSSION

Our study provides preliminary evidence that the sociodemographics of neighboring areas may play a unique role in the distribution of tobacco retailer density in a census tract. In most cases, a focal tract that was surrounded by census tracts that had a higher proportion of individuals living below 150% FPL, non-Hispanic Black residents, and Hispanic or Latino residents, was associated with greater tobacco retailer density, above and beyond the impact of the focal tract sociodemographics.

Tract-level poverty demonstrated both positive focal and neighboring associations with tobacco retailer density. Our adjusted results indicated that tracts with a higher proportion of residents living below 150% FPL also had higher tobacco retailer density, and neighboring higher poverty areas further contributed to greater retailer density. These results are consistent with the only other study to examine neighboring sociodemographic effects, which found that the average median household income of neighboring tracts was associated with a decrease in tobacco retailer density in a focal tract in a sample of Maryland counties.⁷⁷

When controlling for urbanicity and other tract-level sociodemographics, we found that higher neighborhood proportion of non-Hispanic Black residents was associated with less tobacco retailer density (per 1000 people and per land area) within a focal tract. This negative association was consistent with another U.S.-based study.⁷⁵ However, by fitting a SDEM, we were additionally able to examine the *neighboring* sociodemographic effect on focal tract retailer density. We found that this neighboring effect was positive and larger than the negative focal tract effect, resulting in an overall positive total effect across the sample. This finding suggests that areas made up of several tracts with a higher concentration of Black residents may actually have greater tobacco retailer density, resulting in an overall disparity.

For area proportion of Hispanic or Latino residents, there was no focal tract effect on retailer density per 1000 people. However, we did find neighboring and total effects, indicating a fewer number of retailers per 1000 people in tracts with a higher proportion of Hispanic or Latino residents. This suggests that a focal tract that has neighbors with a higher proportion of Hispanic or Latino residents may actually be protective against the number of tobacco retailers per 1000 people. There is evidence that ethnic enclaves could have some protective health effects due to factors such as decreased discrimination and increased social organization.¹⁴⁰ Additionally, ethnic enclaves may facilitate ethnic-minority owned retailer growth.¹⁴¹ In neighborhoods with high social cohesion, there may be more collective efficacy to remove tobacco products from retailers.

In research, we are often limited to using administrative boundaries (e.g., census blocks, census tracts, counties) as proxies for neighborhoods. Assessments of disparities in tobacco retailer density have been used to justify policy interventions in the retail environment and to track their impact.²² Each of our study results suggest that the relevant spatial context for understanding disparities in tobacco retailer density might be larger than a single census tract. Residential segregation by sociodemographic characteristics may have resulted in tracts with similar sociodemographics being next to one another over time,^{142,143} Furthermore, the tobacco industry has a legacy of targeting tobacco products and related marketing in neighborhoods with a greater proportion of some marginalized groups,^{62,63,67,120,121,144} and the industry has examined the distribution and connectivity of neighborhoods across several adjacent administrative boundaries in doing so.¹³² Given the spatial distribution of both people with shared social characteristics and targeted tobacco product and marketing, total effects of area characteristics may be particularly important to consider. Spatial analyses like the ones used in this study may

more comprehensively capture the impact of area characteristics on tobacco retailer density and may be useful to researchers and practitioners looking to assess and track disparities in the retail environment over time.

Some of our results also underscore the importance of measurement validity for density measures. While the magnitude and significance of associations were the same across retailer density measures for percent Black residents and those living below 150% FPL, this was not the case for percent Hispanic or Latino residents. When measuring tobacco retailer density as the number of retailers per square mile, we found that all the spatial effects actually indicated *greater* tobacco retailer density for tracts with a higher proportion of Hispanic or Latino residents. Additional theoretical discussion on whether there are conceptual differences between per capita and per land area measures of tobacco retailer density, as well as longitudinal studies assessing the predictive validity of these measures on tobacco use behaviors, are needed to better explain why these associations may differ.

Several considerations should be made when interpreting the results of this study. First, data from this study are cross-sectional and therefore, we cannot make any claims about temporality or causality. Second, although we identified retailers based on store types that are most likely to sell tobacco, this list may include retailers that do not sell tobacco, or there could be tobacco retailers missing; however, we have no reason to believe that this error is systematic. Third, our study includes an almost near census of all tracts in the contiguous U.S., and we are therefore, statistically overpowered. At the same time, a major strength of this study is that it is national in scope and this near census may actually be closer to estimating the true population parameters at the tract level. Finally, while we used census tracts as a measure of a focal and neighboring spaces, other area units may be more appropriate, such as census block groups or

locally-recognized neighborhoods. Regardless of the area units chosen, our study results suggest that neighboring attributes may need to be considered to fully understand the processes that may be contributing to tobacco retailer density in a specific area.

CONCLUSIONS

This is the first study to investigate how neighboring tract sociodemographic characteristics may be associated with tobacco retailer density at a national level. We find local and regional disparities in tobacco retailer density by neighborhood composition of race, ethnicity, and poverty. Our study indicates that the neighboring characteristics of an area may be important for understanding the full magnitude of observed disparities in tobacco retailer density. Understanding the different aspects of a neighborhood space that are partly attributable to these sociodemographic disparities may help local jurisdictions better define and prioritize certain neighborhoods when designing and tracking the impact of pro-equity tobacco retailer reduction policies.

CHAPTER 5. ASSOCIATIONS OF COUNTY TOBACCO RETAILER DENSITY WITH ADULT SMOKING STATUS AND CESSATION BEHAVIORS, UNITED STATES, 2014-2015 (STUDY 3)

INTRODUCTION

In the United States (U.S.), cigarette smoking is responsible for more than 480,000 deaths per year, accounting for 1 out of every 5 deaths.¹ While smoking prevalence has decreased over the last several decades, 13.7% of adults still smoked in 2019.² Smoking behavior may be influenced by tobacco retailer density, which is a measure of the concentration of tobacco retailers (e.g., total number of retailers per 1000 people) in a geographic area. In a 2012 nationwide study, adult smoking prevalence was greater in counties with higher tobacco retailer density; however, this association was only observed in metropolitan counties.¹³⁰ An increased chance of being a current smoker is also higher for those living in neighborhoods with greater retailer density.^{17,76} For example, researchers in Scotland recently conducted a 2000-2015 longitudinal study linking maternal birth records to self-reported smoking behavior and neighborhood tobacco retailer density.⁹⁴ Even after controlling for several variables including year of delivery, area income deprivation, metropolitan/rural residential location, mother's age, and neighborhood maternal smoking prevalence, researchers found that mothers living in areas with highest retailer density had a 39% excess risk of being a smoker during pregnancy.⁹⁴

Some studies have also documented decreased cessation intentions and behaviors for smokers living in areas with greater tobacco retailer density. In a national sample of adult smokers, non-daily smokers living in areas with high tobacco retailer density reported having

decreased intentions to quit smoking in the next 6 months.¹⁶ In a separate longitudinal cohort study of adult smokers living in 8 media market areas across the U.S., researchers found that 2007 tobacco retailer density was associated with reduced 30-day smoking abstinence and lower pro-cessation attitudes (measured in 2008 and 2010), but only in high poverty areas.⁹⁸ In contrast to these studies, others have found no significant associations between retailer density and cessation behaviors.^{19,100}

Very few studies have assessed whether specific store types are associated with smoking behaviors, yet the prevalence of tobacco marketing, which can cue smoking behaviors,¹⁰ differs by tobacco retailer type.¹¹⁷ For example, tobacco stores have the highest average number of tobacco marketing materials, followed by gas and convenience stores.¹¹⁷ This same pattern also occurred for the proportion of retailers with exterior tobacco marketing and tobacco product price promotions.¹¹⁷ Given that the majority of smokers purchase their cigarettes at gas and convenience stores,¹⁴⁵ availability to these stores may be particularly important for smoking behaviors. For example, a California study found that convenience store retailer density was positively associated with the number of cigarettes an individual smoked per day.⁹⁵

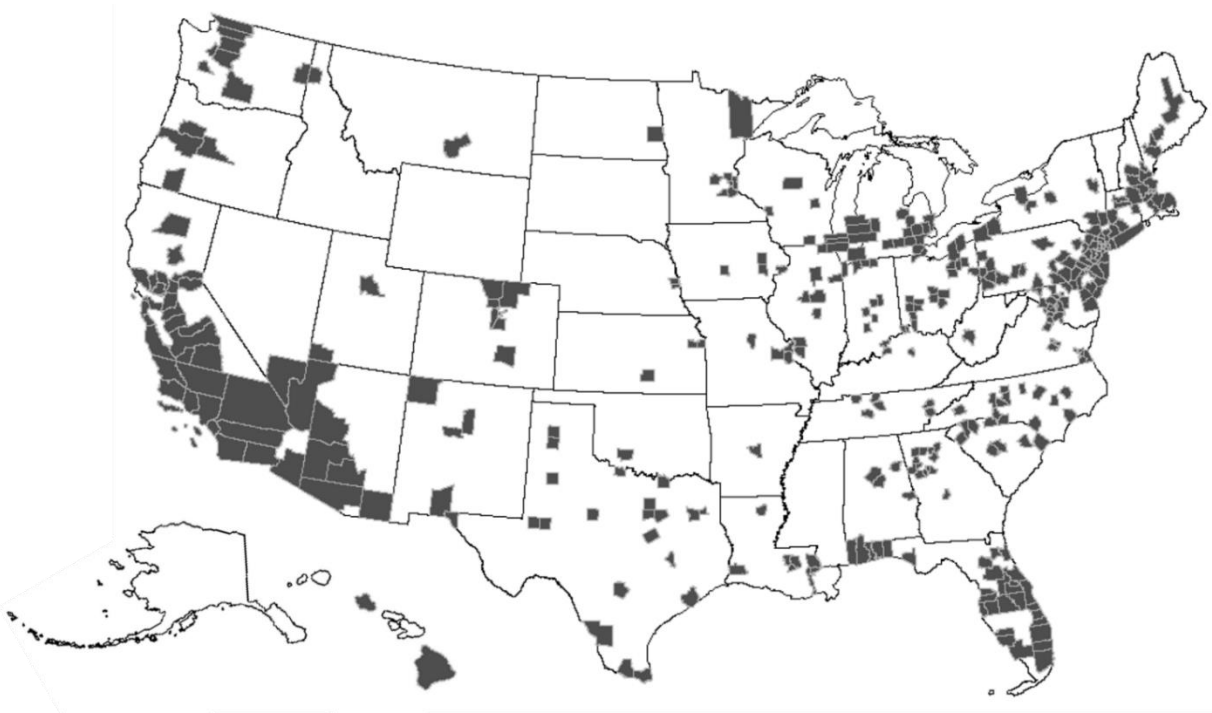
This 2014-2015 study investigates associations of tobacco retailer density and gas and convenience store density with multiple smoking behaviors (i.e. smoking status, quit attempt, quit length) in a large sample of adults living in metropolitan counties across the U.S. Tobacco retailer reduction policies have been implemented at the county level,²³ and documenting whether and how county retailer density is associated with individual smoking behaviors across the nation may provide policymakers with information that may be useful for designing and implementing retailer reduction policies in their communities.

METHODS

Tobacco Use Supplement (TUS)

Smoking behavior data were drawn from the 2014-2015 Tobacco Use Supplement (TUS) of the Current Population Survey.¹⁴⁶ The TUS is sponsored by the National Cancer Institute and is administered every 3-4 years to collect nationally and state representative data about tobacco use from the civilian, adult (18 years and older) non-institutionalized population in the U.S.¹⁴⁶ The 2014-2015 TUS is based on interviews with adult members of participating households of the Current Population Survey in July 2014, January 2015, and May 2015. The TUS assigned county-level identifiers to respondents residing in counties with more than 100,000 people. After merging all three waves of the TUS, we excluded those individuals who were inadvertently interviewed twice (n=10,290), those residing in counties with 100,000 or less people (n=131,522), and individuals who did not report a smoking status (n=734), resulting in an overall sample of 88,850 respondents (61,545 self-respondents; 27,305 proxy respondents) living in 368 counties across 44 states (Figure 5.1). Proxy respondents only answered smoking status questions for those respondents that were to be interviewed for the TUS, but were not present at the time of interview.

Figure 5.1. Counties of Individual Respondents, 2014-2015 Tobacco Use Supplement, United States (N=368)



Smoking Status (Self- and Proxy- Respondents)

Both self- and proxy- respondents (Analytic Sample 1, N=88,850) were asked, “Have you smoked at least 100 cigarettes in (your/his/her) entire life?” Those responding “Yes” were then asked, “Do you now smoke cigarettes every day, some days, or not at all?” Responses were coded as “Never Smoker,” “Former Smoker,” “Some-day smoker,” and “Every-day smoker.” For analysis purposes, we categorized “Never Smoker” and “Former Smoker” as current non-smokers. We then created three binary indicator variables (1=yes) for every-day smoker (vs. non-smoker); some-day smoker (vs. non-smoker); and every-day smoker (vs. some-day smoker).

Quit Attempt in Last 12 Months among Current Smokers (Self-Respondents)

Among self-respondents, every- and some- day smokers (Analytic Sample 2, N=7332) were asked questions about past 12-month quit attempts. Some-day smokers smoking less than 12 days in the past 30 days were asked, “During the past 12 months, have you tried to quit

smoking completely?"; every- and some- day smokers smoking 12 or more days during the past 30 days were asked, "During the past 12 months, have you stopped smoking for one day or longer because you were trying to quit smoking?" and "During the past 12 months, have you made a serious attempt to stop smoking because you were trying to quit – even if you stopped for less than a day?" Prior research indicates that excluding quit attempts that last less than day may be underestimating serious quit attempts, and individuals who quit for less than 24 hours may suffer from greater nicotine addiction.¹⁴⁷⁻¹⁴⁹ We therefore combined these three questions into a single quit attempt binary indicator (1=yes) representing whether any quit attempt was made in the past 12 months, regardless of the quit length.

Quit Length for Current Smokers Reporting Quit Attempt of One Day or Longer (Self-Respondents)

Self-respondent every- and some- day smokers reporting a single quit attempt of 1 day or longer (Analytic Sample 3, N=2915) were asked, "During the past 12 months, what is the length of time of this single quit attempt where you stopped smoking because you were trying to quit smoking?" while those with more than one quit attempt were asked this same question but about the quit attempt that lasted the longest. We converted quit length (originally recorded as days/weeks/months/year) into the total number of days and additionally excluded those quit lengths that were greater than 365 days to limit analyses to quit attempts that began in the past year.

County-Level Tobacco Retailer Density

The U.S. Census Bureau uses North American Industry Classification System (NAICS) codes to classify business establishments in the U.S. Using reported tobacco product sales data from the most recent 2012 Economic U.S. Census, we identified NAICS codes that account for

approximately 99% of all retail tobacco product sales (i.e. convenience stores; gasoline stations; gasoline stations with convenience stores; warehouse clubs and supercenters; tobacco stores; supermarkets and other grocery stores; pharmacies and drug stores; beer, wine and liquor stores; other general merchandise stores; discount department stores).¹¹⁸ There is no tobacco retailer licensing system in the U.S., so consistent with other studies,^{25,116,117} we created a 2014 national list of probable tobacco retailers using these NAICS codes.

We used ReferenceUSA (RefUSA),¹¹⁹ a database of business establishments that contains both NAICS codes and retailer addresses to identify probable tobacco retailers. We omitted some retailer sub-types (e.g., specialty food markets, compounding pharmacies, marine services stations, independent pharmacies) and those retailers known to not sell tobacco products (e.g., Target, Whole Foods, Trader Joes). Appendix B contains the details of this methodology. There has not been national-level validation of commercial businesses establishment lists, but two local studies in North Carolina¹¹⁶ and Washington²⁵ indicated good validation compared to ground-truthed retailer locations and a state licensing list, respectively.

We used a spatial join in ArcMap 10.5 to assign each retailer to its respective county and then summed the total number tobacco retailers within each county. Using total population data from the 5-year 2010-2014 ACS (in Social Explorer),^{112,115} we then divided the total number of tobacco retailers by the population of each county (and converted to per 1000 people). We additionally combined convenience and gasoline stores into a single category, “gas and convenience stores,” and then calculated the total number of gas and convenience stores per 1000 people. These data were then merged to the reported county of residence of each TUS respondent.

Analysis

The TUS includes respondents nested within counties. Respondents from the same county may have more similar smoking behaviors than those from other counties due to many reasons, such as exposure to county policies that regulate smoking behaviors. To account for this within-county dependence, we used SAS 9.4¹⁵⁰ to fit general estimating equation models with an exchangeable working correlation matrix, which adjusts both parameter estimates and standard errors to account for this dependence. For smoking status and quit attempt outcomes, we specified a logit function, and for quit length (number of days), we specified a negative binomial function.

Several individual-level sociodemographic characteristics are associated with smoking status and may also influence the counties that people choose reside in, and thus, their tobacco retailer density. Consistent with other studies investigating associations of retailer density with smoking behaviors¹⁵¹ we included several individual-level control variables in adjusted models: race/ethnicity (non-Hispanic White, Black, Asian or Hawaiian/Pacific Islander, American Indian/Alaskan Native, Other Multi-race, and Hispanic or Latino ethnicity [any race]), household income (below \$50,000, at or above \$50,000), educational attainment (less than high school, high school graduate, some college/associate's degree, bachelor's degree or more), age, and sex (male, female).

RESULTS

Analytic Sample Characteristics

Table 5.1 describes smoking behavior, individual-level demographic, county-level demographic, and tobacco retailer density characteristics for each of the analytic samples described above. Descriptive means and frequencies were not adjusted for sampling differences.

For the full sample (Analytic Sample 1, N=88,850), the majority of respondents reported being non-smokers (88.2%), and about 3% and 9% reported being some-day and every-day smokers, respectively. In the full sample, retailers per 1000 people and convenience stores per 1000 people had a Pearson correlation coefficient of 0.66 (not shown).

Analytic Sample 2 was used to test associations of retailer density with respondent quit attempt in the last 12 months. While there were 7560 self-respondents reporting that they were current smokers, only 7332 (97.0%) of these respondents reported whether they had a quit attempt in the last 12 months. Analytic Sample 3 was used to test associations of retailer density with quit lengths of one day or longer. While there were 3433 self-respondents reporting that they had a quit attempt in the last 12 months, only 2915 (84.9%) of these respondents reported a quit length between one and up to 365 days.

Table 5.1. Descriptive Sample Characteristics for Analytic Samples, 2014-2015 Tobacco Use Supplement, United States

	Analytic Sample 1: Full Sample (N=88,850)	Analytic Sample 2: Self- Respondent Smokers (N=7332)	Analytic Sample 3: Self- Respondent Smokers with Quit Attempt (N=2915)
	N (%)	N (%)	N (%)
Smoking Status			
Non-smoker	78,403 (88.2)	-	-
Some day smoker	2391 (2.7)	1705 (23.3)	899 (30.8)
Every day smoker	8056 (9.1)	5627 (76.8)	2016 (69.2)
Quit attempt in last 12	-	3433 (46.8)	-
Quit length (days), <i>Mean (SD)</i>	-	-	44.8 (77.1)
Race and Ethnicity			
Non-Hispanic White	54,491 (61.3)	5026 (68.6)	1935 (66.4)
Non-Hispanic Black	10,033 (11.3)	1021 (13.9)	451 (15.5)
Non-Hispanic Asian or Hawaiian/Pacific Islander	7201 (8.1)	288 (3.9)	110 (3.8)
Non-Hispanic American Indian/Alaskan Native	483 (0.5)	58 (0.8)	27 (0.9)
Non-Hispanic Other Multi-race	1288 (1.5)	113 (1.5)	50 (1.7)
Hispanic or Latino ethnicity (any race)	15,354 (17.3)	826 (11.3)	342 (11.7)
Household Income			
Below \$50,000	38,461 (43.3)	4547 (62.0)	1821 (62.5)
At or above \$50,000	50,389 (56.7)	2785 (38.0)	1094 (37.5)
Educational Attainment			
Less than high school	9689 (10.9)	1082 (14.8)	419 (14.4)
High school graduate	23,724 (26.7)	2697 (36.8)	1032 (35.4)
Some college/associates degree	24,620 (27.7)	2429 (33.1)	1016 (34.9)
Bachelor's degree or more	30,817 (34.7)	1124 (15.3)	448 (15.4)
Age, <i>Mean (SD)</i>	47.9 (17.8)	46.9 (15.1)	45.4 (15.0)
Sex			
Male	41503 (46.7)	3763 (51.3)	1429 (49.0)
Female	47,347 (53.3)	3569 (49.7)	1486 (51.0)
County-Level Sociodemographics, <i>Mean (SD)</i>			
Percent non-Hispanic Black	13.4 (13.4)	14.3 (13.8)	14.6 (14.2)
Percent living below 150% FPL	9.1 (2.5)	9.3 (2.4)	9.3 (2.4)
County-Level Tobacco Retailer Density, <i>Mean (SD)</i>			
Retailers per 1000 people	1.1 (0.2)	1.1 (0.2)	1.1 (0.2)
Gas and convenience stores per 1000 people	0.4 (0.1)	0.4 (0.1)	0.4 (0.1)

Smoking Status

Both unadjusted and adjusted models indicated that there was no significant effect of retailer density on the likelihood that a respondent was a some-day vs. non-smoker (Table 5.2). When comparing every-day smokers to non-smokers, we found that even after controlling for several individual-level factors, both a greater number of tobacco retailers per 1000 people (aOR, 1.57; 95% CI, 1.30-1.90) and a greater number of convenience stores per 1000 people (aOR, 3.20; 95% CI, 2.32-4.43) were associated with a higher odds of a respondent being an every-day smoker. Both measures of retailer density were also associated with a higher likelihood of a respondent being an every-day vs. some-day smoker.

Table 5.2. Associations of Tobacco Retailer Density with Individual Smoking Status, 2014-2015 Tobacco Use Supplement, United States (N=88,850)

	Some-day vs. non-smoker				Every-day vs. non-smoker				Every-day vs. some-day			
	Unadjusted		Adjusted		Unadjusted		Adjusted		Unadjusted		Adjusted	
	OR	95% CI	aOR	95% CI	OR	95% CI	aOR	95% CI	OR	95% CI	aOR	95% CI
Tobacco retailers per 1000 people	1.46	1.09-1.96	1.20	0.89-1.62	2.02	1.62-2.52	1.57	1.30-1.90	1.52	1.10-2.09	1.44	1.09-1.91
Gas and convenience stores per 1000 people	2.01	1.26-3.23	1.42	0.88-2.28	5.87	4.19-8.23	3.20	2.32-4.43	3.82	2.20-6.64	2.60	1.68-4.01

Note: We used generalized estimating equations to account for the nesting of individuals within counties in all models. Unadjusted models only include the tobacco retailer density measure (specified in each row) while adjusted models include covariates for respondent age, sex, income, educational attainment, and race/ethnicity.

In subsequent analyses, we standardized both retailer density measures to compare the magnitude of statistically significant adjusted associations. We did not find evidence that one retailer density measure exhibited a stronger association compared to the other (Table 5.3).

Table 5.3. Standardized Associations of Tobacco Retailer Density with Individual Smoking Status, 2014-2015 Tobacco Use Supplement, United States (N=88,850)

	Every-day smoker vs. non-smoker		Every-day smoker vs. some-day smoker	
	Adjusted		Adjusted	
	aOR	95% CI	aOR	95% CI
Tobacco retailers per 1000 people	1.10	1.06-1.15	1.08	1.02-1.15
Gas and convenience stores per 1000 people	1.15	1.11-1.21	1.12	1.07-1.19

Note: We used generalized estimating equations to account for the nesting of individuals within counties in all models. Tobacco retailer density measures were standardized so that associations are representative of a one standard deviation difference. Adjusted models include covariates for respondent age, sex, income, educational attainment, and race/ethnicity.

Quit Attempts and Quit Length

In both unadjusted and adjusted models (Table 5.4), we did not find any significant associations between measures of tobacco retailer density and the odds of a respondent having a quit attempt in the last 12 months. Similarly, retailer density was not significantly associated with quit length.

Table 5.4. Associations of County Tobacco Retailer Density with Individual Quit Attempt in the Last 12 Months (N=7332) and Quit Length (N=2915), 2014-2015 Tobacco Use Supplement, United States

	Quit Attempt in Last 12 Months				Quit length (Days)			
	Unadjusted		Adjusted		Unadjusted		Adjusted	
	OR	95% CI	aOR	95% CI	OR	95% CI	aOR	95% CI
Tobacco retailers per 1000 people	1.07	0.85-1.34	1.02	0.81-1.29	0.93	0.71-1.21	0.99	0.75-1.30
Gas and convenience stores per 1000 people	1.04	0.69-1.56	1.03	0.68-1.55	1.00	0.59-1.70	1.17	0.70-1.97

Note: We used generalized estimating equations to account for the nesting of individuals within counties in all models. Unadjusted models only include the tobacco retailer density measure (specified in each row) while adjusted models include covariates for respondent age, sex, income, educational attainment, and race/ethnicity.

Sensitivity Analyses

In sensitivity analyses for smoking status and cessation behaviors, we additionally included controls for county-level proportion of Black residents and those living below 150% of the federal poverty level: associations were unchanged and area-level controls were not significant (not shown); therefore, we present and discuss the more parsimonious models that only included individual-level controls.

DISCUSSION

Using a large national sample of adults living in metropolitan counties, we found that tobacco retailer density was associated with a greater likelihood of an individual being an every-day smoker, as compared to both some-day and non-smokers. These results extend those of previous studies that have documented associations between retailer density and current smoking status, both domestically and internationally.^{17,76} A greater supply of tobacco products may make it easier to obtain tobacco products to sustain every day smoking. Additionally, areas with more retailer density may also expose individuals to more tobacco product marketing,^{8,9} which could cue impulse purchases in daily smokers.^{10,11,13} For example, in a sample of 206 adult daily smokers, 22% made unplanned cigarette purchases after entering a tobacco retailer, and 8% reported purchasing cigarettes after seeing point-of-sale marketing.¹³ Daily smokers may be more addicted to nicotine,^{152,153} and therefore more responsive to point-of-sale product availability and marketing than non-daily smokers. The tobacco retailer environment may be an especially important point of intervention for daily smokers given increased health risks. While non-daily smokers have higher all-cause mortality risks than never smokers, this risk is even higher for daily smokers.¹⁵⁴ Furthermore, survival is shorter for daily smokers.¹⁵⁴ Finally, in

areas with greater tobacco retailer density, smoking and tobacco use may be more socially normalized, which may further support daily smoking.

We do not find evidence, however, that greater tobacco retailer density is associated with the likelihood that an individual is a some-day smoker (vs. non-smoker). These results are similar to a study in Australia that did not find significant associations.³⁴ A subset of non-daily smokers include ‘social smokers’ who are typically younger and primarily use tobacco when in social settings, such as bars.¹⁵⁵⁻¹⁵⁷ Social smokers typically partake in light tobacco use and may also be less nicotine dependent than daily smokers.^{156,157} Studies indicate that adolescents who borrow cigarettes from social sources tend to smoke fewer cigarettes per day, and higher cigarette prices may actually result in more adolescent smokers borrowing vs. purchasing cigarettes.¹⁵⁸ It is plausible that adult non-daily smokers may also be less likely to purchase tobacco products in the retail setting, relying on social groups for their primary tobacco product source.¹⁶

Our results do not support associations between tobacco retailer density and either quit attempts in the past 12 months or quit length. These null findings are similar to some other studies.^{19,100} For example, Reitzel et al. found that retailer density was not a significant predictor of cigarette smoking abstinence in a longitudinal sample of adult smokers who were motivated to quit smoking.¹⁹ Our measure of tobacco retailer density may not best capture risks to relapse posed in the environment. In Reitzel et al., researchers found that residential *proximity* to the nearest tobacco retailer, rather than density, had a significant inverse relationship with smoking abstinence.¹⁹ Residential distance to a tobacco retailer, representing an easily accessible supply of tobacco products and marketing that a person may be more likely to interact with more frequently, may be more influential on smoking behaviors than simply the overall concentration

of retailers in a neighborhood.¹⁵⁹ Our study results suggest that retailer density may matter more for sustaining current smoking behavior than for quitting behaviors.

In this study, we used two different measures of tobacco retailer density: the number of retailers per 1000 people and the number of convenience stores per 1000 people. For all outcomes, we document similar results in terms of magnitude and significance across these two measures. Gas and convenience stores constitute the largest proportion of tobacco retailers, have greater tobacco marketing and promotions,¹¹⁷ and the majority of adult smokers purchase cigarettes from these store types,¹⁴⁵ therefore, gas and convenience stores may represent a greater potential smoking risk compared to other store types such as pharmacies, mass merchandisers or liquor stores. In the absence of licensing system and associated validated tobacco retailer lists in much of the country, many researchers and communities are tasked with building their own retailer lists. Results from our study indicate that compiling a list of gas and convenience stores may be a sufficient proxy for a list that includes all types of tobacco retailers (e.g., supermarkets, pharmacies, etc.), at least for the purpose of examining associations with smoking behavior. However, our study results may not be generalizable to all other study populations or geographic areas.

Finally, some considerations should be made when interpreting the results of this study. First, a major challenge of place-based health research is that geo-identifiers of where people live are often limited or unavailable, due to confidentiality protections. Therefore, researchers are often left to use geo-identifiers that may not reflect what is most salient to the population or the health phenomena under study.^{160,161} In this study, the smallest geo-identifier available was at the county-level, which may be too large of an area to capture the spaces where individuals spend time. However, understanding whether county-level retailer density is associated with individual-

level smoking behaviors is informative. Counties are often the government level with jurisdiction for implementing public health policies. Rock County (Minnesota) and Rockland, Albany, and Erie counties (New York) are examples of counties that have implemented various policies focused on tobacco retailer reduction.²³ Additionally, while our sample is limited to individuals residing in metropolitan counties, metropolitan areas may be particularly important places in which to investigate the role of tobacco retailer density on smoking behavior. Individuals living in metropolitan areas travel less distance per day²⁹ and may also have a higher tobacco retailer density.^{7,25} Second, as both retailer density and smoking status are measured in the same year, we cannot determine whether retailer density leads to someone being a some-day or every-day smoker. Longitudinal studies are needed to determine if there is a causal relationship and to disentangle what mechanisms (e.g., exposure to marketing, product pricing) may be contributing to these associations. Finally, as discussed prior, there is no national licensing list of tobacco retailers and we therefore, had to create a probable list, consistent with several studies in the past. There may be both tobacco retailers missing from this list, as well as retailers on the list that do not sell tobacco products; however, we have no reason to believe that this potential error is systematic.

CONCLUSIONS

Among a national sample of adult smokers living in metropolitan counties, we find that greater tobacco retailer and gas and convenience store density is associated with a higher probability of someone being an every-day smoker, as compared to either a non-smoker or some-day smoker. The tobacco retailer environment, paired with other targeted cessation efforts, may be an important point of intervention for decreasing smoking behaviors, including consumption frequency.

CHAPTER 6. ASSOCIATIONS OF TOBACCO RETAILER DENSITY WITH COPD-RELATED HOSPITAL OUTCOMES, UNITED STATES, 2014 (STUDY 4)

INTRODUCTION

Tobacco use is the leading cause of preventable death in the United States (U.S.), estimated to cause more than 480,000 deaths annually.¹ Although smoking rates have declined over the past decade, nearly 14% of adults smoke,² increasing the risk for premature death and/or disability. The health consequences of smoking are well documented, contributing to cardiovascular disease, chronic obstructive pulmonary disease (COPD), and one third of cancer deaths.^{1,3} Furthermore, the health and financial costs due to smoking are enormous, amounting to over \$170 billion each year in the U.S.⁵

The World Health Organization recognizes the importance of the built environment on health.⁶ Tobacco retailer availability may influence smoking prevalence and is often operationalized as the number of tobacco retailers per population (i.e. tobacco retailer density). In 2012, U.S. counties with the greatest tobacco retailer density had a 0.86% higher smoking prevalence compared to those with the smallest retailer density.¹³⁰ In places with greater tobacco retailer availability, there may be lower travel costs to obtain tobacco products,⁷ and more marketing,^{8,9} which could cue smokers to use^{10,11} and purchase products,^{10,12,13} reducing smoking cessation.⁹⁸

Few studies have investigated associations with tobacco-related health outcomes. Research conducted in Baltimore (Maryland) found that in 2011, the number of tobacco retailers per 10,000 population was significantly associated with a lower life expectancy, greater age-

adjusted mortality, and greater rates of death from chronic lower respiratory disease.³⁵ A 1997 cross-sectional study in Louisiana investigated census tract-level associations of tobacco retailers per 1000 people with birthweight-for-gestational-age and gestational age at birth and found no significant results in models that adjusted for both neighborhood-level socioeconomic factors and individual-level factors.¹⁶² In Western Australia, retailer density was associated with a greater diagnosis of and hospitalization for heart disease among smokers.³⁴

COPD is a pulmonary disease that includes emphysema and chronic bronchitis and can obstruct normal breathing.^{101,102} Primary cigarette smoking is the main cause of COPD development, but exposure to secondhand smoke and air pollution may also contribute to its development or exacerbation.¹⁰² In the U.S., smoking causes as many as 8 out of 10 COPD-related deaths.¹ Between 2014-2015, more than 15.9 million adults reported that they had been medically diagnosed with COPD; however, variation exists across states (Hawaii: 3.7% vs. West Virginia: 12.0%).¹⁰² In 2010, the economic costs due to COPD were \$32.1 billion and projected to reach \$49 billion by 2020,¹⁰³ averaging to over \$4000/year per COPD patient.¹⁰² Smoking can exacerbate COPD, leading to hospital admissions,¹⁰⁴ which account for the greatest cost of COPD-related care.^{102,105} Additionally, smoking cessation is the most important modifiable determinant in COPD management,¹⁰² associated with a 40% reduced risk of COPD hospital admission.¹⁰⁶ In places where the tobacco retail environment may prompt greater tobacco use or undermine successful cessation, there may be greater hospitalization due to COPD exacerbation.

The burden of COPD is estimated to increase substantially over the next 15 years (by 182% from 2010-2030);¹⁰⁵ identifying potential place-based factors that may contribute to the problem could help health systems plan for the associated care burden, prioritize places most in need of preventive health resources, and generate innovative retail environment programs and

policies. Prior cross-sectional studies found that inpatient hospitalization charges for the state of California in 1993 and 1999 were significantly and positively associated with the number of tobacco retailers in a neighborhood.^{32,33} The study samples included both off-premise (e.g., grocery stores) tobacco retail outlets and restaurants and bars. It was not until 1998 that California became the first state to require smoke-free workplaces, bars, and restaurants.¹⁶³ In these studies, therefore, it is plausible that the associations documented were primarily explained by direct secondhand smoke exposure in restaurants and bars (an environmental trigger), rather than the retail availability of tobacco products.

With the growing enactment and implementation of state-level smoke-free air laws, exclusion of restaurants and bars from retailer density measures may be important. This could allow researchers to better investigate if associations persist when solely measuring the *off-premise* tobacco retail environment where people purchase tobacco products and are exposed to tobacco product marketing. The purpose of this cross-sectional study is to update and extend the limited number of health-related studies to a national sample of counties. We describe associations between tobacco retailer density (excluding restaurants and bars) and COPD-related inpatient hospital discharge data observed at a single point in time (2014).

MATERIALS & METHODS

To examine associations of retailer availability with COPD-related hospital discharge data, we acquired and merged several data sources, described below.

Data Sources and Measures

Tobacco Retailer Density

There is no national licensing system of stores that sell tobacco products for in-person consumer purchase (i.e. tobacco retailers). Furthermore, the American Lung Association

estimates that only 38 states require a tobacco retailer to have a license to sell cigarettes,¹⁶⁴ and some states may only update licensing lists periodically. The Census Bureau classifies business establishments using the North American Industry Classification System (NAICS), which assigns a store type code (i.e. NAICS code) to all business establishments in the U.S. ReferenceUSA (RefUSA)¹¹⁹ is a national database of business establishments that contains NAICS codes and geographic indicators (e.g., address, city, latitude, and longitude) for each retailer.

Using tobacco product sales data from the latest 2012 Economic U.S. Census, we identified a list of ten NAICS codes (i.e. convenience stores; gasoline stations; gasoline stations with convenience stores; warehouse clubs and supercenters; tobacco stores; supermarkets and other grocery stores; pharmacies and drug stores; beer, wine and liquor stores; other general merchandise stores; discount department stores), which account for approximately 99% of *all* retail tobacco product sales.¹¹⁸ Using these ten NAICS codes and the 2014 RefUSA, we created a national list of probable tobacco retailers, similar to previous studies.^{25,116,117} Specific retailer sub-types (e.g., specialty food markets, compounding pharmacies, marine services stations) and retailers known to not sell tobacco products (e.g., Target, Whole Foods, Trader Joes) were excluded from the sample. Appendix B describes this methodology in further detail. Though national validation of commercial lists, such as RefUSA, has not been conducted, two studies have indicated good validation when compared to ground-truthed retailer locations (three counties in North Carolina)¹¹⁶ and tract-level retail density using a state licensing list (Washington).²⁵

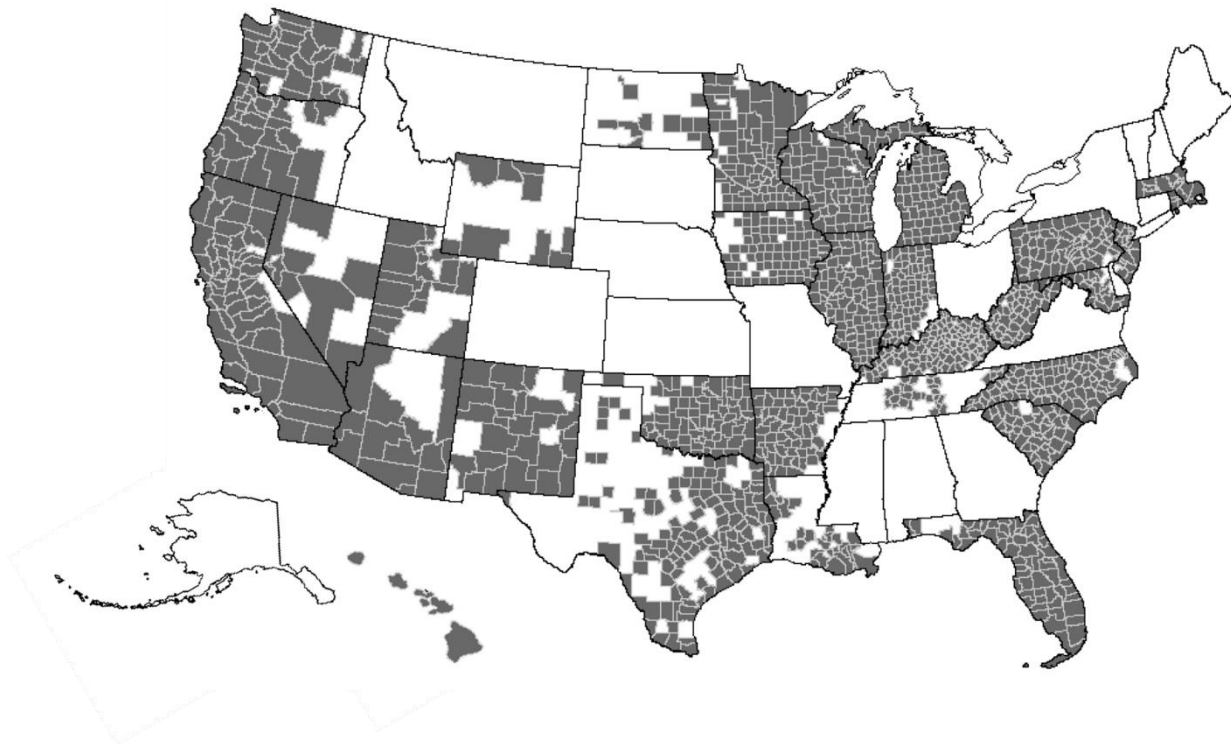
We used a spatial join in ArcMap 10.5 to assign each retailer to its respective county. To measure tobacco retailer availability, we calculated tobacco retailer density per 1000 residents by

summing the number of retailers in each county, dividing this sum by the total county-level population, and multiplying this figure by 1000. We additionally created quartiles of this measure to investigate potential threshold effects that may not be apparent when using a continuous measure of retailer availability.

COPD-Related Hospital Discharge Data

The Healthcare Cost and Utilization Project (HCUP) is the largest U.S. longitudinal healthcare database and aggregates data from state and private data organizations, hospitals, and the federal government as part of the Agency for Healthcare Research and Quality.¹⁶⁵ The publicly available 2014 HCUP State Inpatient Database (SID) includes COPD-related hospital inpatient discharge data for a sample of 1510 counties across 31 states in the U.S. (Figure 6.1). Not all states participate in the publicly available HCUP-SID, and statistics are not reported for any estimates that are unreliable or that could potentially identify an individual. The sample includes nearly half (48.1%) of counties in the U.S. where approximately 69.4% of the 2014 U.S. population resided.

Figure 6.1. Counties in Publicly Available Healthcare Utilization Project State Inpatient Database (HCUP-SID), United States, 2014 (N=1501)



The primary study outcome of interest is the total number of COPD-related hospital discharges in a county. We additionally investigate associations of retailer density with two other outcomes that may be of interest to practitioners and policymakers: COPD-related total number of days spent in the hospital and total hospital costs for providing care for all COPD-related inpatient stays (rounded to the nearest dollar). Data are classified by HCUP-SID as “COPD-related” based on Clinical Classification Software (CCS), which uses International Classification of Diseases (ICD) codes to create an overall clinically meaningful category that researchers can then use to assess outcomes related to particular illnesses.¹⁶⁶ See Appendix C for a list of the 15 ICD-9 codes used to classify a hospital discharge as due to “Chronic obstructive pulmonary disease and bronchiectasis.” HCUP-SID statistics are based on the patient’s county of residence, rather than the county where the treatment hospital is located;¹⁶⁵ our analysis therefore assessed

both tobacco retailer availability and COPD-related hospital outcomes in reference to place of residency.

Control Variables

Tobacco retailer density may be higher in urban areas,²⁵ and rural areas have higher rates of COPD diagnosis and related complications.¹⁶⁷ The U.S. Department of Agriculture has developed Rural-Urban Continuum Codes (RUCC) which can be combined to designate counties as urban or rural based on population size and adjacency to metro areas.¹⁶⁸ Using 2013 RUCC, we created an urbanicity variable designating counties as either metropolitan, urbanized non-metropolitan, or rural (Appendix D)

To control for potential confounders documented in other studies,^{32,33} we included county-level estimates of percent aged 45 years or older, percent male, percent Hispanic or Latino ethnicity, percent Black, and percent living below 150% of the federal poverty level (FPL) in adjusted models. Demographic data were from the 2010-2014 American Community Survey (ACS), a survey of a nationally representative sample of households conducted by the U.S. Census Bureau,¹¹² and downloaded from Social Explorer.¹¹⁵

Better air quality may be associated with neighborhoods with less disadvantage, which have been shown to be associated with both tobacco retailer density⁷⁵ and COPD.^{101,102} We used the data from the U.S. Environmental Protection Agency's Air Quality System (AQS), which measures air pollution through the use of an Air Quality Index (AQI).¹⁶⁹ Data from the AQS have been deemed the gold standard for determining outdoor air pollution in urban areas.¹⁷⁰ Not all counties have AQI data, but out of the 1510 counties in the 2014 HCUP-SID, 616 counties had median AQI data (40.8% of total sample). As a sensitivity test, we used the subsample of

616 counties and compared the results of analyses using the continuous measure of tobacco retailer density between models that did and did not include median AQI.

Analysis

All analyses were completed using SAS 9.4. Sample characteristics (mean, frequency, standard deviation, range) were calculated for both the full HCUP-SID sample (N=1510) and for the air quality control sample (N=616). We also present the mean age-sex standardized value, provided by HCUP-SID, of each COPD-related health outcome by quartile of retailer density for the full sample.

Negative Binomial Regression Models

Prior to fitting any models, we investigated the distribution of each COPD-related hospital outcome for the full sample, which indicated overdispersion in the count outcomes. To account for overdispersion, we fit negative binomial regression models and tested associations between both continuous and quartiles of tobacco retailer density and each COPD-related hospital outcome. As the population-at-risk for COPD-related hospital outcomes varies between counties, we included an offset (i.e. natural log of the total county-level population) in each model. We investigated correlation coefficients between control variables and retailer availability and did not find evidence of high collinearity. Finally, all models included state indicators (i.e. fixed effects) to control for both the nesting of counties within states and any omitted time-invariant state-level factors. We present both unadjusted models, which only include state fixed effects, and adjusted models, which additionally include all control variables described above.

RESULTS

The full sample included a total of 1510 counties: the average number of counties nested within states was 48.7. The air quality control sample included a total of 616 counties nested within 30 states: the average number of counties nested within states was 20.5. Table 6.1 describes sample characteristics for both the full and the air quality control samples. Compared to national county-level population estimates (not shown), the full sample had counties with a lower percent of non-Hispanic Black (7.2 vs. 12.2) and Hispanic or Latino (9.4 vs. 16.9) residents, and a slightly higher percent of residents living below 150% FPL (27.6 vs. 25.2) and those aged 45 or older (44.3 vs. 40.1).

Table 6.1. 2014 HCUP Sample Characteristics, County-Level, United States

Measure	Full Sample (N=1510)		Air Quality Control Sample (N=616)	
	Mean/Percent (SD)	Range	Mean/Percent (SD)	Range
Total population (count)	144,297 (425,383)	2883-9,974,203	294,675	4031-9,974,203
Tobacco retailers per 1000 people	1.40 (0.45)	0.45-5.09	1.22 (0.36)	0.45-2.94
COPD-Related Hospital Outcomes				
Total number of discharges	257.1 (599.9)	11-10,749	480.7 (880.7)	11.0-10,749.0
Total number of days in the hospital	1092.8 (2714.4)	24-48,059	2079.5 (4003.0)	26.0-48,059.0
Total costs for all hospital stays, \$	2,108,703 (5,445,304)	44,995- 115,105,788	4,032,521 (8,062,465)	65,019- 11,5105,788
Percent non-Hispanic Black	7.2 (11.4)	0-73.9	7.2 (9.5)	0-62.9
Percent Hispanic or Latino ethnicity	9.4 (14.0)	0-95.7	12.6 (15.8)	0.1-95.4
Percent below 150% FPL	27.6 (8.1)	7.1-58.6	25.8 (7.6)	7.1-52.3
Percent aged 45 or older	44.3 (6.2)	21.5-74.9	42.8 (6.4)	21.5-63.5
Percent male	50.0 (2.0)	45.6-69.7	49.6 (1.5)	46.6-62.1
Urbanicity				
Metropolitan	44.2	-	66.6	-
Urbanized non-metropolitan	31.6	-	22.6	-
Rural	24.2	-	10.9	-

Compared to the full sample, the air quality control sample was more metropolitan and urbanized, had lower average retailer density (1.22 vs. 1.40), had a greater proportion of Hispanic or Latino residents (12.6% vs. 9.4%), and had a higher mean of all COPD-related hospital outcomes. All other characteristics were similar between the two samples.

Negative Binomial Regression Results

Controlling for all other variables in the full model (Table 6.2), one additional retailer per 1000 people was associated with a 19% (IRR, 1.19; 95% CI, 1.12-1.27) higher COPD-related hospital discharge rate. We found similar positive and significant associations for the number of days in the hospital and aggregate costs of hospital stays. An additional retailer per 1000 people was associated with 1.22 (95% CI, 1.14-1.30) times the number of days stayed in the hospital, and with a 30% (IRR, 1.30; 95% CI 1.21-1.39) higher aggregate cost (\$) per population.

Table 6.2. Associations of Tobacco Retailer Availability (Retailers per 1000 people) and COPD-Related Hospital Outcomes, United States, 2014 (N=1510)

	Total number of discharges		Total number of days in the hospital		Aggregate costs for all hospital stays, \$	
	Unadjusted IRR (95% CI)	Adjusted IRR (95% CI)	Unadjusted IRR (95% CI)	Adjusted IRR (95% CI)	Unadjusted IRR (95% CI)	Adjusted IRR (95% CI)
Tobacco retailers per 1000 (continuous)	1.64 (1.54-1.73)	1.19 (1.12-1.27)	1.60 (1.50-1.70)	1.22 (1.14-1.30)	1.70 (1.60-1.81)	1.30 (1.21-1.39)
Tobacco retailers per 1000 (quartiles)						
Q1: 0.45-1.07	<i>ref</i>	<i>ref</i>	<i>ref</i>	<i>ref</i>	<i>ref</i>	<i>ref</i>
Q2: 1.08-1.32	1.31 (1.23-1.40)	1.12 (1.05-1.18)	1.31 (1.23-1.41)	1.14 (1.07-1.22)	1.39 (1.30-1.49)	1.19 (1.12-1.28)
Q3: 1.33-1.64	1.51 (1.41-1.61)	1.15 (1.07-1.22)	1.49 (1.39-1.60)	1.18 (1.10-1.27)	1.55 (1.44-1.66)	1.22 (1.13-1.31)
Q4: 1.65-5.09	1.81 (1.69-1.94)	1.22 (1.13-1.32)	1.76 (1.64-1.90)	1.25 (1.15-1.36)	1.90 (1.76-2.05)	1.32 (1.23-1.46)

Note: All models include a state fixed effect indicator. Adjusted models additionally control for county-level percent non-Hispanic Black, Hispanic or Latino ethnicity, living below 150% of the federal poverty level, aged 45 years or older, male, and urbanicity.

Analyses of quartiles of retailer density suggest this relationship may differ by level of retailer density. For example, compared to counties with the lowest retailer density (Q1: 0.45-1.07), counties with the highest retailer density (Q4: 1.65-5.09) had a 22% (IRR, 1.22; 95% CI, 1.13-1.32) higher discharge rate, those in Q3 (1.33-1.64) had a 15% (IRR, 1.15; 95% CI, 1.07-1.22) higher discharge rate, and those in Q2 (1.08-1.32) had a 12% (IRR, 1.12; 95% CI, 1.05-1.18) higher discharge rate.

In Table 6.3, we describe model-predicted averages of each CODP-related hospital outcome by quartile of tobacco retailer density. Those counties with the lowest retailer density (Q1: 0.45-1.07) had an average of 199.4 (95% CI: 189.3-210.0) COPD-related discharges per 100,000 people while counties with the highest retailer density (Q4: 1.65-5.09) had 243.9 discharges per 100,000 population (95% CI: 231.4-257.1), representing a 44.5 difference. Additionally, compared to counties with the lowest retailer density, those counties with the highest retailer density had 196.9 more days in the hospital and \$543,450 higher total hospital costs per 100,000 population.

Table 6.3. Model-Predicted Average COPD-Related Hospital Outcome Rates for Quartiles of Tobacco Retailer Density, United States, 2014 (N=1510)

	Total number of discharges per 100,000 population	Total number of days in the hospital per 100,000 population	Total costs (\$) for all hospital stays per 100,000 population
	Mean (95% CI)	Mean (95% CI)	Mean (95% CI)
Q1 (0.45-1.07)	199.4 (189.3-210.0)	790.9 (746.5-838.0)	1,601,040 (1,506,570-1,701,440)
Q2 (1.08-1.32)	222.5 (218.1-239.4)	903.9 (859.1-951.2)	1,912,820 (1,813,370-2,017,720)
Q3 (1.33-1.64)	228.5 (218.1-239.4)	932.6 (886.1-981.5)	1,945,970 (1,845,420-2,051,990)
Q4 (1.65-5.09)	243.9 (231.4-257.1)	987.8 (932.8-1046.0)	2,144,490 (2,020,110-2,276,510)

Note: All models include a state fixed effect indicator. Adjusted models additionally control for county-level percent non-Hispanic Black, Hispanic or Latino ethnicity, living below 150% of the federal poverty level, aged 45 years or older, male, and urbanicity.

Using the smaller air quality control sample and the continuous measure of tobacco retailer density, we fit and compared adjusted models that included and excluded median AQI as a control variable. The magnitude, direction, and significance of associations were unchanged or similar (largest change: 1.46 [95% CI, 1.28-1.66] vs. 1.44 [95% CI, 1.27-1.65]), and the direction and significance were identical across all outcomes; therefore, we focus our interpretation and discussion on the adjusted results of the larger full analytic sample.

DISCUSSION

After controlling for a number of area-level factors, counties with higher retailer availability had greater COPD-related discharges, hospital stays, and financial costs. While there are very few studies investigating relationships between tobacco retailer availability and health outcomes in general, our findings are consistent with two related cross-sectional studies that also focused on area-level COPD-related hospital outcomes. Lipton and colleagues document significant positive associations between the number of tobacco retailers and COPD hospital charges per capita in California in both 1993 and 1999.³³ Specifically, in 1999, they found that a higher count of tobacco retailers in California zip codes was significantly associated with 0.23 higher COPD hospitalization counts and \$4,838.17 higher COPD-related hospital charges.³² Our study corroborates these findings on a national level. Additionally, a strength of our study is that we limited our analyses to off-premise tobacco retailers; therefore, the associations documented may better reflect the relationship between the tobacco retailer environment (and not other venues, such as restaurants and bars, that may have direct secondhand smoke exposure) and COPD hospitalizations. While comprehensive smoke-free air policies are one of the most effective tobacco control policies and may additionally protect against COPD-related

hospitalizations,^{163,171} our results suggest that the tobacco retail environment may also be an important factor for public health practitioners and policymakers to consider.

Greater retailer availability may result in higher smoking intensity and decreased chances of quitting, both of which may contribute to COPD exacerbation, resulting in hospital admissions.^{102,104} Though we cannot make causal interpretations or claims of temporality due to our cross-sectional study design, we indeed find that counties with greater retailer density are expected to have a 19% higher discharge rate, and the number of days stayed in the hospital upon admission is also significantly higher. This could partially be due to COPD exacerbation from smoking behaviors that are potentially associated with tobacco retailer availability.

In this study, we additionally examined associations between retailer density and COPD-related financial costs. In adjusted models, we found that when comparing two counties, a county with a 1-unit higher retailer density would be expected to have a 30% higher rate of COPD-related costs. Several communities are implementing policies designed to reduce tobacco retailer availability, including San Francisco and New York City.^{22,172} Understanding the potential long-term health implications related to different levels of tobacco retailer availability may help policymakers anticipate future burdens on the healthcare system, especially for financially costly diseases such as COPD.

While the current study does not provide evidence for whether these policies will be effective in reducing smoking-related disease, our results do suggest that there are associations between retailer availability and health that deserve exploration over time. Places with high rates of COPD may want to examine the tobacco retailer landscape to better understand the ways in which the local environment could be undermining tobacco control and cessation efforts. However, future longitudinal studies are needed to better disentangle the causal mechanisms and

relationships between tobacco retailer availability, behavior, and resulting health outcomes and financial costs.

Several considerations should be made when interpreting the results of this study. First, this is a cross-sectional study and therefore, we cannot conclude that retailer density leads to higher COPD-related hospital admissions or costs. We chose outcome variables related to COPD-related exacerbation, rather than COPD development, recognizing that exacerbation may be more tied to the immediate environment in the short-term, whereas disease development may be impacted by exposure to risks over longer time periods, require lagged density measures to fully investigate these relationships. To the best of our knowledge, this is the first study that uses a multi-state sample to investigate associations of tobacco retailer availability and related health outcomes. However, as the analytic sample does not include all states and additionally includes state-level fixed effects, generalizability cannot be made to the overall national level or to other time periods. Because there is no national tobacco retailer list, we had to generate a probable list of tobacco retailers; however, this generated list does not represent stores with verified tobacco sales. There could be retailers on the list that are not actually tobacco retailers, or there could be tobacco retailers missing from this list. We have no reason to believe that this potential error is systematic, however. Finally, tobacco retailer availability is a latent construct. We chose to operationalize retailer availability as the number of retailers per population; however, this measure may not truly capture how available tobacco products are to a population. Other factors of accessibility, such as retailer hours of operation, marketing and pricing of products, and someone's proximity and resources to reach retailers may also be important components of operationalizing availability. Finally, while HCUP-SID statistics are based on the patient's

county of residence, it is entirely plausible that patients spend time in other counties with varying retailer availability that may additionally impact their smoking or cessation behaviors.

CONCLUSION

Smoking causes COPD, and the health and financial costs due to this burden are immense. Availability of tobacco in the retail environment could increase smoking and reduce successful cessation. In a national sample, we document significant associations between tobacco retailer density and COPD-related hospital discharges, days spent in the hospital, and financial costs. As COPD-related cost are projected to grow substantially in the next decade, our study provides evidence that the tobacco retailer environment may be an important point of intervention to potentially prevent and decrease hospital admissions and growing financial costs.

CHAPTER 7. DISCUSSION AND CONCLUSION

OVERVIEW AND THEORETICAL FOUNDATION

The overall objectives of this dissertation were to examine inequities in the distribution of tobacco retailers (Study 1 and 2), and to further investigate whether tobacco retailer density is associated with smoking behaviors (Study 3) and smoking-related disease (Study 4) across the nation. Several theoretical frameworks discuss how the physical or built environment can contribute health-promoting or health-harming resources that may affect health. Bernard and colleagues discuss that individuals living in the same neighborhoods share positive and negative resources, and living in close proximity to negative resources may in turn affect health and produce and sustain health inequities.³⁷ Furthermore, I presented a conceptual model in Chapter 2 that is heavily grounded in Diez Roux & Mair's *Neighborhoods and Health* theoretical framework, which posits that processes such as discrimination and residential segregation by race, ethnicity, or socioeconomic status have resulted in the unequal distribution of resources across space.²⁷ Taken together, these theoretical frameworks recognize that built environment resources may impact health, and that discrimination by social distinction results in the spatial stratification³⁸ of individuals, resulting in social groups having differential access to both material and social resources.^{27,36,37}

IMPLICATIONS FOR HEALTH AND HEALTH EQUITY

Previous studies have hypothesized and found that tobacco retailers are a health-harming resource, and thus, may be an important point of intervention for decreasing smoking behaviors

and related disease. Two of the studies in this dissertation lend additional support to this claim. Results from Study 3 indicate that retailer density was associated with a higher likelihood of a respondent being an every-day vs. (non- or some-day smoker). However, retailer density was not significantly associated with either quit attempts in the last 12 months or quit length. Study 4 describes associations between county-level tobacco retailer density and county-level rates of COPD-related discharges, hospital length stays, and total hospital costs. Our model predicted results indicated that compared to counties with the lowest retailer density per 1000 people (0.45-1.07), those counties with the highest retailer density (1.65-5.09) had 44.5 more discharges per 100,000 population, 196.9 more days in the hospital per 100,000 population, and \$543,450 higher total hospital costs per 100,000 population. Taken together, these studies indicate that reductions in tobacco retailer density warrant consideration as possible public health interventions, though other targeted cessation interventions may also be needed to help individuals fully quit smoking.

That tobacco retailer density is associated with both smoking and related disease is even more concerning in light of evidence from Study 1 that builds on previous evidence that tobacco retailers may be more available in the neighborhoods where high priority populations for tobacco control reside. We consistently documented greater tobacco retailer density in census tracts with a higher proportion of residents living below 150% of the federal poverty level. Furthermore, Study 2 results indicated that it is not just the sociodemographic characteristics of the immediate neighborhood that might be contributing to tobacco retailer density, but neighboring area characteristics as well. Taken together, we can imagine that neighborhoods, whether narrowly defined as census tracts or at somewhat larger levels, with a health-harming resource such as tobacco retailers may pose hazardous conditions for some high priority groups. These inequities

in the distribution of tobacco retailers may put these groups at a higher risk of tobacco use behaviors and related disease.

IMPLICATIONS FOR FUTURE RESEARCH

This dissertation also indicates the need for a greater discussion on and testing of the construct validity of various area-level tobacco retailer density measures. Tobacco retailer availability is a latent construct intended to capture how available tobacco products (and potentially exposure to marketing) are for a population. However, other factors of accessibility, such as retailer hours of operation, marketing and pricing of products, and someone's proximity and resources to reach retailers may also be important components of operationalizing availability and exposure. To date, most studies use a single measure of tobacco retailer density to evaluate neighborhood disparities, which further limits comparability across studies. Our results indicate that common measures of retailer density may not be capturing similar aspects of the built environment. In Study 1, we assessed and compared associations of four common measures of tobacco retailer density (i.e. total count of tobacco retailers, retailers per 1000 people, retailers per land area, retailers per roadway) in 2014 with tract-level sociodemographic characteristics in the contiguous U.S. The direction and significance of associations between retailer density and percent non-Hispanic Black, Hispanic or Latino, and vacant housing units were sensitive to the retailer density measure operationalized.

Conceptual and qualitative work is needed to better understand how people actually interact with tobacco retailers, which may better inform our understanding of both the similar and different aspects of the environment that these measures may be capturing. Research that incorporates and compares different neighborhood-level measures of retailer density to individual-level activity spaces is needed to fully understand whether and how individuals may

be interacting with available tobacco retailers and if we are reliably capturing these interactions with area-level measures of retailer density. Related, future research that investigates the predictive validity of various retailer density measures with smoking behaviors and health outcomes may also be important. This work may also be useful for providing insight on how people actually define their neighborhood space.

This dissertation also contributes to theoretical and methodological discussions on how places are related to each other in space, and enhances our current understanding of place-based tobacco-related health disparities. To date, the overwhelmingly majority of research only considers how sociodemographics may relate to retailer density within the same place. However, Study 2 suggests that the relevant spatial context for understanding disparities in tobacco retailer density might be larger than a single census tract. While we found that a higher focal tract percent non-Hispanic Black was associated with fewer tobacco retailers per 1000 people within a focal tract, we also found that that a higher proportion of non-Hispanic Black residents in the *neighbors* of a focal tract was associated with a greater tobacco retailer density per 1000 people. In other words, the neighboring tract sociodemographics resulted in an overall observed disparity. Our study results suggest that factors beyond a single area may contribute to disparities in tobacco retailer density in a specific area, and future research may want to begin measuring these spatial processes.

IMPLICATIONS FOR POLICY

Various places, such as San Francisco, Philadelphia, Rock County (Minnesota), and Rockland, Albany, and Erie counties (New York) have recognized the likely relationship between tobacco retailer density and smoking, and have implemented various tobacco retailer reduction policies to reduce smoking behaviors and demographic disparities in potential tobacco

retailer exposure. For example, San Francisco has designated a limit on the total number of tobacco retailers in a district while Philadelphia has designated a cap on the total number of retailers per 1000 people in a district. Other policies have focused on specific types of tobacco retailers, such as pharmacies or tobacco shops. This dissertation provides additional evidence that tobacco retailer density reduction policies have the potential to decrease smoking and related disease and may also ameliorate place-based health disparities.

Policymakers designing and implementing retailer reduction policies may be considering various measures of retailer density, and future research and local-level discussion is needed to try to better understand which retailer density measures may best capture the aspects of the built and social environment most tied to consumer attitudes, behavior, and community-level tobacco use patterns. Results from this dissertation also suggest that policymakers may want to consider the distribution of certain tobacco retailer types (pharmacies, tobacco shops) in their local communities. These regulations may have a differential impact on tobacco product availability and subsequent marketing in certain neighborhoods and could result in an unintended consequence of worsening place-based disparities.

While our study results are national in scope, focused on census tracts, and may not be fully generalizable to other areas, jurisdictions that are designing tobacco retailer reduction policies in an effort to reduce tobacco retailer density may want to consider the sociodemographic make-up of multiple adjacent neighborhoods; for example, prioritizing reducing tobacco retailer density in those neighborhoods that are surrounded by higher poverty areas or those with a higher proportion of non-Hispanic Black residents.

STRENGTHS AND LIMITATIONS

Using two large national samples, we document that tobacco retailer density is associated with both ongoing smoking behaviors and COPD-related illness and costs. A strength of both studies is that they extend local studies to national samples, though metropolitan counties comprise the majority of the sample, so results may not be generalizable to other geographies or more rural areas. We also update the only previous national study (using 2000 sociodemographics and 2007 retailer density) to evaluate tract-level racial, ethnic, and socioeconomic disparities in tobacco retailer density, and our results indicate a persistence of disparities in 2014. We further contribute to the disparities literature in several ways, including by using different measures of retailer density to help increase comparability of findings to past and future studies, investigating disparities in the distribution of pharmacies and tobacco shops (which are commonly targeted in tobacco control policies), and measuring and discussing how characteristics of neighboring areas may also contribute to retailer density in an area.

However, a major limitation of all four studies is that they are cross-sectional, and causality cannot be determined. The presence of tobacco retailers likely means that there is more tobacco product marketing,⁸ and several studies have indicated exposure to tobacco marketing is associated with sustained smoking behaviors.^{10,11} However, even in countries that have banned retail tobacco marketing, the mere display of tobacco products may be an important precursor to tobacco product exposure and subsequent use.^{173,174} Considering reverse causality, even if smokers are locating in places with higher retailer density, this is a cause for concern given that this product availability and associated marketing may sustain smoking. Additionally, areas with higher tobacco retailer density may imply greater demand, resulting in more smoking and secondhand smoke, both of which exacerbate COPD and can result in hospitalizations. Policies

that reduce the availability and marketing of tobacco products have the potential to remove cues to initiate or continue smoking,^{10,11,125} which may decrease smoking behaviors and related disease. This may be especially important for those areas with disproportionately higher tobacco retailer density: reducing retailer density in these areas may help ameliorate tobacco-related health disparities over time.

Another limitation of this dissertation is that we had to generate a probable list of tobacco retailers; however, this generated list does not represent stores with verified tobacco sales. There could be retailers on the list that are not actually tobacco retailers, or there could be tobacco retailers missing from this list. We have no reason to believe that this potential error is systematic, however.

Finally, while this dissertation does not provide evidence for whether tobacco retailer reduction policies will be effective, our results do suggest that there are associations between retailer availability and health that deserve exploration over time. Longitudinal and multilevel studies are needed to try to fully understand and disentangle what mechanisms (e.g., product availability, product marketing, normalization of smoking) may be influencing and interacting with one another to ultimately affect health and observed disparities.

CONCLUSION

This dissertation is grounded in theoretical frameworks that posit that the built environment and neighborhood resources may protect or harm health of individuals and populations. Additionally, due to structural systems of oppression, such as residential segregation, health inequities may develop and persist over time.⁴¹ This dissertation provides additional evidence that in national and metropolitan samples, the tobacco retailer environment is associated with smoking behaviors and smoking-related illness. Importantly, this research

reaffirms past literature that stark neighborhood-level disparities in tobacco retailer density continue to persist across the nation. This dissertation also stimulates a discussion on the need for research on the construct and predictive validity of measures of retailer density, as well as consideration of how neighborhoods may interact with one another. A better understanding of these measures and concepts is needed to fully understand and intervene upon these neighborhood-level interactions that may result in smoking behaviors, smoking-related disease, and the sustainment and reproduction of tobacco-related health inequities

APPENDIX A: 2010 RURAL-URBAN COMMUTING AREA CODES (RUCA)

The United States Department of Agriculture’s most recent 2010 Rural-Urban Commuting Area Codes (RUCA)¹¹⁴ dataset contains ten primary codes and 21 secondary codes, which can be used to designate census tract urbanicity level.¹⁷⁵ The different codes take into account population density, urbanization, and commuting patterns based on 2010 Census Bureau population data and 2006-2010 American Community Survey (ACS)¹¹³ commuting data. Below is a list of all of the 2010 RUCA primary and secondary codes and their descriptions.

1 Metropolitan area core: primary flow within an urbanized area (UA)	
1	No additional code
1.1	Secondary flow 30% to 50% to a larger UA
2 Metropolitan area high commuting: primary flow 30% or more to a UA	
2	No additional code
2.1	Secondary flow 30% to 50% to a larger UA
3 Metropolitan area low commuting: primary flow 10% to 30% to a UA	
3	No additional code
4 Micropolitan area core: primary flow within an Urban Cluster of 10,000 to 49,999 (large UC)	
4	No additional code
4.1	Secondary flow 30% to 50% to a UA
5 Micropolitan high commuting: primary flow 30% or more to a large UC	
5	No additional code
5.1	Secondary flow 30% to 50% to a UA
6 Micropolitan low commuting: primary flow 10% to 30% to a large UC	
6	No additional code
7 Small town core: primary flow within an Urban Cluster of 2,500 to 9,999 (small UC)	
7	No additional code
7.1	Secondary flow 30% to 50% to a UA
7.2	Secondary flow 30% to 50% to a large UC
8 Small town high commuting: primary flow 30% or more to a small UC	
8	No additional code
8.1	Secondary flow 30% to 50% to a UA
8.2	Secondary flow 30% to 50% to a large UC
9 Small town low commuting: primary flow 10% to 30% to a small UC	
9	No additional code
10 Rural areas: primary flow to a tract outside a UA or UC	
10	No additional code
10.1	Secondary flow 30% to 50% to a UA

10.2	Secondary flow 30% to 50% to a large UC
10.3	Secondary flow 30% to 50% to a small UC
99 Not coded: Census tract has zero population and no rural-urban identifier information	

There are several recommended ways to combine codes to designate a census tract's urbanicity level.¹⁷⁵ For this dissertation, a three-part RUCA designation (i.e. Urban, Large Rural City/Town, Small and Isolated Small Rural Town) was used, described below.

RUCA Designation	RUCA Codes Included
Urban	1.0, 1.1, 2.0, 2.1, 3.0, 4.1, 5.1, 7.1, 8.1, 10.1
Large Rural City/Town	4.0, 5.0, 6.0
Small and Isolated Small Rural Town	7.0, 7.2, 8.0, 8.2, 9.0, 10.0, 10.2, 10.3

**APPENDIX B: REFERENCEUSA NATIONAL TOBACCO RETAILER LIST
METHODOLOGY**

OVERVIEW

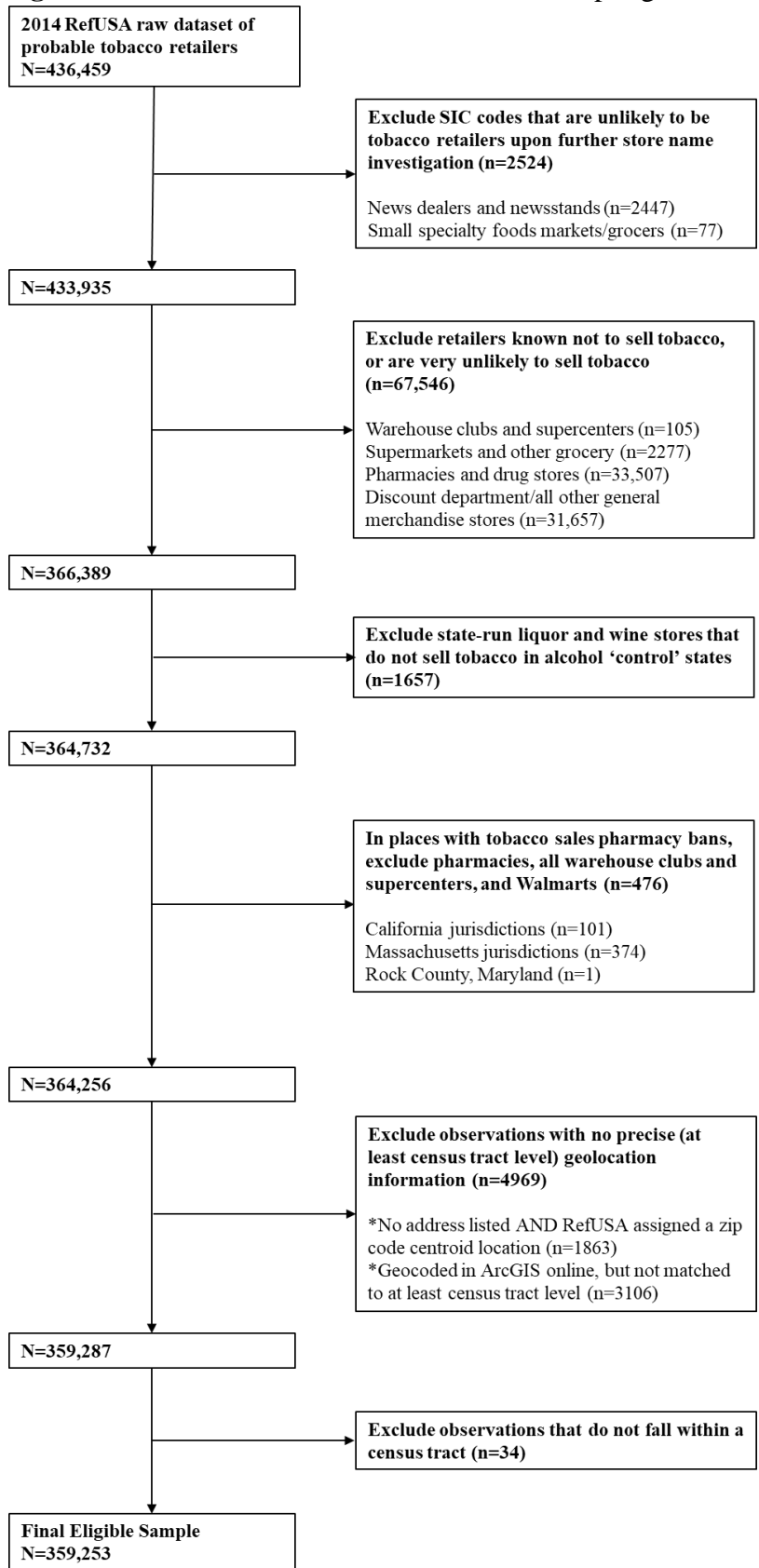
There is no national licensing system of stores that sell tobacco products for in-person consumer purchase (i.e. tobacco retailers), and the American Lung Association estimates that only 38 states and D.C. require a tobacco retailer to have a license to sell cigarettes; furthermore, some states may only update licensing lists periodically.¹⁶⁴ In the absence of national lists, researchers often focus on those types of stores that usually carry tobacco products, and create measures of density based on these likely tobacco retailers. The Census Bureau classifies business establishments using the North American Industry Classification System (NAICS), which assigns both a NAICS code and retailer description to all business establishments in the United States (U.S.).¹¹⁸ Table B.1 lists the 11 NAICS codes most likely to be tobacco retailers based on the store type’s percent of stores that sold tobacco (determined by using the 2012 U.S. Economic Census and tobacco product code 20150: cigars, cigarettes, tobacco, & smokers’ accessories, excluding sales from vending machines operated by others) and the store type’s percent of retail tobacco sales.

Table B.1. NAICS Codes of Probable Tobacco Retailers

NAICS	Description	% tobacco retailers	% of retail tobacco sales
447110	Gasoline Stations with Convenience Stores	92.1	49.1
452910	Warehouse Clubs and Supercenters	88.1	13.9
453991	Tobacco Stores	100.0	10.5
445110	Supermarkets and Other Grocery Stores	64.9	7.3
446110	Pharmacies and Drug Stores	53.4	7.1
445120	Convenience Stores	86.4	5.6
447190	Other Gasoline Stations	27.9	2.4
445310	Beer, Wine, and Liquor Stores	49.2	2.4
452990	All Other General Merchandise Stores	34.2	0.4
452112	Discount Department Stores	26.3	0.3
451212	News dealers & Newsstands	38.0	0.0

ReferenceUSA (RefUSA)¹¹⁹ is a national database of business establishments, provided at no cost through University of North Carolina libraries. RefUSA lists Standard Industrial Classification (SIC) codes and a business establishment's geographic indicators (e.g., address, city, latitude, and longitude). RefUSA provided a NAICS to SIC crosswalk, and by using the NAICS codes listed in Table B.1 and the list of 2014 RefUSA business establishments, we created an initial list of 436,459 probable tobacco retailers. Figure B.1 indicates the overall sampling methodology used to yield our final sample of 359,253 probable tobacco retailers across the U.S. in 2014.

Figure B.1. 2014 RefUSA Tobacco Retailer Sampling Methodology (N=359,253)



REFUSA DECISION RULES

To yield our final sample of probable tobacco retailers, we employed several rules to the RefUSA dataset. First, we omitted all SIC codes that fell under News Dealers and Newsstands, as inspection of the most frequent store names (e.g., Hudson News) did not indicate known tobacco retailers. We additionally excluded specialty grocers and food stores, as we thought these were unlikely to consistently sell tobacco products (Table B.2).

Table B.2. Additional SIC Codes to be Omitted from Eligible Sample

NAICS Code	SIC Codes	Count	Decision
445112 News Dealers and Newsstands	599402 MAGAZINES-DEALERS	2447	Exclude from eligible sample. These 3 SIC codes make up the entire NAICS code 445112, and thus, the entire NAICS code will be omitted from the sample.
	599401 NEWS DEALERS		
	599403 NEWSRACKS		
445110 Supermarkets and Other Grocery	541106 MARKETS-KOSHER	7	Exclude from eligible sample.
	541107 GROCERS-ETHNIC FOODS	68	Exclude from eligible sample.
	541109 GROCERS-TAKE-OUT FOODS	2	Exclude from eligible sample.

After omitting those SIC codes described in Table 2, we had a sample of **433,935 retailers**. We then examined SIC codes and store names within each store type category in order to determine inclusion or exclusion criteria based on known or likely retailers that sell tobacco products. The final store type categories (7 total) and their specific inclusion and exclusion criteria are described in Table B.3, below.

Table B.3. Final RefUSA Store Type Categories and Inclusion and Exclusion Criteria

Store Type	NAICS Code	Inclusion and Exclusion Criteria
1. Convenience and/or Gasoline Stores	445120, 447190	Included SIC Code: 541103 CONVENIENCE STORES Included SIC codes from NAICS 447190: 554104 GAS-LEADED/LEAD-FREE

Store Type	NAICS Code	Inclusion and Exclusion Criteria
		<p>554101 SERVICE STATIONS-GASOLINE & OIL 554103 TRUCK STOPS & PLAZAS 554111 DIESEL EXHAUST FLUID</p> <p>Excluded SIC codes from NAICS 447190: 554105 KEROSENE 554107 OILS-LUBRICATING-RETAIL 554106 MARINE SERVICE STATIONS 554110 ALTERNATIVE FUELS 554112 ELECTRIC CHARGING STATION</p> <p><i>Note:</i> Gasoline Stations with Convenience Stores is not a NAICS code readily available in RefUSA (and could not be reliably created with the use of multiple SIC codes upon investigation of store names). For this reason, Other Gasoline Stations and Convenience Stores were combined into a single category, Convenience and/or Gasoline stores.</p>
2. Warehouse Clubs and Supercenters	452910	<p>Included SIC code: 531110 WHOLESALE CLUBS</p> <p>All store names with at least 50 observations under this SIC code (i.e. Sam's Clubs, Costco, BJs Wholesale) are known tobacco retailers, except for DirectBuy (furniture warehouse store). Therefore, we only excluded DirectBuy (n=105).</p>
3. Tobacco Stores	453991	<p>Included SIC codes: 599303 CIGAR & CIGARETTE LIGHTER FLUIDS 599301 CIGAR CIGARETTE & TOBACCO DEALERS-RETAIL 599302 SMOKE SHOPS & SUPPLIES 599304 CIGAR & CIGARETTE LIGHTERS-RETAIL 599305 CIGARETTE OUTLET 599306 ELECTRONIC CIGARETTES</p>
4. Supermarkets and Other Grocery Stores	445110	<p>Included SIC codes: 541101 FOOD MARKETS 541104 FOOD PRODUCTS-RETAIL 541105 GROCERS-RETAIL</p> <p>Excluded SIC codes: 541102 SNACK PRODUCTS 541108 GROCERS-HEALTH FOODS</p>

Store Type	NAICS Code	Inclusion and Exclusion Criteria
		<p>541110 GROCERY PICKUP-CURBSIDE</p> <p>Also, excluded the following retailer companies known not to sell tobacco products: Aldi’s, Trader Joes, Whole Foods, Wegmans, Schwans Home Service (n=2277). Any observations that included these retailer company names in the store name variable were <i>excluded</i> from the eligible sample in an effort to be more conservative (i.e. less likely to have false positives). For example, “MOUNTAIN EARTH WHOLE FOODS” and “COOK COUNTY WHOLE FOODS CO-OP” were excluded from the eligible sample and assumed to be related to Whole Foods.</p>
5. Pharmacies and Drug Stores	446110	<p>Included SIC code: 591205 PHARMACIES</p> <p><i>Within</i> SIC code 591205 PHARMACIES, <i>only included</i> those store names with at least 100 observations, as smaller, independent pharmacies may be less likely to sell tobacco products. However, excluded Target pharmacies, as these are known not to sell tobacco products. Note that while CVS stopped selling tobacco products September 3, 2014, we include CVS in the retailer sample as Aims 1, 2, and 4 use data for the entirety of 2014. While Aim 3 uses data from July 2014-May 2015, participants in the sample may have still been exposed to CVS as a tobacco retailer (e.g., those reporting quit attempts in the past 12 months in May 2015 may have tried quitting when CVS still sold tobacco products).</p> <p><i>Note:</i> Only observations that had store names that had exact derivatives of these company names were <i>included</i> in the eligible sample in an effort to be more conservative (i.e. less likely to have false positives). For example, “RITE VALUE PHARMACY” and “RITE WAY DRUGS” were excluded from the sample because they did not have “Rite Aid” in their store names.</p> <p>Excluded SIC codes: 591209 ALLERGY RESISTANT PRODUCTS 591210 CONVALESCENT SUPPLIES 591211 DRUGS-CRUDE</p>

Store Type	NAICS Code	Inclusion and Exclusion Criteria
		<p>591204 ELASTIC STOCKINGS 591203 FIRST AID SUPPLIES 591202 HEALTH CARE PRODUCTS 591201 MEDICINES-PATENT & PROPRIETARY 591207 PHARMACEUTICAL CONSULTANTS 591208 RAZOR SHARPENERS & STROPPER 591206 TOILET ARTICLES 591212 HOMEOPATHIC REMEDIES 591213 SUN TAN SUPPLIES 591214 COMPOUNDING 512227 MARIJUANA DISPENSARY</p> <p>REMOVED pharmacies, all Warehouse Clubs and Supercenters, and all Walmarts (as almost all Walmarts have pharmacies) in locations with pharmacy tobacco sales bans, specified below: California: San Francisco (city), Richmond (city), Santa Clara County (unincorporated areas) Massachusetts: Abington, Acton, Amherst, Arlington, Ashland, Athol, Barnstable, Barre, Bedford, Berkley, Billerica, Boston, Brewster, Brookline. Buckland, Chatham, Chelsea, Concord, North Dartmouth, South Dartmouth, Dedham, Deerfield, Dracut. Easton, Edgartown, Everett, Fairhaven, Fall River, Falmouth, Fitchburg, Gardner, Gill, Gloucester, Grafton, Greenfield, Harwich, Hatfield, Haverhill, Lee, Lenox, Leominster, Lowell, Lynn, Malden, Melrose, Middleboro, Middleton, Montague, Needham, New Bedford, Newton, North Attleboro, Oxford, Pittsfield, Reading, Revere, Rochester, Rockport, Salem, Saugus, Shelburne Falls, Somerville, Southborough, Springfield, Stockbridge, Sudbury, Sunderland, Townsend, Uxbridge, Wakefield, Wareham, Watertown, Wellesley, West Boylston, West Springfield, Westford, Westport, Westwood, Whately, Winchester, Worcester, Yarmouth Port Minnesota: Rock County</p>
6. Beer, Wine, and Liquor stores	445310	<p>Included SIC codes: 592104 BEER & ALE-RETAIL 592102 LIQUORS-RETAIL</p>

Store Type	NAICS Code	Inclusion and Exclusion Criteria
		<p>592103 WINES-RETAIL</p> <p>Excluded SIC codes: 592101 COCKTAIL MIXES 592105 CORDIALS 592106 DAIQUIRI SHOPS 592107 TASTING ROOMS</p> <p>Excluded state-run* liquor and wine stores that do not sell tobacco in control states (total excluded 1657). Search terms were determined by consulting National Alcohol Beverage Control Association (NABCA) factsheets, consulting with respective government officials, and examining store names.</p> <ol style="list-style-type: none"> 1. Alabama (161) 2. Idaho (65) 3. New Hampshire (78) 4. North Carolina (334) 5. Pennsylvania (678) 6. Utah (78) 7. Virginia (263) <p>*While there are some local jurisdictions in Maryland, Minnesota, Alaska, and South Dakota that operate a ‘control’ model, there is no comprehensive list of these localities, or comprehensive records onto whether or not they have retailers that permit the sales of tobacco products. Therefore, only state-level alcohol control rules (described above) will be applied to the eligible sample.</p>
7. Discount Department and All Other General Merchandise Stores	452112, 452990	<p>Included SIC code from NAICS 452112: 531102 DEPARTMENT STORES</p> <p>Excluded SIC codes from NAICS 452112: 531112 GOVERNMENT-DEPARTMENT STORES 531104 RETAIL SHOPS 531109 MERCHANDISE MARTS 531101 RESIDENT BUYERS 531108 HOME & PERSONAL CARE PRODUCTS 531111 CLOTHING-WATERPROOF</p> <p>Included SIC code from NAICS 452990: 533101 VARIETY STORES</p> <p>Excluded SIC codes from NAICS 452990:</p>

Store Type	NAICS Code	Inclusion and Exclusion Criteria
		<p>539903 BEAD STRINGS 539906 CAR SEATS-CHILDREN 533104 CLOTHES POSTS 539902 COUNTRY STORES 539905 FARMERS CO-OP RETAIL STORES 539901 GENERAL MERCHANDISE-RETAIL 533105 HULA SUPPLIES-RETAIL 533103 SOAP MITTS 539907 SPONGES-RETAIL 539904 TOTE BOXES PANS & TRAYS 533102 TRADING POSTS</p> <p>Within SIC 531102 and SIC 533101, only included retailer companies: 99 Cents Only, Alco, Dolgencorp/Dollar General, Family Dollar, Fred’s Super Dollar, Kmart, Shopko, Walmart. (Note: while Dollar Tree acquired Family Dollar in 2014, Dollar Tree does not sell tobacco products).</p> <p><i>Note:</i> Only observations that had store names that included exact derivatives of these company names were <i>included</i> in the eligible sample in an effort to be more conservative (i.e. less likely to have false positives). For example, “99 CENT & MORE OUTLET STORE” and “VICKY’S 99 CENTS & UP” were excluded from the sample because they did not have “99 Cents Only” in their store names.</p>

IDENTIFYING MULTIPLE RETAILERS AT A SINGLE LOCATION

After cleaning the 2014 RefUSA following the above described guidelines, the RefUSA dataset included a total of **364,256 observations**. We then examined the presence of duplicate geo retailers (i.e. multiple retailers located at the same geolocation) using the RefUSA-provided latitude/longitude fields. The RefUSA dataset also includes a variable, MATCH_LEVEL_2010, which indicated the geographic scale that the retailer latitude/longitude was matched to (from most precise to least precise: 0 = site or business level; B = building parcel; ZIP+4 = block/tract

level using zip-code +4 and street data; ZIP+2 = block/tract level using zip-code +2 and street data; Z = centroid of zip code).

Table B.4. Frequency of RefUSA Latitude/Longitude Location Matches

MATCH_LEVEL_2010	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	307,345	84.38	307345	84.38
2 = Zip+2	6326	1.74	313671	86.11
4 = Zip+4	27090	7.44	340761	93.55
B = building parcel	1	0.00	340762	93.55
Z = zip-centroid	23494	6.45	364256	100.00

Visual inspection of duplicate geo retailers with site-level geolocation match (MATCH_LEVEL_2010=0) seem to indicate that observations could likely be independent retailers. For example, there was a maximum of 7 retailers at a single geolocation, and it seems feasible based on store names (CONAME) and NAICS codes (NAICS_Created) that these are truly 7 different tobacco retailers (shown below). Therefore, we included all duplicate geo retailers where MATCH_LEVEL_2010=0.

COUNT	ABI	CONAME	MATCH_LEVEL_20	NAICS_created
7	103789012	ASIAN MARKET		0 Supermarkets and Other Grocery
7	416122350	CROPDUSTER901		0 Tobacco Stores
7	433915509	DOLLAR GENERAL		0 Discount Department and All Other General Merchandise Stores
7	435611636	SAM'S MARKET		0 Supermarkets and Other Grocery
7	493146690	FIJIAN MARKET & NINETY-NINE		0 Supermarkets and Other Grocery
7	806332425	HENRY'S LIQUOR		0 Beer, Wine, and Liquor Stores
7	907154736	CARVER'S DISCOUNT & CIGARETTES		0 Tobacco Stores

Visual inspection of duplicate geo retailers with zip-street geolocation match (=ZIP+4) also seem to indicate that observations could likely be independent retailers, though pharmacies included within grocery stores may be counted as two separate retailers. Furthermore, inspection of addresses of some duplicate geo retailers seem to indicate that observations may be located on

the same street but at different locations (e.g., CAPITOL ST # 3 vs. 1160 CAPITOL ST).

Therefore, we included all duplicate retailers where MATCH_LEVEL_2010 = ZIP+4.

COUNT	ABI	CONAME	MATCH_LEVEL_20	NAICS_created
9	357508100	EL TIGRE FOOD STORE II		2 Convenience and/or Gasoline Stores
9	677111684	MAW & PAW'S CARRY OUT		2 Convenience and/or Gasoline Stores
9	207515586	SMOKER FRIENDLY		2 Tobacco Stores
9	403210597	WALMART PHARMACY		2 Pharmacies and Drug Stores
9	434749029	KMART PHARMACY		2 Pharmacies and Drug Stores
9	443530951	WALMART SUPERCENTER		2 Discount Department and All Other General Merchandise Stores
9	453611295	KMART		2 Discount Department and All Other General Merchandise Stores
9	718234594	PARMAR 34		2 Convenience and/or Gasoline Stores
9	971907480	MOUNTAINEER MART		2 Supermarkets and Other Grocery
9	971907761	RICH OIL		2 Convenience and/or Gasoline Stores
9	992204537	DOLLAR GENERAL		2 Discount Department and All Other General Merchandise Stores
9	2943074	BUCHE'S		2 Supermarkets and Other Grocery

Visual inspection of duplicate geo retailers with zip-street geolocation match (=ZIP+2) also seem to indicate that observations could likely be independent retailers, though pharmacies included within grocery stores may be counted as two separate retailers. Furthermore, inspection of addresses of some duplicate geo retailers seem to indicate that observations may be located on the same street but at different locations (e.g., 779 BEVERLY PIKE vs. 702 BEVERLY PIKE). Therefore, we included all duplicate retailers where MATCH_LEVEL_2010 = ZIP+2. However, as Zip+2 have less precision in point accuracy than site and Zip+4, we additionally used ESRI ArcGIS to geocode and assign these addresses a more precise latitude/longitude.

COUNT	ABI	CONAME	MATCH_LEVEL_20	NAICS_created
6	137861290	KROGER PHARMACY		4 Pharmacies and Drug Stores
6	230191439	CVS/PHARMACY		4 Pharmacies and Drug Stores
6	401618219	KROGER		4 Supermarkets and Other Grocery
6	402595447	MI TIERRA MEXICAN STORE		4 Supermarkets and Other Grocery
6	543601892	MARATHON FOOD CTR		4 Convenience and/or Gasoline Stores
6	938072634	DOLLAR GENERAL		4 Discount Department and All Other General Merchandise Stores

Visual inspection of duplicate geo retailers with zip code centroid geolocation match (=Z) seem to indicate that these could likely be independent retailers. Inspection also show that many of the addresses listed are different for duplicate geo retailers. Thus, we additionally used ESRI ArcGIS to geocode and assign these addresses a more precise latitude/longitude to keep in the

sample. However, there were 1863 observations that had no address and were assigned a zip code centroid and thus could not be assigned a tract-level point location – these were excluded from the eligible sample.

Geocoding Duplicate Geo Retailers with ZIP+2 or ZIP Centroid Matches

In total, there were 27,957 retailers with address data that RefUSA assigned a geolocation match level of ZIP+2 or ZIP centroid. Using the ArcGIS Online World Geocoding Service tool, all of these observations were re-matched to a latitude/longitude. However, 3106 observations were not matched to a precise enough geographic scale that a census tract could be assigned. Brief visual inspection indicated that many of these observations had addresses with PO boxes, or simply had company names/cities listed. These 3106 observations were excluded from the eligible sample.

Reinvestigating Duplicate Retailers

After removing the 4969 observations that could not be assigned a precise (i.e. at least census tract geolocation) and re-assigning latitude/longitude to those observations described above, the RefUSA sample included **359,287** probable tobacco retailers. We reinvestigated duplicate geo retailers. The largest number of retailers at a single address was seven, and all observations seemed like they could be plausible independent retailers, but possibly located in a strip mall. Visual inspection of other duplicate geo retailers indicated similar patterns; therefore, no additional retailers were excluded from the sample.

CONAME	ADDR	CITY	STATE
ASIAN MARKET	1100 CARVER RD # E	MODESTO	CA
CROPDUSTER901	1100 CARVER RD # T	MODESTO	CA
DOLLAR GENERAL	1100 CARVER RD	MODESTO	CA
SAM'S MARKET	1100 CARVER RD # A-1	MODESTO	CA
FIJIAN MARKET & NINETY-NINE	1100 CARVER RD # 2	MODESTO	CA
HENRY'S LIQUOR	1100 CARVER RD # A	MODESTO	CA
CARVER'S DISCOUNT & CIGARETTES	1100 CARVER RD # G	MODESTO	CA
BIG 8 FOOD STORES	1840 N LEE TREVINO DR	EL PASO	TX
FAMILY DOLLAR STORE	1840 N LEE TREVINO DR # 501	EL PASO	TX
BARRELL HOUSE 14	1840 N LEE TREVINO DR	EL PASO	TX
LOWE'S BIG 8	1840 N LEE TREVINO DR	EL PASO	TX
KERN PLACE CIGARS	1840 N LEE TREVINO DR # 110	EL PASO	TX
WESTERN BEVERAGES	1840 N LEE TREVINO DR # 200	EL PASO	TX
XCLUSIVE VAPOR	1620 N SCHOOL ST # G1B	HONOLULU	HI
TIMES SUPER MARKET	1620 N SCHOOL ST # 106	HONOLULU	HI

EXCLUDING RETAILERS OUTSIDE OF U.S. GEOGRAPHIC BOUNDARIES

Finally, using ArcMap 10.5 and U.S. Census Bureau County Tiger/Line Shapefiles¹⁷⁶, we spatially mapped the geolocation of each retailer to confirm that all retailers were located within a U.S census tract. There were 34 observations that did not fall within census tract boundaries (further investigation indicated that many were located in bodies of water). We excluded these 34 observations from the sample, resulting in a final eligible analytic sample of **359,253 probable tobacco retailers across the U.S. in 2014.**

**APPENDIX C: CHRONIC OBSTRUCTIVE PULMONARY (COPD) RELATED
CLINICAL CLASSIFICATION SOFTWARE (CCS) CODES, UNITED STATES, 2014**

ICD-9 Code	Description
490	Bronchitis, not specified as acute or chronic
491.0	Simple chronic bronchitis
491.1	Mucopurulent chronic bronchitis
491.2	Obstructive chronic bronchitis
491.20	Obstructive chronic bronchitis without exacerbation
491.21	Obstructive chronic bronchitis with (acute) exacerbation
491.22	Obstructive chronic bronchitis with acute bronchitis
491.8	Other chronic bronchitis
491.9	Unspecified chronic bronchitis
492.0	Emphysematous bleb
492.8	Other emphysema
494	Bronchiectasis
494.0	Bronchiectasis without acute exacerbation
494.1	Bronchiectasis with acute exacerbation
496	Chronic airway obstruction, not elsewhere classified

APPENDIX D: 2013 RURAL-URBAN CONTINUUM CODES (RUCC)

The United States Department of Agriculture’s most recent 2013 Rural-Urban Continuum Codes (RUCC) contain nine parent codes, which can be combined to designate counties as metropolitan or non-metropolitan.¹⁶⁸ To create the 2013 RUCC, all counties were designated as metro or non-metro, based on 2010 Census population size. Each county’s adjacency to metro areas was also taken into account. Some researchers have indicated that a simple dichotomy of metropolitan vs. non-metropolitan may not fully capture variation in urbanization,¹⁷⁷ and instead recommend a three-part category, such as metropolitan, urbanized non-metropolitan, and rural.¹⁷⁸ The table below lists the nine RUCC code descriptions and their three-part categorization used in analyses.

Description	Three-Part Categorization
Counties in metro areas of 1 million population or more	Metropolitan
Counties in metro areas of 250,000 to 1 million population	Metropolitan
Counties in metro areas of fewer than 250,000 population	Metropolitan
Urban population of 20,000 or more adjacent to a metro area	Urbanized non-metropolitan
Urban population of 20,000 or more not adjacent to a metro area	Urbanized non-metropolitan
Urban population of 2,500 to 19,999 adjacent to a metro area	Urbanized non-metropolitan
Urban population of 2,500 to 19,999 not adjacent to a metro area	Rural
Completely rural or less than 2,500 urban population adjacent to a metro area	Rural
Completely rural or less than 2,500 urban population not adjacent to a metro area	Rural

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