An Analysis of Racial Disparity in the Distribution of Alcohol Licenses and Retailers in Orange County, California

by

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To my wife Linda and mother-in-law Joyce.
With your support everything is possible.

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Fight On!

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ABC	California Department of Alcoholic Beverage Control
ACS	American Community Survey
API	Application Programming Interface
GIS	Geographic Information System
GISci	Geographic Information Science
HTTP	Hypertext Transfer Protocol
LG18	LandScan Global 2018
MAUP	Modifiable Area Unit Problem
OC	Orange County, California
SSI	Spatial Sciences Institute
U.S.	United States
USC	University of Southern California
USEPA	United States Environmental Protection Agency
WGS	World Geodetic System

Abstract

Systemic racism, institutional racism, structural racism: these are the terms used to describe unequal minority participation in job markets, over representation in the criminal justice system, and lack of access to and enjoyment of clean and safe neighborhoods. Studies in social justice and environmental justice are now starting to quantify structural racism by utilizing Geographic Information Systems and applying analytic methods of Geographic Information Science. One area ripe for study of structural racism is whether race-neutral laws and regulations promote race-neutral distributions in the built environment or perpetuate existing structural racism.

The distribution of alcohol retailers in Orange County, California, provided an opportunity to explore how a race neutral regulation—in operation for over two decades—has impacted the built environment. Exploring the distribution of alcohol retailers informs our understanding of structural racism because a higher density of retailers has been correlated with negative impacts on neighborhoods such as increased crime, negative health outcomes, and poverty. Moreover, California's alcohol licensing regulations are race-neutral and as such do not consider race as a factor in determining the approval or rejection of a license application.

This study analyzed the February 18, 2020 inventory of active off-site retail sales alcohol licenses in Orange County and compared the distribution of licenses with race/ethnicity across the county. The comparison was repeated at two spatial scales: census tract and a scaled population grid based on the Oak Ridge National Laboratory's LandScan 2018 dataset with 30 arc-second cells (~ 0.5 miles). This study found that Hispanic populations were consistently overrepresented in census tracts and cells where alcohol licenses were found. This result suggested that requiring laws and regulations to avoid recognition of race is insufficient to ensure race-neutral distributions of benefits and detriments in the built environment.

Chapter 1 Introduction

Few would argue that buying a six-pack of beer, a bottle of wine, or fifth of whiskey at the corner market is a racist act. Take California for example; first, the buyer is required to meet race-neutral age identification requirements and have legal tender. Second, in order to sell alcohol a retailer must apply for and be granted a license based on race neutral criteria codified in state law as Business and Professions Code § 23958 (AB 1994, BPC 2019). Notwithstanding the race neutral context of buying/selling alcohol, could the density of alcohol retailers in the built environment, which has already been found to have a negative impact on neighborhoods, provide evidence of structural racism?

As Palma Strand explains in *The Invisible Hands of Structural Racism in Housing: Our Hands, Our Responsibility*, structural racism arises when minority neighborhoods continue experiencing unequal burdens compared to white neighborhoods (Strand 2019). So, to explore structural racism in the built environment requires comparing the distribution of burdens found in predominantly minority communities to nearby majority white communities. Moreover, we can use the density of alcohol retailers as a proxy for burden because we know from studies such as *Alcohol Retail Density and Demographic Predictors of Health Disparities: A Geographic Analysis*, that a higher density of alcohol retailers in a community is a likely risk factor for increased crime, negative health outcomes, and poverty (e.g. Berke et al. 2010; Halonen et al. 2013; Young, Macdonald, and Ellaway 2013; Dwivedi et al. 2019). In other words, if the distribution of alcohol retailers in California is similar across the white and minority communities, then we can have confidence that the application of race neutral licensing requirements has facilitated a race neutral distribution of the burdens associated with higher density of alcohol retailers; otherwise, an unequal distribution suggests that structural racism has played a part in the unequal distribution of those burdens. This approach is similar to that used in studies like *Food Swamps Predict Obesity Rates Better Than Food Deserts in the United States* which explored the prevalence of obesity as a function of how the local built environment introduces significant biases for individuals (and households) as to the potential choices for diet and physical activity (Cooksey-Stowers et al. 2017; Liu et al. 2015; Hurvitz et al. 2009).

To be clear, structural racism does not require overt acts of racial animus or racial intent to discriminate. It can be the result of many presumably race-neutral actions that when added together over time perpetuate historical racial segregation, discrimination, and injustice as reflected in the built environment. It can arise as emergent phenomena in novel ways, for example a race-neutral data mining algorithm intended to identify patients in greatest need of medical intervention instead reinforced minority unequal access to health care. It can be the continuation of historical racial profiling, such as when historically redlined, predominantly minority neighborhoods do not enjoy the same economic advantages as nearby white neighborhoods. It can occur when a neighborhood council implements a crime-free, race-neutral ordinance prohibiting landlords from renting to tenants who have had contact with the criminal justice system, which in operation prevents minorities from accessing housing in that neighborhood.

While some form of structural racism has existed for as long as segregated, disadvantaged communities have developed in societies, the study of structural racism has only become a topic of direct research in the last several decades (Groos et al. 2018). Much of the initial structural racism research was in the form of social justice studies conducted by social scientists looking at societal level effects, such as incarceration rates or negative health outcomes of minorities. However, there is now an increasing trend of research in the growing field of environmental justice, among other disciplines, to utilize Geographic Information Systems (GIS) to develop and apply techniques and methods of Geographic Information Science (GISci) to identify and quantify structural racism as part of the physical built environment in our communities (Groos et al. 2018; Kim and Chun 2019).

One alarming theme that appears consistently across nearly all the social and environmental justice studies is that minority communities continue to experience a disproportionate share of negative social and economic outcomes, including poorer quality of life, higher crime rates, higher concentration of toxic dumps, fewer banks, and fewer green spaces. This leads to the question: How and why does the phenomenon of structural racism continue when the United States has had robust anti-discrimination laws in place at every level of government for at least the last sixty years? To begin to answer the question requires a deeper discussion of the terms and concepts commonly used in identifying and describing structural racism as well as understanding how the historical echoes of racism have contributed to the rise and continuation of structural racism in American society (Pulido, Sidawi, and Vos 1996). This background also provides context as to why exploring the distribution of alcohol retailers for evidence of structural racism is important.

1.1 Essential Concepts: Structural Racism and Disparate Distribution

To begin to understand the importance of identifying and remedying structural racism in our society requires establishment of a working definition and discussion of the term itself and two additional related terms: racially neutral and disparate impact. First, the term “structural racism” is typically defined as unconscious and implicit biases—as opposed to intentionally discriminatory choices—within institutions, agencies, businesses, and society that continue the status quo of socio-economic disadvantages experienced by racial, ethnic, or other minorities

(Strand 2019; Baroca and Selbst 2016). Structural racism is also generally synonymous and interchangeable with the terms "institutional racism" and "systemic racism." While some individuals in a society, community, or institution may have a covert—or even overt—racist agenda, that does not automatically give rise to structural, systemic, or institutional racism. Although, if a racist agenda is left unaddressed, it can eventually manifest in various forms as structural racism.

Next, the term "racially neutral" refers to the language of a law, policy, regulation, or practice that is: 1) absent of all mention of race, or 2) has an included racial component which on its face operates in a race-neutral fashion (e.g., tracking race for census purposes). In practice, however, to be effectively race-neutral requires more than the mere absence of words denoting race. This distinction is critical because racially neutral language when put into operation through policies, practices, or algorithms can still produce unintended/unexpected detriments that are born disproportionately by racial, ethnic, or other minorities (Archer 2019; Obermeyer et al. 2019; Kau, Fang, and Munneke 2018).

Another term for this result is "disparate impact." A detrimental outcome resulting from a race-neutral law, policy, or practice reflected as a racial or ethnic minority receiving unequal treatment or an unintended detriment when compared to a non-minority (Fisher, Kelly, and Romm 2006; Rolok 2011). For example, in *An Unintended Consequence of Mortgage Financing Regulation—A Racial Disparity*, the authors showed empirically that race-neutral mortgage fair-lending laws—prohibiting lenders from considering race and ethnicity—had the unintended consequence of non-white borrowers paying more than whites over the life of their mortgages (Kau, Fang, and Munneke 2018). The cause appeared to be related to different prepayment habits exhibited between white and non-white borrowers not being taken into account when mortgage contract prices were calculated. Prepayments operate as a risk to lenders because they reduce the total value that a lender expects to receive when offering a loan. Thus, a lower likelihood of prepayment is associated with a less risky loan and should result in a lower interest rate for the borrower. This has led to an unintended consequence: the fact that non-whites generally do not pay their mortgages off early as often as whites cannot be factored into determining loan risk when calculating the loan contract price, which allows the accelerated pay off tendencies of whites to inflate the mortgage contract prices for all borrowers. As a result, the operation of the racially neutral law has precipitated a racially skewed detrimental economic outcome for minorities.

A second, but distinct, related term is “disparate impact.” As Nancy Rolok makes clear in *New Methodology: Measuring Racial or Ethnic Disparities in Child Welfare*—a study of the unequal representation of minority children in the Illinois welfare population—the term “disparate” is not the same as “disproportionate.” Specifically, the two terms represent different evaluative concepts. Disparity requires an evaluation of equality and tends to be subjective; the evaluator will likely consider multiple abstract factors such as decision points, access to services, and absence of negative outcomes. Disproportionality frequently refers to objective evaluations, often in the form of comparisons between percentages (Rolok 2011).

Here it should be noted that disparate impact as defined in this thesis is broader than the current legal assessment of disparate impact as framed by the U.S. Supreme Court. In *Texas Department of Housing and Community Affairs*, a case holding that plaintiffs may bring disparate impact claims related to government allocation of tax credits in low income housing, the Supreme Court specified that a disparate-impact is more than just a statistical disparity, there must be a correlation between the racial imbalance and the policy or policies causing that disparity (Texas Dept of Housing 2015). However, this legal definition whitewashes the fact that there is almost always some pre-existing disparity in the environment affecting a minority population such that it will be impossible to find a simple correlation between a policy and a particular disparity. Although it is laudatory that the Supreme Court recognized the existence of racial disparity, it is this type of simplistic, color-blind approach to disparate impact that allows structural racism and segregation to occur, acquire legal approval, and continue.

Finally, this study introduces the term “disparate distribution,” which adds spatial and temporal dimensions to the concept of disparate impact. Disparate distributions arise when communities with predominantly non-white populations experience decreased access to positive environmental conditions (banks, grocery stores, parks etc.) or increased exposure to detrimental environmental conditions (dumps, toxic industry, pollution, etc.) as compared to areas with predominantly white populations. Thus, for this thesis, the concept of disparate distribution focuses on whether a facially neutral policy (regulation, algorithm, etc.) contributes to burdens (or decreases positive environmental factors) on a predominantly non-white population, which is experiencing disparate neighborhood impacts. In practice, to identify a disparate distribution requires analysis of the impacted communities since laws, regulations, and policies are not operating in a vacuum but rather in a complex web of dynamic, inter-dependent spatial, temporal, political, and social factors.

An informative example of this approach can be found in *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations* where the study authors were attempting to discern why a race neutral algorithm was under-selecting blacks for inclusion in a high-risk patient intervention program (Obermeyer et al. 2019). They found that black patients, even though they presented with the same or greater health risks than whites, generated less health care costs which were assumed to be a primary predictor of patients most likely to benefit from intervention. Thus, black patients—the ones who were actually most likely to benefit from intervention—were under-selected by a race-neutral algorithm because they do not seek health care as often as similarly situated white patients.

1.2 Structural Racism Persists After Racist Policies and Practices Have Ended

While neighborhood redlining—the practice of highlighting minority neighborhoods in order to exclude those residents from favorable mortgage opportunities—began in the 1930s and was banned by the late 1960s, the practice literally set in concrete (and asphalt) certain aspects of today's built environment that are at least partially responsible for poor and minority communities experiencing exposure to higher land surface temperatures than surrounding neighborhoods (Hoffman, Shandas, and Pendleton 2020; Strand 2019). For example, a recent study compared the historically redlined neighborhoods with their surrounding non-redlined neighborhoods and found that nearly 94% of the redlined areas experienced greater land surface temperatures relative to the non-redlined areas (Hoffman, Shandas, and Pendleton 2020). Basically, the study posits that the act of excluding residents of poor and minority neighborhoods from access to the same mortgages offered to whites led to the lack of meaningful real estate investment in those communities and subsequent depressed land values. Over time, those depressed land values became favorable opportunities for impermeable surface land use projects such as commercial tracts, industrial facilities, and freeways. Unfortunately for the residents in those redline-impacted communities, impermeable surfaces are more effective at absorbing heat and solar energy and later radiating heat back into the environment when the land surface temperature should otherwise be cooling.

In a broader sense, it has been forcefully argued that today's racial disparities continue to exist because "the present is strongly tied to the past" (Johnson and Hoopes 2019, 5). To disclaim the existence of institutional or structural racism by disconnecting historical events from today's social and political patterns is a "historical fallacy."

Thus, while redlining did not create the heat pockets lingering over poor communities, it may have laid the groundwork for a course of events leading to the disparate impact experienced by poor communities of greater heat exposure than nearby affluent neighborhoods (Hoffman, Shandas, and Pendleton 2020). Moreover, without concerted and focused commitment to remedy these inequities, the resulting built environment often continues to reinforce the lower land values—and attendant latent and patent disparities—of the affected neighborhoods (Strand 2019).

1.3 Racially Neutral Policies May Not Address Structural Racism

The Civil Rights Act of 1968 was passed to correct centuries of direct maltreatment of minorities seeking fair housing in America. From that point in time forward, the national mandate compels racial neutrality in housing laws, policies, and practices. As a practical matter, this mandate prohibited race from being taken into account when calculating or distributing housing related benefits, services, detriments, and entitlements. While the basic public policy is sound, the reality of drawing a line at 1968, and requiring race neutrality from that moment forward ignores the very real disparities that minorities were experiencing prior to 1968 because of the centuries of direct and over discrimination (Strand 2019; Johnson and Hoopes 2019).

One simple analogy would be to imagine a track meet where minority runners are held at the starting line at the beginning of the race and the event judge notices they have been held back. But instead of restarting the race or making allowances for the distance already run by the non-held runners, the judge declares all runners are now to be treated the same and allowed to run freely from that moment forward. Thereafter, even though all runners now experience equal treatment, the biased results of that initial race continue as factors in determining objective race results which in turn determines the upcoming track meets runners may attend and lane selection priority of the initial runners and future generations of their teammates. This is so because in competitive track and field, a runner's past wins give them an ongoing advantage in future meets. In other words, the future is defined by the past. But alas, reality is much more complex than the simple track meet analogy.

To illustrate these complexities, consider that many local municipalities and government agencies have begun adopting racially neutral crime-free housing ordinances and programs; these programs are portrayed as a race-neutral approach to address the laudable goal of reducing crime and ensuring safe neighborhoods (Archer 2019). In a jurisdiction under this regime, private landlords are required to screen their tenants and evict those having contact with criminal legal system (regardless of the reason for the contact or how many years have passed since the contact). Now, consider that African Americans experience disproportionately higher rates of arrests and convictions compared to their proportion of the general population (Archer 2019; Johnson and Hoopes 2019; NAACP 2015). According to the NAACP, African Americans make up 33% of those incarcerated for drug offenses whereas they represent only 12.5% of drug users (NAACP 2015). While reducing crime and promoting safety is an important community concern, these ordinances in reality operate to exclude minorities from residing in the implementing jurisdiction and force them into surrounding communities (Archer 2019). This occurs as minorities (especially African Americans) are first removed from the crime-free community through evictions and then new arrivals continue to be excluded from entry. Furthermore, it is highly likely that the segregative effect is magnified because the evictions and resulting exclusion of minorities occur at their higher rate of contact with the criminal system, not their lower proportion of the general population.

Sadly, there is a potentially even darker disparate impact lurking beyond the direct segregative effects of these racially neutral policies. A 2009 study found that in large urban cities, the rate of violent crimes increased relative to the magnitude of segregation (Krivo, Peterson, and Kuhl 2009). It further found that while the minority segregated communities bear the brunt of this increased violence, all neighborhoods across highly segregated cities experience greater violent crime than more integrated cities. Thus, in an ironic twist, a racially neutral ordinance to reduce crime may actually increase crime and perpetuate systemic segregation. "Recognizing these fundamental realities of the interconnections of race, place, and inequality is required for understanding race-ethnic differences in a host of arenas, including in levels of criminal violence" (Krivo, Peterson, and Kuhl 2009: 1766).

These disparate impacts extend far beyond the intersection of policies, crime, and housing (Obermeyer et al. 2019; Groos et al. 2018). For example, a 2018 review of 165 scholarly works studying structural racism, dated between January 1, 2007 through December 31, 2017, in PubMed and Embase databases identified twenty original studies quantifying structural racism related to population health, mortgage discrimination, and political participation in addition to the traditional topics of crime and housing (Groos et al. 2018).

In general, unintentionally racially-biased outcomes may result when applying race-neutral policies or algorithms to diverse populations with latent racial biases (Obermeyer et al. 2019; Barocas and Selbst 2016). Studies of big data and data driven processes provide examples of this occurring while examining potential societal factors at play. For example, search engines results include more ads for arrest records when search terms include black-identifying names compared to terms with white-identifying names (Sweeney 2013). Minorities pay more over the life of a mortgage because mortgage lenders calculate mortgage rates on the assumption that all borrowers present the same prepayment risk, even though white borrowers prepay much more frequently (Obermeyer et al. 2019). Blacks have unequal access to high-risk medical intervention programs because insurance algorithm screening for candidate patients does not account for lower health care costs of black populations even though they have highest health risk factors (Barocas and Selbst 2016).

Looking more closely at race-neutral mortgage fair-lending laws (discussed above in Section 1.1), a study revealed a disparate impact resulting from lenders using race-blind prepayment risk formulas that cannot take into account race-based prepayment patterns (Kau, Fang, and Munneke 2018). Prepayment occurs when a home is sold, refinanced, or outright paid off and is a risk to the lender because it reduces the expected total value of the loan by the amount of the lost interest over the contractual life of the loan. Lenders account for this risk by adjusting various terms of the loan, one of which is to increase the loan interest rate (with a subsequent increase in dollar amount of monthly payments). Because the prepayment risk formula is based on the prepayment patterns of the entire pool of borrowers—whites and non-whites—the subset of borrowers who do not prepay (mostly non-whites) are punished in the form of higher monthly payments over their longer loan payment period.

There is an open question as to why whites prepay more frequently than non-whites, but there are some anecdotal explanations. Generally, borrowers with better credit scores tend to prepay more frequently (whites). Borrowers with higher value properties (whites) or properties that rise in value more quickly (whites) tend to prepay more frequently. Borrowers with higher education (whites) tend to prepay more frequently. On the other hand, borrowers with lower credit scores (non-whites) tend to prepay less frequently, and also default more frequently. Borrowers in less desirable locations (non-whites) tend to prepay less frequently. Borrowers with mortgage provisions that penalize prepayment (non-whites) tend to prepay less frequently. While the knee jerk response is to exclaim that everyone can prepay, that whitewashes the reality that non-whites are generally starting at an economic disadvantage.

Moreover, not accounting for differing black/white population dynamics when applying race neutral processes can literally be life threatening. For example, a study examining a race neutral algorithm used by health insurance companies to direct high-risk patients into intervention programs found that the algorithm under screened high-risk black patients into the programs (Obermeyer et al. 2019). The researchers evaluating the algorithm found that while the implementation used rational variable selections and risk criteria—prior year health costs and biomarkers for health among other non-race variables—the underlying population had latent racial dynamics. Specifically, black patients generated less medical expense per health status. Since the algorithm based future risk on prior costs, and white patients generated higher costs per health status, they had a higher representation at the highest risk scores.

Again, there is an open question as to why black patients generate lower costs per health status, but there are anecdotal explanations. Compared to white patients, black patients have more emergency visits and costs related to dialysis, but require less outpatient specialist costs and fewer inpatient surgical costs. There may be other underlying socio-economic barriers to seeking medical care such as lack of access to transportation, unavailability of child care, and inability to take time off from work (Obermeyer et al. 2019). Finally, evidence suggests that lack of common racial background between doctor and patient may result in patients seeking less care or result in other negative health outcomes (Alsan, Garrick, and Graziani 2019; Obermeyer et al. 2019).

Just as the impact of decades of redlining did not end immediately in 1968 with the passage of the Civil Rights Act, the impact of inherent racial disparities in social, political, and spatial domains do not immediately disappear with the invocation of race neutral language. Ultimately, inclusion and understanding of latent and patent racial disparities is necessary before policies, programs, and algorithms can be tailored to operate in race neutral fashion.

1.4 California Alcohol Retail Sales Licensing Regulations

In the early 1990's, California legislators deliberated on the link between alcohol, poverty, and crime and determined that a statewide approach to alcohol licensing was needed (AB 1994). As a result, in 1994 California passed racially neutral, statewide legislation—Business and Professions Code § 23958—to curtail the issuance of alcohol sales licenses in areas already experiencing high crime or over-concentration of alcohol retailers (AB 1994, BPC 2019). The legislation also assigned the California Department of Alcoholic Beverage Control (ABC) the sole responsibility for evaluating and issuing alcohol sales licenses across the state.

On its face, the California law specifying the terms and conditions for evaluating and issuing alcohol sales licenses is racially neutral. Some of the major factors considered for issuing a license are total county population, local crime, and census tract-level population (BPC 2019). Moreover, the when, what, and where of locations of high crime rates and over-concentration of licenses—as well as what constitutes public convenience and necessity—are constantly evolving determinations. Among the many factors used to make these determinations, the ABC must evaluate crime statistics compiled yearly by local law enforcement, census tract-level population information based upon most recent U.S. decennial (or special) census, and annual county-level population information compiled by the Demographic Research Unit of the California Department of Finance (BPC 2019 § 23958.4). Moreover, a license applicant may petition to establish that the census tract-level population has increased from value initially relied upon by the ABC.

Additionally, the ABC must solicit and consider input from local governing entities (city councils, administrative districts, city managers, etc.). These local entities may support the issuance of licenses to local businesses for "Public Convenience or Necessity" in otherwise proscribed locations (Drummond 2014, BPC 2019). For example, in 2004, the Yorba Linda City Manager made a finding in support of a CVS Pharmacy receiving an alcohol sales license as it "would afford city residents the ability to purchase alcoholic beverages … while shopping for other convenience items" and "reduce the length and number of vehicular trips …, thereby reducing traffic" (Drummond 2014). Moreover, a license applicant can also petition on its own behalf for a public convenience or necessity exemption. However, while the legislative mandate requires that the ABC consider factors "which may affect the public welfare and morals…," there is no mandate to evaluate disparate impacts or disparate distributions (BPC 2019 § 23958).

Finally, the ABC administers 54 unique license categories pertaining to alcohol sales or transactions (see Appendix 1). This thesis focused on two license types—Type 20 Off-Sale Beer & Wine and Type 21 Off Sale General. These are the only licenses that grant establishments permission to transact retail sales of sealed containers of alcohol for off premise consumption, i.e. grocery stores, liquor stores, convenience stores, gas stations, etc. Of the two licenses, type 20 is the more restrictive—authorizing only beer and wine sales—while type 21 permits the sale of all packaged alcohol products. However, at no point in the license application process is race of the licensee or racial composition of the community considered or a factor in granting or rejecting a license, regardless of the type of license sought or the nature of the establishment seeking a license.

1.5 Study Area: Orange County, California

Orange County (OC) was selected because of its size, demographic diversity, and range of socioeconomic conditions. These factors make OC an ideal study area to explore structural racism across a diverse urban landscape. OC is located on the southern coast of California, between Los Angeles and San Diego Counties. The county covers 948 square miles, and with a 2010 Census population count of over 3 million, it ranks as the third-most populous county in California and sixth-most in the nation (OCHS 2020). Figure 1 shows the ACS 2017 population estimates (N=3,155,816) of OC broken down by census tract, using three colors to highlight the predominant race in each tract. According to the 2017 American Community Survey (ACS) Demographic and Housing Estimates, the majority of OC's population was non-Hispanic whites (~41%) followed closely by Hispanics of any race (~34%), and Asians (~20%) (U.S. Census Bureau 2017). In the figure, the "Dominant Population" was determined by comparing the ACS race and ethnicity variables for each census tract and selecting whichever race/ethnicity had the highest estimate value. Because the figure is intended as an aid for visualizing the general OC population, the margins of errors were not evaluated to determine if any particular best- or worst-case margin of error scenarios would result in a different dominant census tract population being displayed.

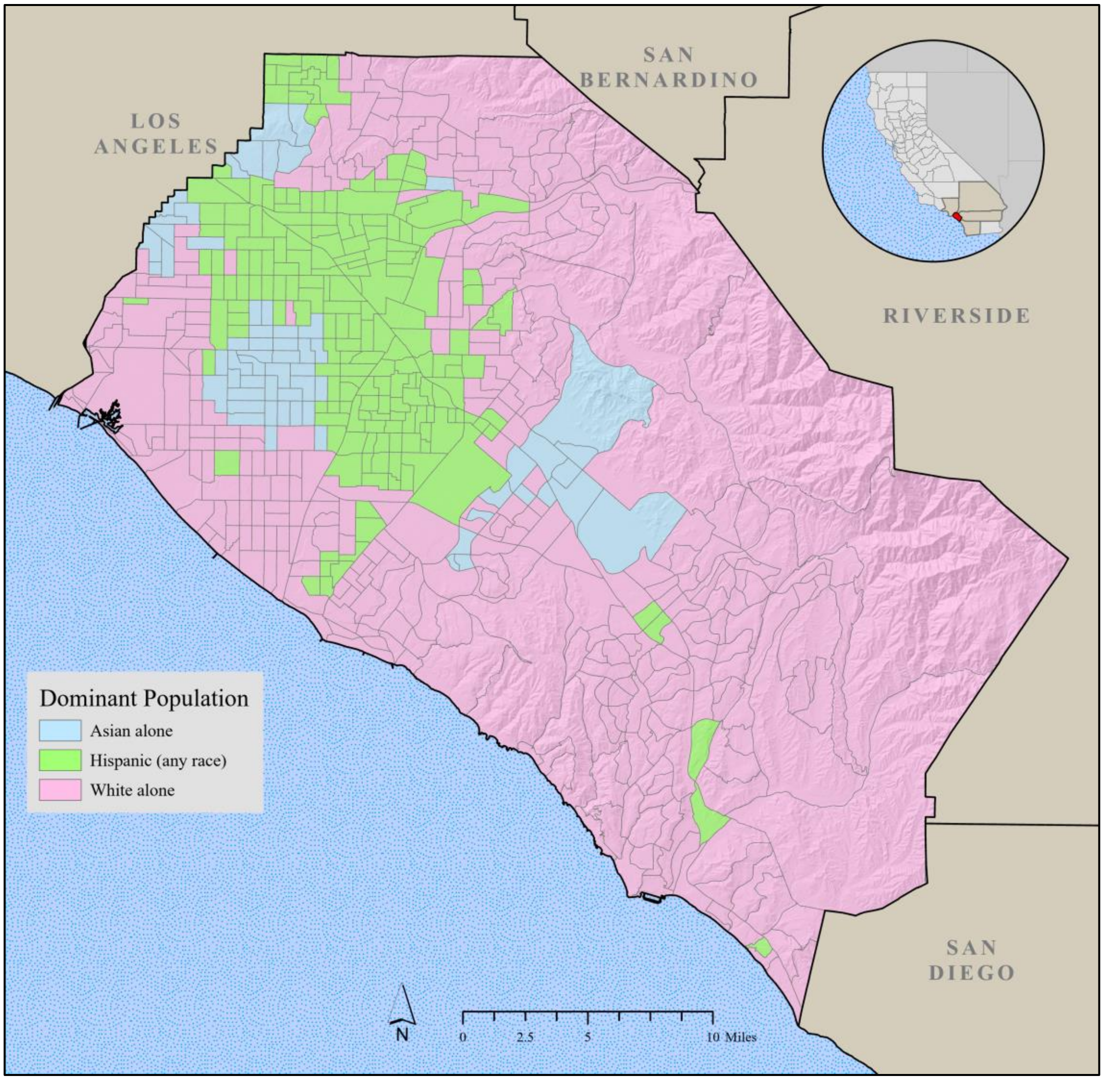


Figure 1 Dominant Racial/Ethnic Group per Census Tract, Orange County, CA

OC also has a diverse economy base that includes tourism (Disneyland), Fortune 500 companies (Broadcom, Western Digital, and First American Corporation), and fashion (Oakley, Inc., Hurley International, and Vans). According to the U.S. Census Bureau, between 2014 to 2018, 65.5% of the total population over 16 years old was employed in the civilian labor force (U.S. Census Bureau 2020). In that same period, 85% of the population 25 and older had a high school diploma and 39.9% had a Bachelor's degree or higher. However, the U.S. Census Bureau also estimated that in 2018, 10.5% of the population was in poverty.

Geographically, the northern portion of the county tended to have a greater proportion of minorities, older developed neighborhoods, and denser population which resulted in areally smaller census tracts. The southern portion of the county was more recently developed and tended to have fewer minorities and areally larger census tracts. The coastal side of the county had the greatest concentration of wealth, while the eastern portion of the county was the least developed. These geographic variations in distributions of populations, minorities, and wealth provided an excellent landscape for exploring whether a race neutral regulation manifested a race neutral distribution in the built environment.

1.6 Thesis Objective and Research Questions

This thesis set out to evaluate the potential existence of structural racism in the form of disparate distributions of alcohol licenses and retailers and attempted to answer the following questions:

- What is the relationship between the presence and absence of alcohol licenses/retailers and the relative percentages of associated Asian/Hispanic/White populations?
- How does the relationship of race/ethnicity (percentage Asian/Hispanic/White) and the distribution of alcohol licenses/retailers manifest at different spatial scales of areal aggregation?
- Does the disparate distribution assessment vary depending upon the choice of spatial scale and aggregation?

Specifically, this thesis looked at how the application of a racially neutral alcohol sales licensing framework has combined with private market forces to influence the spatial distribution of alcohol retailers in OC and compare the distribution of alcohol retailers between predominantly racial minority communities and majority white communities in order to quantify if a disparate distribution has occurred. This was accomplished by utilizing a GIS to aggregate and analyze census tract and scaled population grid cell populations with and without alcohol point of sale retailers to measure variations in racial/ethnic proportions.

The ultimate goal of this thesis is to provide an analytical framework for spatially evaluating racially neutral zoning/licensing policies and their unexpected consequences in the form of disparate distributions. In other words, it builds upon the idea that correcting institutional or structural racism to realize actual race-neutrality requires recognition that in America the playing field for minorities is not inherently level to begin with and that blind insistence on race-neutral language may inadvertently reinforce systemic and structural disparities and segregation (Krivo, Peterson, and Kuhl 2009; Kim and Chun 2019; Johnson and Hoopes 2019).

1.7 Thesis Organization

The next chapter, Chapter Two, details the recent research within the U.S. for exploring disparate impacts of environmental burdens and benefits on various racial minority communities compared to majority white communities. This related work sets the framework for the alcohol retailer density distribution comparison methods that were used in this thesis. Chapter Three details the methodology for how this study was conducted and describes in detail the data sources and spatial analysis that was performed. Chapter Four presents the analytic results and discusses whether there is support for the hypothesis that structural racism is occurring and being reinforced in the built environment. Finally, Chapter Five discusses the significance of these results and the how they relate to refining racially neutral regulation in future legislation or public policy so that historical racial disparities can be corrected.

Chapter 2 Related Work

Minorities—whether racial, ethnic, or disadvantaged economic groups—in urban settings tend to experience some form of disparity more frequently than white populations (Krivo, Peterson, and Kuhl 2009; Kim and Chun 2019; Kubrin and Hipp 2016; Fisher, Kelly, and Romm 2006; Hoffman, Shandas, and Pendleton 2020). However, studies looking into issues of disparity or inequity may not use those terms but instead frame the issue as a lack or imbalance of environmental or social justice. Ultimately, these concepts are intertwined: disparity and inequity arise when there is a lack of environmental or social justice and vice versa. Referring to United States Environmental Protection Agency's (USEPA) definition of environmental justice helps make this clear: environmental justice is "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies" (USEPA 2018).

Regardless whether framed in the negative (disparity) or the positive (justice), empirical evidence continues to show that environmental risks are not equitably distributed across racial groups (Kim and Chun 2019; Unger et al. 2020). This is important because, as many observers have come to recognize, disparity contributes to the creation or continuation of communities or populations experiencing greater exposure to crime or pollution; likewise, disparity is often a contributing factor that accounts for decreased access to green spaces and healthy food choices (Krivo, Peterson, and Kuhl 2009; Kim and Chun 2019, Cooksey-Stowers et al. 2017). Moreover, disparity also occurs in less easily detectable forms such as increased incarceration rates, increased environmental heat exposure, and greater negative health outcomes (Johnson and Hoopes 2019; Hoffman, Shandas, and Pendleton 2020; Dwivedi et al. 2019).

It is easy to imagine that problems of causation and correlation may arise because there are numerous factors that may contribute to the rise or continuation of disparity for any particular group or population and because disparity can occur in so many patent and latent forms. Moreover, when considering disparate impact, it is important to consider that there may be lingering echoes of historic decisions, practices, and policies on today's population and built environment (Pulido, Sidawi, and Vos 1996; Johnson and Hoopes 2019). Furthermore, just as the built environment is not the result of a single decision or building, disparity is not the result of a single factor. Rather, both are functions of the totality of the circumstances at the nexus of the moment of observation of a population in situ with the built environment (Pulido, Sidawi, and Vos 1996). The following sections review recent works examining these issues and shed light on how disparate impacts on poor and minority communities and populations may arise as a result of race neutral policy influencing the built environment through race neutral decisions such as where to locate a liquor store.

2.1 Density of Alcohol Retailers and Disparate Distributions

As a general premise, the local built environment introduces significant biases for individuals (and households) as to the potential choices for diet, physical activity, entertainment, transportation, employment, etc. (Drewnowski et al. 2019; Cooksey-Stowers et al. 2017; Hurvitz et al. 2009). Moreover, one of the seminal studies on the topic of alcohol retailer density, "Alcohol Retail Density and Demographic Predictors of Health Disparities: A Geographic Analysis," confirmed that urban alcohol retailer density correlated with poverty and minority populations, among other things, at the national level (Berke et al. 2010). Similarly, studies have correlated that increased access to alcohol at the local level, by way of greater density of alcohol retailers in a community, is a likely risk factor for increased crime, negative health outcomes, and poverty (e.g. Berke et al. 2010, 1967; Halonen et al. 2013, 295; Young, Macdonald, and Ellaway 2013, 124-125; Dwivedi et al. 2019, 105742).

Studies examining similar issues are often expressed in terms of environmental justice—a field of research examining and quantifying degrees to which all people enjoy healthy environments, protection from health hazards, and access to community decision-making processes—a framework particularly suited for investigating disparate distributions (USEPA 2018; Kim and Chun 2019). Specifically, these studies focus on quantifying environmental inequity by observing the differential distributional outcomes of environmental risks that are borne by different social populations (Kim and Chun 2019). Broadly speaking, an environmental risk is the chance that a stressor—any chemical, biological, or physical entity that may trigger an adverse outcome—produces a harmful effect to health or the community. Some recent examples of stressors from an environmental justice perspective include pollution, proximity to fringe lenders and unlicensed cannabis dispensaries, and lack of access to green space (Kim and Chun 2019; Kubrin and Hipp 2016; Unger et al. 2020; Wolch, Byrne, and Newell 2014). Thus, the concentration of alcohol retailers can be evaluated for environmental inequity by analyzing the distribution like other dissociative environmental risks, such as pollution sources, payday lenders, cannabis dispensaries, and parking lots or associative environmental benefits such as grocery stores and parks.

However, while the density of alcohol retailers in a community correlates with negative social impacts, there is an open question as to whether reducing that density would result in a corresponding reduction of negative outcomes (Hippensteel et al. 2018). Moreover, care should be taken to ensure that the selected spatial unit of analysis is appropriate for the topic of study and that data underlying the study supports the planned methods of analysis (Montello and Sutton 2013).

2.2 Spillover and MAUP: Influences of and on the Built Environment

The built environment can be described as the socio-physical environment resulting from both current and historical human influences through patterns of activity, land use choices, and human-made structures and infrastructure (Popkin, Duffey, and Gordon-Larsen 2005). Moreover, the built environment evolves over decades from many physical, legal, and policy factors including health, safety, cost, traffic patterns, preserving historic architecture, etc. (Texas Dept of Housing 2015; Popkin, Duffey, and Gordon-Larsen 2005). Simultaneously, the local built environment introduces myriad options and limitations for individuals (and households) as to choices for diet, physical activity, entertainment, transportation, employment, etc.

Importantly, the local built environment has been shown to be a powerful predictor of the health of the local population (Drewnowski et al. 2019). Likewise, various micro-level physical characteristics of the built environment have been found to induce or deter violent crime (He, Páez, and Liu 2017). For example, structures in the built environment—such as bridges—provide shelter for homeless, and thus the structure locations can be used to predict homeless populations and homeless-related crime (Yoo and Wheeler 2019). Even fringe banks—payday lenders and check cashers—appear to be spatially concentrated in low-income and minority population neighborhoods, and robbery hot spots are often found within a block of a fringe bank location (Kubrin and Hipp 2016).

On the other hand, the racial composition of a local population may also correlate highly with certain characteristics of the built environment. For example, race alone can predict the likelihood of hazardous waste sites (Kramar et al. 2018). Likewise, at the census tract level, the risk of pollution exposure increases with increases in minority populations (Kim and Chun 2018). However, without careful consideration of the spatial effects on the accuracy, precision, and efficacy of analytical methods, built-environment-to-population and population-to-built-environment influences are at best general associations and do not necessarily allow for causal inferences to be made (Drewnowski et al. 2019; Kim and Chun 2018; Kogure and Takasaki 2019, Oka and Wong 2016).

One important consideration is the potential influence of spatial spillover effects: spatial linking between neighborhoods and/or the spatial proximity between points of observations or measurements (Oka and Wong 2016; Tobler 1970). For example, census tracts (a common enumeration unit) are often treated as discrete information pools where the population or a population characteristic is monolithic across the entire area. While this may be an acceptable assumption for inhabitants at the census tract center or immobile populations, it may not accurately reflect how people live or make decisions for those near the edge or on the boundary (Oka and Wong 2016). In other words, population mobility or exposures from outside the enumeration unit undermines the assumption that the enumeration unit alone fully depicts the environment.

One remedy for spillover issues is to derive spatial weighted variables based on the areal data (Oka and Wong 2016). While there are many ways to generate spatially weighted variables, the various methods tend to fall within one of two schemes: binary weighting and spatial kernels. Under binary weighting approaches, the derived variables are computed based on adjacent or contiguous enumeration units. On the other hand, spatial kernels generate a derived variable based on all the enumeration units within a defined distance and apply a distance decay multiplier to reduce the contribution of more distant enumeration units.

Likewise, choice of spatial scale and boundaries can profoundly impact the significance of observations and the accuracy and precision of spatial and statistical analysis results (Jelinski and Wu 1996; Dark and Bram 2007; Smith and Sandoval 2018). These two interrelated issues—often described as scale and zone effects—are widely known as the modifiable areal unit problem (MAUP). The scale effect recognizes that aggregating smaller areal units into larger units results in a loss of data variation. Figure 2 (a-c) shows the classic MAUP example of scale effects: as data is aggregated from (a) into larger units (b and c) the mean value does not change, but the variance declines. Figure 2 (d-f) also shows the zone effect: the choice of zone boundary—even when holding the number of spatial units constant (b and d; c, e, and f)—can impact both the mean and variance (Jelinski and Wu 1996; Dark and Bram 2007).

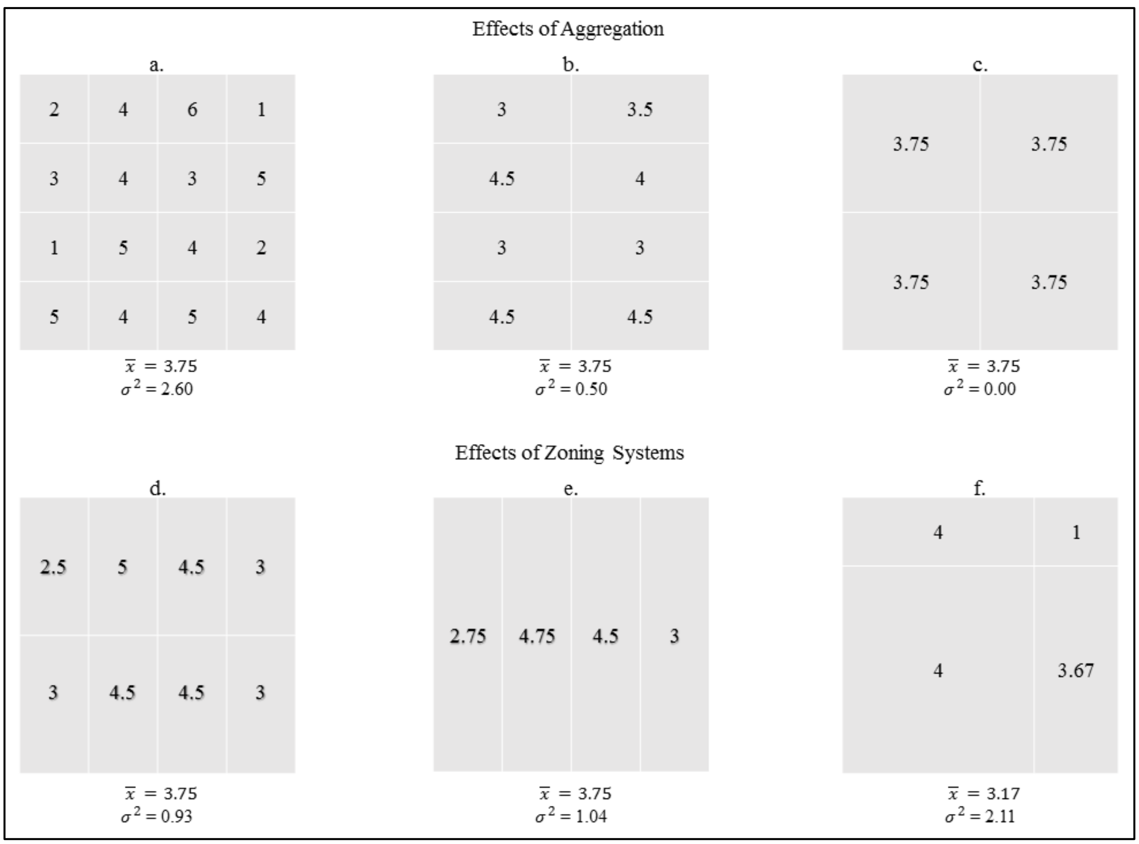


Figure 2 Examples of Two Interrelated MAUP Issues (Jelinski and Wu 1996)

Basically, as spatial data is aggregated into new larger spatial units, there are likely unintended smoothing or filtering functions occurring (Jelinski and Wu 1996). This occurs as part of the transformation function, loss due to over generalization, or loss when differing smaller units are recharacterized and combined to a single category over a larger unit.

2.3 Improving Results and Avoiding MAUP: Two Areal Aggregation Scales

One way to reduce MAUP, improve accuracy of results, and increase insight into relationships and patterns is to utilize multiple spatial scales (Smith and Sandoval 2018). Moreover, incorporating at least one finer-scale geographic unit can provide additional insight into patterns that arise at different scales.

2.3.1. Scale 1: Census Tracts

A frequently relied upon resource for socio-economic and demographic data is the U.S. Census which acquires and maintains multiple datasets relevant to performing spatial analysis on the American landscape and population at various administrative boundary levels, including county and census tract levels. Census tracts, like all political and administrative demarcations—i.e. counties, school districts, congressional districts, etc.—are artificial geographic constructs with shapes and sizes chosen for specific political and administrative purposes without regard to spatial analysis (Smith and Sandoval 2019; Berke et al. 2010; Fisher et al. 2006). However, census tract boundaries are not entirely arbitrary demarcations; they are delineated by a committee of local demographers and data users based upon boundary and demographic criteria established by the Census Bureau (U.S. Census Bureau 1994).

First, a census tract boundary must be easily identifiable in the field, often following visible, permanent features, including roads, highways, canals, railroads, and power lines. Next, census tracts should enclose populations of 2,500 to 8,000 individuals and include 1,000 to 3,000 housing units, and averaging all census tracts in a county should result in an average census tract population of approximately 4,000 people and 1,500 housing units. Finally, the census tract should enclose a population with similar housing and socio-economic characteristics. Thus, although census tracts do not have an areal boundary definition, the uniform application of Census Bureau guidelines makes census tracts reliable as enumeration units for data aggregation for the Census Bureau and other researchers (Oka and Wong 2016).

However, issues regarding the areal variability of census tracts must still be addressed before performing spatial analysis. The first issue relates to the spillover concept, which looks at whether the population or variables under study are confined completely within census tracts or may exist, influence, or be influenced by factors outside the tract boundaries (Oka and Wong 2016; Berke et al. 2010). For example, a pollution source in one census tract may impact a community that is just across the street in a different census tract. Likewise, individuals are mobile and will often work and shop in locations completely outside their home census tract.

The second issue, MAUP, relates to how the choice of areal unit may lead to distinct analytic outcomes (Smith and Sandoval 2019; Oka and Wong 2016). MAUP relates to the alternative outcomes that arise—depending upon the choice of scale and boundaries—when data is aggregated to larger areal units or disaggregated to smaller areal units. Unless these factors are accounted for, results may be misleading due to underestimations or misspecifications of study area characteristics.

Figure 3 provides an example of MAUP and spillover issues with OC census tract boundaries and license locations. First, census tracts are the result of aggregating two or more census block groups (shown in light blue outline), which in turn were the aggregation of two more census blocks (not shown). Each aggregation has the potential to introduce data loss or uncertainty. Moreover, census tracts presume continuity of the underlying population(s), but that presumption is hard to reconcile with irregular sizes and shapes of census tract boundaries such as between census tracts 637.01, 637.02, and 636.05. Likewise, licenses for this study were aggregated at the census tract level, and many licenses were within 100 feet or less of a census tract boundary while the tract interior was often devoid of licenses. A slight change in boundary location would completely alter the census tract license counts and distribution analyses.

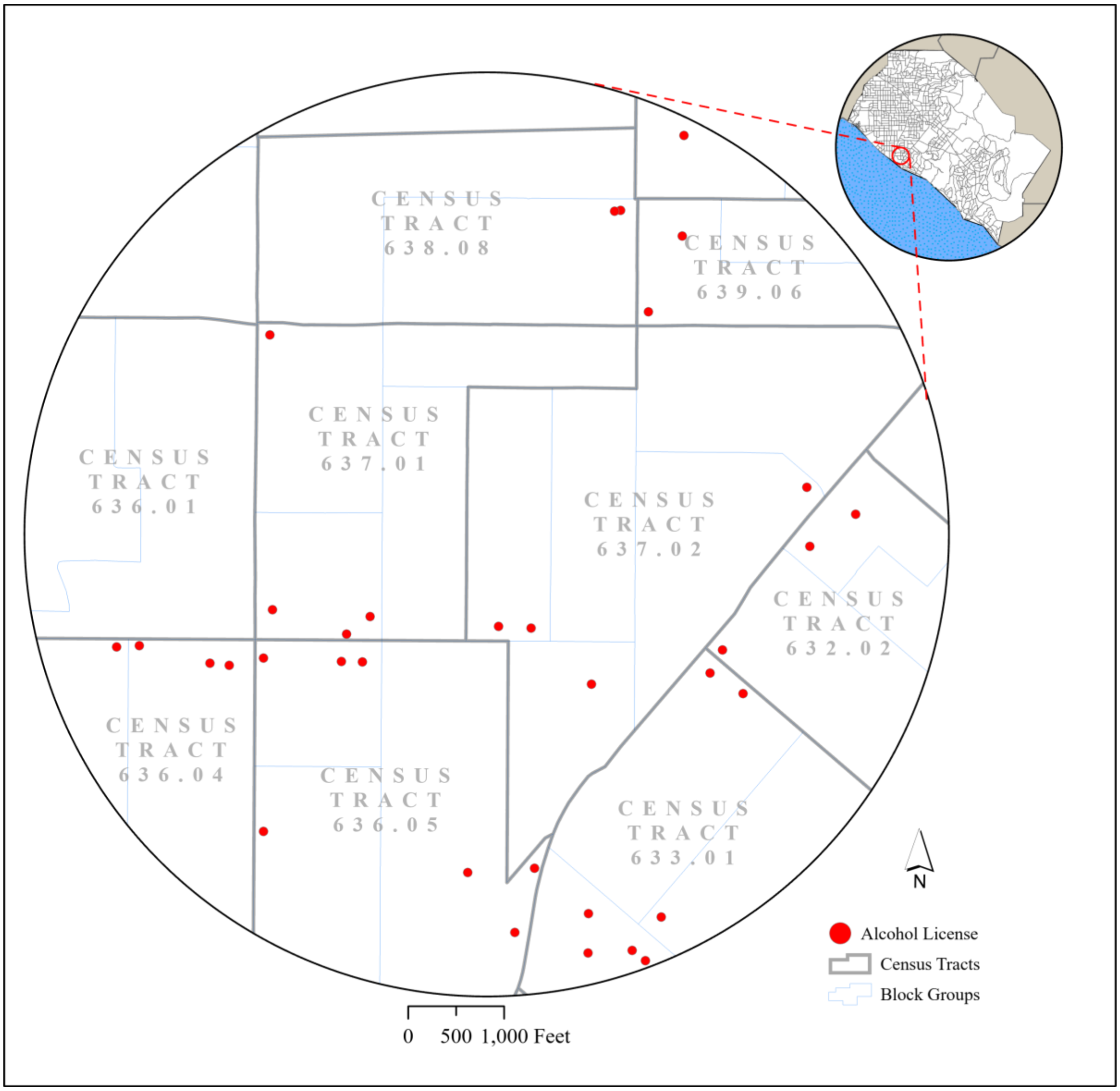


Figure 3 Example of MAUP and Spillover:
Irregular Census Tract Boundaries and License Locations

Second, the close proximity between license locations and the census tract boundaries implicates spillover issues. For example, would residents in the western half of census tract 638.08 be more inclined to visit the license locations on the census tract's eastern border, or the license location in the northwest corner of census tract 637.01?

2.3.2. Scale 2: Scaled Population Grid

Using a combination of spatial scales can improve the identification of patterns and increase the accuracy and precision of analytic results (Smith and Sandoval 2019). When data does not exist at a chosen scale, spatial interpolation methods can be used to create new spatial units at different scales. For example, Risk Terrain Modelling (RTM) is often employed in analyzing crime at finer scales and relies upon spatial interpolation to create uniform grids from larger aggregated spatial units such as census tracts (Smith and Sandoval 2019; Youngmin and Wheeler 2019).

Moreover, the accuracy and precision of spatial interpolation methods can be improved with the inclusion of ancillary data (Ruther, Leyk, and Buttenfield 2015). This is often termed dasymetric mapping and is used to refine spatial estimates when the underlying data was aggregated into spatial units defined for convenience of enumeration rather than data aggregation. For example, land cover information or other remotely sensed data can be used to refine population density estimates in census tracts, counties, or other administrative boundaries (Leyk et al. 2019).

The Oak Ridge National Laboratory's LandScan Global 2018 (LG18) is an example of an ancillary dataset of global population distribution that can be used for dasymetric refinement (Rose et al. 2019, Leyk et al. 2019). The LG18 utilizes multiple spatial and population modeling approaches to create an interpolated grid surface composed of 30 arc-second cells (~ 0.5 miles) based on the World Geodetic System (WGS) 84 datum. Each cell is assigned an integer value representing the ambient population count estimate of the earth's surface covered by the cell. However, the LG18 is a gross population estimate only, it does not include any information regarding race/ethnicity or other socio-economic demographics data.

Datasets such as LG18 are often used for the binary dasymetric refinement of target areas to include only populated areas (Ruther, Leyk, and Buttenfield 2015). Moreover, the ancillary grid cells themselves may become the analytic spatial unit after interpolation of the source data and ancillary data (Leyk et al. 2019). However, care should be taken that the target grid scale represents an appropriate proxy for the intended analysis and does not introduce increased local imprecision.

One of the oldest and simplest areal interpolation methods for generating a new spatial unit is based on areally weighting the data between the source and target spatial units (Ruther, Leyk, and Buttenfield 2015). The process works by first creating "atoms," which are an areal quantum resulting from the spatial intersection of source and target boundaries (see Figure 4). Fractions of the source data are then assigned to the atoms based on the proportion of the source area encompassed by the atom. The process is repeated for all intersections of the source and target boundaries. Atoms are then reassembled into target zones by summing the individual atom values of the atoms that are encompassed by the target boundaries:

$$\hat{y}_t = \sum_s \frac{A_{st}}{A_s} y_{s,} \tag{1}$$

where $\hat{y}_t$ is the estimated population count in target zone (t), y_s is the source (s) population count, A_s is source area, and A_{st} is the atom area.

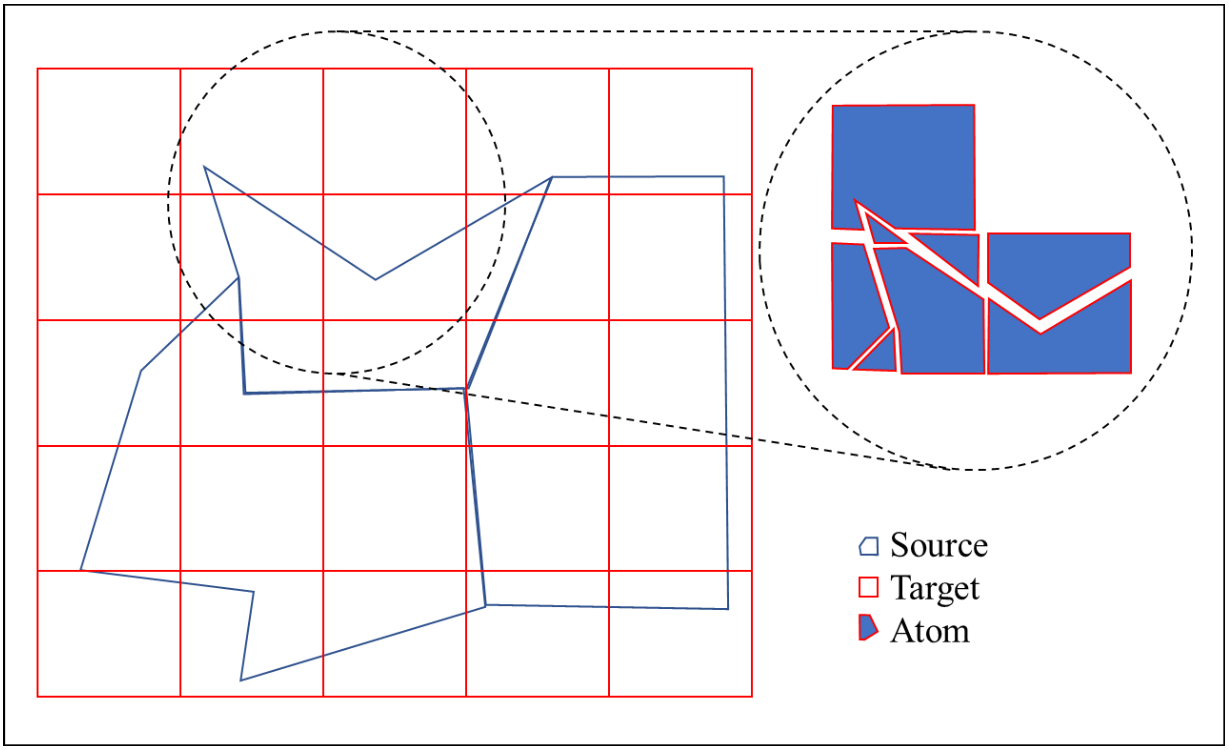


Figure 4 Creating Atoms from Source and Target Boundaries

Chapter 3 Data Sources and Methodology

At the heart of this study is the simple premise that a race-neutral alcohol retail sales license regulation should produce a distribution of retailers where the aggregate of local race/ethnicity population proportions near the retailers follows the county-wide race/ethnicity proportions. In other words, the absence of a race-neutral distribution function is presumed if the aggregate race/ethnicity population proportions near alcohol retailers deviates from county-wide proportions by something more than nominal differences and margins of error.

This premise can be applied to the study of license distributions in OC because the locations of licensed alcohol retailers are known and the county is mostly composed of three uniquely identified racial/ethnic subpopulations which are quantified by ACS Table DP05 race/ethnicity population estimates (U.S. Census Bureau 2017). Asian and Hispanic (all races) are two minority subpopulations and White (non-Hispanic) is the majority subpopulation. The remaining ACS populations estimates include Black and multiple race/ethnicity combination subpopulations, but these remain subpopulations are so small that ACS estimates are often overshadowed by margins of error.

While the premise is simple, issues with MAUP and spillover effects, if not addressed, could likely introduce errors that attenuate or exaggerate the population proportions calling into question whether the observations are reliable. There are also different possible distribution patterns for the various types of retailers (i.e. grocery stores versus gas stations). In order to mitigate these spatial and license/retailer issues, two different areal aggregation systems—census tracts and a scaled population grid based on LandScan cells—were selected to provide complimentary areal coverage and the license holders were categorized into one of seven categories using standard business data analytic classification systems.

This work relied upon several types of spatial, categorical, and population data, from multiple sources. Moreover, none of the data were directly useable for analysis in their original format. Table 1 details the data sets and sources relied upon for this study. The following sections discuss the study area and the purpose, source, and transformations associated with each data set.

Table 1 Datasets and Sources

Dataset	**Description**	**Format**	**Data Type**	**Spatial Scale**	**Reporting Period**	**Source**
Alcohol Licenses	License Type and Addresses of California alcohol licensees	.csv	Point data in the form of street addresses in text fields	Point locations in census tracts	2019	Department of Alcoholic Beverage Control
Business Vendor Type Information	Business name, SIC codes, and address of retailers within 5 miles of Orange County	.csv	Point data in the form of street addresses in text fields	Point locations in census tracts	2020	ReferenceUSA (Infogroup, Inc.)
County and Census Tract Boundaries	Administrative boundaries for Orange County, surrounding counties, and census tracts	.shp	Vector data (polygon)	OC and Census tracts of various areal sizes	2018	U.S. Census Bureau TIGER/Line files
Race/Ethnicity	Dataset reporting Non-Hispanic, Hispanic, and other race/ethnicity population estimates	.csv	Data in the form of aggregated census tract population estimates in text fields	Census tracts of various areal sizes	2017	U.S. Census Bureau ACS Table DP05
LandScan Global 2018*	Ambient population distribution	ESRI GRID	Raster data (integer value: number of people)	30 arc-second cells, approx. 0.25 sq mi	2018	Oak Ridge National Laboratory

* "This product was made utilizing the LandScan 2018™ High Resolution Global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy. The United States Government has certain rights in this Data Set. Neither UT-BATTELLE, LLC NOR THE UNITED STATES DEPARTMENT OF ENERGY, NOR ANY OF THEIR EMPLOYEES, MAKES ANY WARRANTY, EXPRESS OR IMPLIED, OR ASSUMES ANY LEGAL LIABILITY OR RESPONSIBILITY FOR THE ACCURACY, COMPLETENESS, OR USEFULNESS OF THE DATA SET."

3.1 OC Alcohol Retailer License Data

As indicated above in Section 1.4, in California, there are two types of license that pertain to retail alcohol sales for consumption off premises: Type 20 for beer and wine only sales and Type 21 for all types of alcohol beverage sales; either of these licenses can be obtained by any type of vendor permitted to sell alcohol, including grocery stores, drug stores, gas stations, liquor stores, and warehouse clubs (i.e. Costco and Sam's Club). The ABC allocates these licenses and maintains a database of the license holders. Because the type of retailer and spatial location of the business was not included in the ABC license data, additional processing steps were required to obtain and add that information.

3.1.1. Acquiring OC Alcohol Retailer License Data

Obtaining California alcohol retailer license data required accessing the ABC website to generate a license information report (ABC 2020). The license data obtained from the ABC was plain text in a comma separated file format where the information was stored in row and column format. In the file, each row was a unique record, and each column represented a field (i.e. name, address, license type, etc.) of information for the record. Moreover, each license was assigned a unique numeric file number value and there was only one record for each license. However, some vendors had multiple licenses for multiple locations, in which case there were multiple records with the same vendor. Likewise, each license type was unique to each location (i.e. there is no unique address that will have two Type 21 licenses); however, locations may have multiple types of licenses. Finally, the license location information was simply the street address of the location in plain text and required subsequent geocoding in order to perform geospatial analysis.

3.1.2. Geocoding Alcohol Retailer License Data

In its raw format, the only spatial information in the licenses data was in the form of several text fields for street addresses. To perform spatial analysis required utilizing a geocoding service in order to convert the street addresses into geographic coordinates—latitude and longitude pairs. For this study, the Google Maps Platform Geocoding Service was chosen to perform the conversion.

The Google Geocoding Application Programming Interface (API) uses a hypertext transfer protocol (HTTP) interface for submitting a street address and receiving a geocoded response (Google 2020). To use the interface, the requester formats an HTTP string with the necessary street address information and sends the string to the google server. After receiving the request, the Google Geocoder responds with an HTTP message that indicates either an error message regarding problems with the request or a geocoded response with additional diagnostic information regarding the accuracy of the response. This sequence of submitting requests and receiving a response was repeated for each address that requires geocoding.

The initial ABC dataset consisted of all licenses (N=122,043) within California, on February 18, 2020. A filter was applied to select only "Active" licenses, of Type 20 or 21, and within Orange, Los Angeles, San Bernardino, Riverside, and San Diego counties (N=12,571). This set of licenses was then geocoded using the Google Map Geocoding API in preparation for additional filtering.

The Google Map Geocoding API appended additional details regarding the success and status of each record submitted for geocoding. Out of the 12,571 records submitted for geocoding, only 1 record returned with an error. However, the record was for a license with a Riverside county address, so it was removed from further evaluation. The remaining geocoded addresses were then filtered several times to further refine the license relevant to this study.

First, a filter was applied to select only licenses (N=3,070) within Orange County or cities bordering Orange County. Next, a spatial filter was applied to select only licenses (N=2,469) within a 5-mile buffer of Orange County (see Figure 5). The geocoding results of these license were then re-evaluated for precision and accuracy.

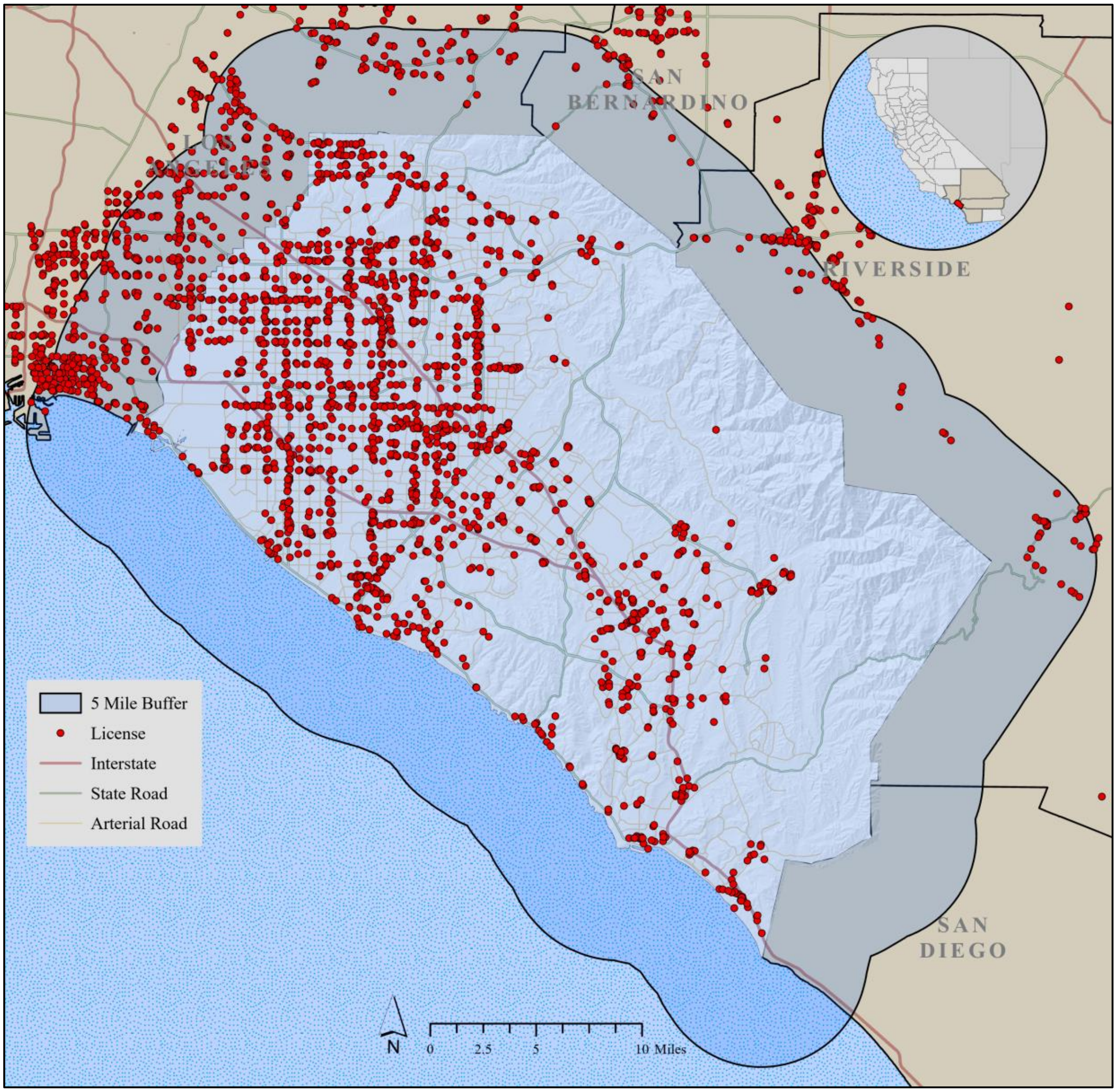


Figure 5 Orange County with 5-Mile Buffer for Filtering Licenses

At the time of this study, the Google Map Geocoding API did not have a direct quantification of precision or accuracy, but did provide text values in two fields that provided an indirect indicium of precision and accuracy. First, a “location_type” field provided an indication of the level of precision; of the 2,469 addresses in the 5-mile buffer, 2,390 were reported by the Google Map Geocoding API as having a “Rooftop” level of precision. The remaining licenses (N=79) were reported as having “Range_Interpolated” (N=53) or “Geometric_Center” (N=26). Second, a “types” field provided an indication of the accuracy with simple descriptors such as “premise,” “street_address,” “subpremise,” etc. After geocoding, all geocoded addresses were reported as having an accuracy of at least “premise.” Thus, while not a direct measure of spatial precision, review of the various combination of text values across all the results suggested the geocoded coordinates were spatially within the bounds of a street block, parking lot, or center of a collection of buildings related to the geocoded addresses. The spatial data was then projected using the California State Plane VI FIPS 0406 coordinate system for further spatial analysis.

3.1.3. Categorizing Alcohol Retailer Types

This study required classifying the vendors into several categories in order to determine if there was any variance in the distributions of the licenses and retailers based on the types of vendors. Table 2 lists the seven broad categories chosen for this study, based upon the North American Industry Classification System (NAICS) codes, of vendor types that potentially sell alcohol for off premises consumption in OC.

Table 2 NAICS Code and Vendor Categories

Code	**Category**
445110	Supermarkets and Other Grocery (except Convenience) Stores
445120	Convenience Stores
4452xx	Specialty Food Stores
445310	Beer, Wine, and Liquor Stores
446110	Pharmacies and Drug Stores
4471xx	Gasoline Stations
4523xx	General Merchandise Stores, including Warehouse Clubs and Supercenters

In its original format, the license data was a plain text file, and the only vendor information was the business name. In order to classify the business entities into vendor categories, it was necessary to cross reference the vendors in the license data with a business information source to identify and categorize by vendor category. The ReferenceUSA business analytics database was utilized to generate a cross reference list of OC and surrounding county businesses using the NAICS codes applicable to this study (Infogroup 2020).

Notwithstanding the use of NAICS codes to select the businesses, the data obtained from ReferenceUSA used the older Standard Industrial Classification (SIC) codes. Fortunately, the SIC codes and business classifications translated to equivalent NAICS codes and classifications selected for this study. Table 3 lists the SIC codes, SIC Category, and a description of the businesses typical of the categories.

Table 3 Vendor Categories by SIC Code

SIC Code	Category	Typical Business	Examples
592102	Liquor Stores	Stores selling primarily alcohol or with Liquor in the name	Frontier Liquor, Food Mart Liquor, Happy's Liquor
554101	Service Stations	Gas stations	Mobil, Union 76, Circle K
541103	Convenience Stores	Smaller markets selling groceries and other conveniences	Circle K, 7 Eleven, Shop-n-Go
531110	Wholesale Clubs	Membership-based stores selling groceries and other consumer goods.	Costco, Sam's Club
531102	Department Stores	Department stores selling groceries and other consumer goods.	Target, Kmart, Walmart
591205	Pharmacies	Pharmacies	Rite Aid, Walgreens, CVS
541105	Grocery Stores	Full size grocery stores	Vons, Ralphs, Food 4 Less

The business data obtained from ReferenceUSA was in plain text file with comma separated fields where the information is stored in row and column format. In the file, each row was a unique business record, and each column represented a field (i.e. name, address, SIC code, etc.) of information for the record. However, some businesses had multiple records depending upon whether the business had multiple locations and/or provided one or more goods or services at each location. For example, Vons (grocery store) had multiple records, some of which were for a number of different locations and others for the goods and services (such as groceries, bakery, and pharmacy) it provided at each location. Moreover, because there was no consistent business name and street address conventions between the ReferenceUSA data and the license data (or even within the datasets themselves), a combination of manual and programmatic matching schemes using street address and business names was employed to match the records between the two datasets.

Of the 2,469 alcohol licenses, 1,928 were matched with a corresponding business analytics record. The majority of the matched records were coded with one of the seven SIC codes selected for this study. However, 230 of the records had SIC codes that did not match the expected SIC codes and the remaining licenses (N=541) were unmatched to any business records.

Of the 230 records with unrecognized SIC codes, 75 were found to have codes that were subcategories of the expected study codes and were reclassified to the corresponding primary code. The remaining 155 records were identified as businesses which had been licensed by the ABC as off-site alcohol retailers but do not typically sell retail packaged alcohol products for off-site consumption; rather, the sales at those businesses were akin to prepared food vendors, catering or party service providers, or otherwise do not sell directly to the general shopping public. These 155 records were coded with temporary business classifications (see Table 4).

Table 4 Temporary Classification of Unmatched Alcohol Retailers

Category	**Example of Retailer/Business**	**N**
Residential	Review of address images indicated a residential property (private home)	3
Specialty Sales	An establishment for wine tasting or entertainment that included wine sales	15
Secondary Sales	A gift shop that sells baskets that may include wine	23
Food Service	Bakeries and delis	28
Internet Sales	ABC website indicates Internet Sales Only	72
Hotel	Hotel gift shops and a nu*Dist* colony	14
	TOTAL	155

Finally, a manual process of name evaluation and review of images from Google Maps was used to categorize any remaining un matched licenses (see Figure 6). The goal of the process was to ensure a consistent outcome to three instances of subjective and objective classification decisions which arose when distinguishing between 1) liquor stores and convenience stores, 2) convenience stores and grocery stores, and 3) convenience stores and gas stations.

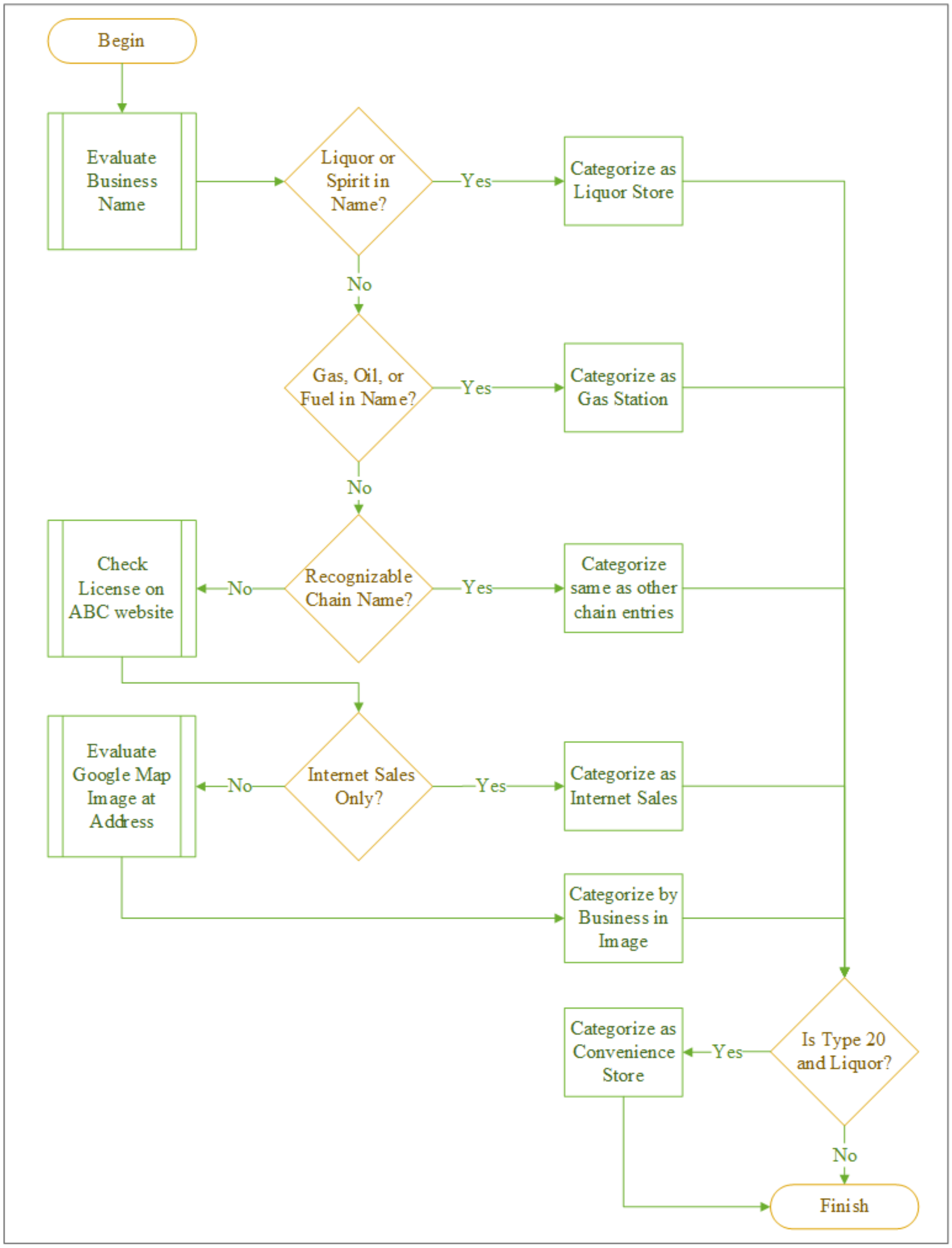


Figure 6 Decision Tree for Categorization Process

For example, the decision between convenience stores and gas stations was primarily an objective decision based upon the name (i.e. Shell, Chevron, Fuel, Oil) or gas pumps evident in an image of the business address. The decision between liquor and convenience stores was a more interesting case as almost 15% of the convenience stores (N=51) had a Type 21 license, while several stores initially identified as liquor stores using the business analytics data had a Type 20 license. The resolution was to bin business chains traditionally associated with convenience stores (i.e. 7 Eleven, Circle K, Alta Dena) as convenience stores even if they had a Type 21 license, while recategorizing all stores identified as liquor stores as convenience stores if they had a Type 20 license.

Finally, while most of the categorization of convenience and grocery stores occurred by matching business analytics data or name identification of chains, a small number of business required a subjective evaluation of the business image at the license address. In this case, images at the license address were reviewed and smaller retailers in strip malls or corner markets were classified as convenience stores while larger markets and mall anchor stores were classified as grocery stores. Figure 7 shows the final results of geocoding and categorization process.

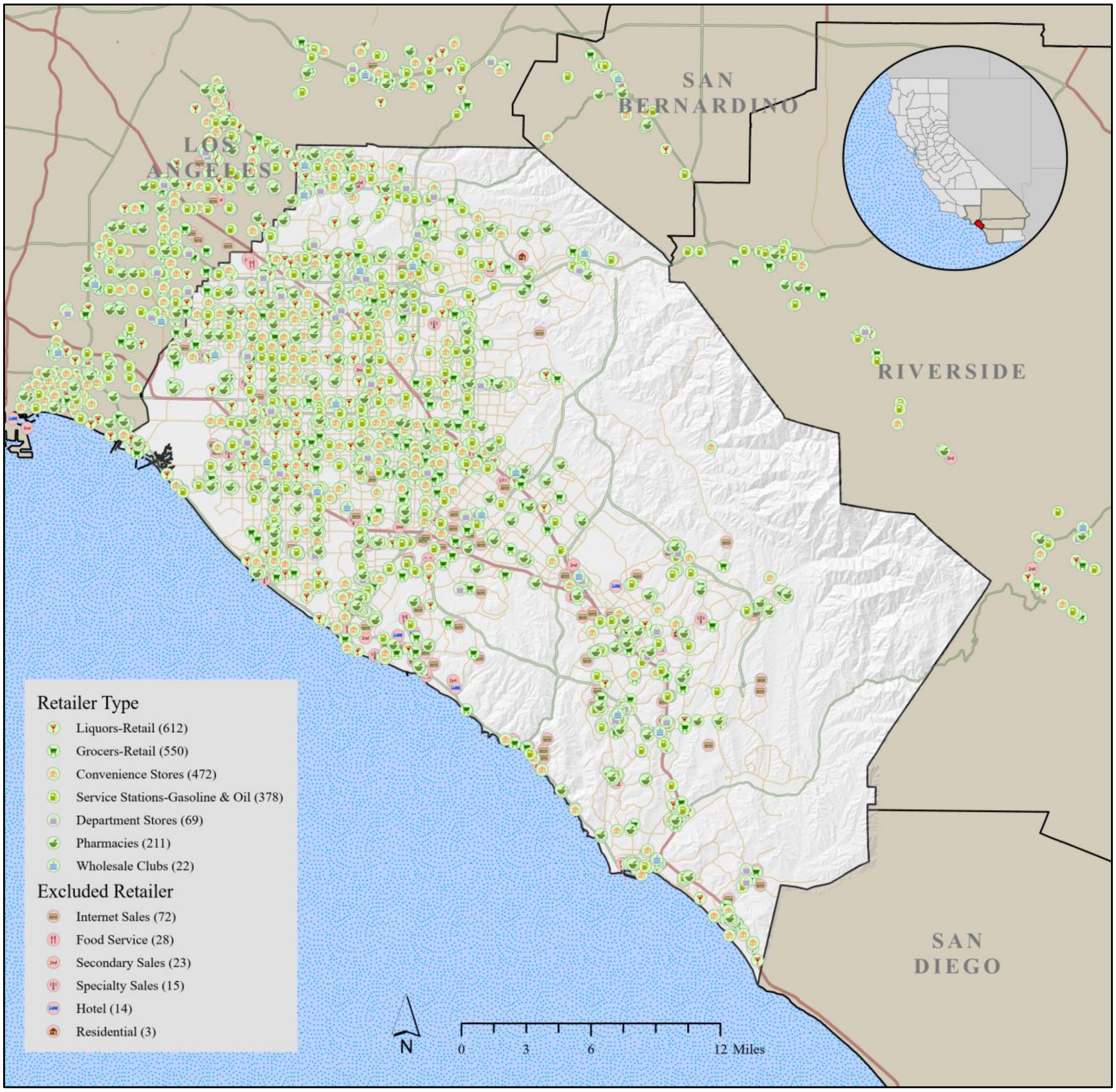


Figure 7 Alcohol Retailers within 5-Mile Buffer of Orange County

3.1.4. Orange County Alcohol Licenses and Retailer Summary

After geocoding and categorizing the alcohol licenses, the license data set was loaded into ArcGIS Pro to select only the licenses within the Orange County boundary as defined by the Census TIGER/Line shapefile. Table 5 summarizes the records (N=1,805) that were selected by this process. As the table indicates, 1,672 licenses records were deemed appropriate for study after excluding 133 licenses from the OC study area based upon a combination of subjective and objective factors (see Section 3.1.3). A license was objectively excluded if it was identified as “Internet Only Sales” on the ABC website; whereas, it was subjectively excluded if there was evidence that the retailer did not sell packaged alcohol to the general public for off premise consumption (i.e. hotel gift shops, residential homes, caterers, bakeries, delis, and a nudist colony). Figure 8 provides summary statistics of the count of alcohol licenses included for this study by type and retailer in each census tract. Figure 9 normalizes the alcohol license statistics by the square-mile-area of each census tract.

Table 5 Orange County License Summary

	Orange County	**Type 21**	**Type 20**
Total Licenses	1,805 (100%)	993 (55%)	812 (45%)
Excluded from Study	133 (7.37%)	16 (0.89%)	117 (6.48%)
Study Licenses	1,672 (92.63%)	977 (54.13%)	695 (38.5%)
Liquor Stores	418 (23.16%)	418 (23.16%)	0
Grocery Stores	412 (22.83%)	300 (16.62%)	112 (6.2%)
Convenience Stores	347 (19.22%)	51 (2.82%)	296 (16.4%)
Gas Stations	270 (14.96%)	15 (0.83%)	255 (14.33%)
Pharmacies	159 (8.81%)	135 (7.48%)	24 (1.33%)
Department Stores	50 (2.77%)	42 (2.33%)	8 (0.44%)
Wholesale Clubs	16 (0.89%)	16 (0.89%)	0

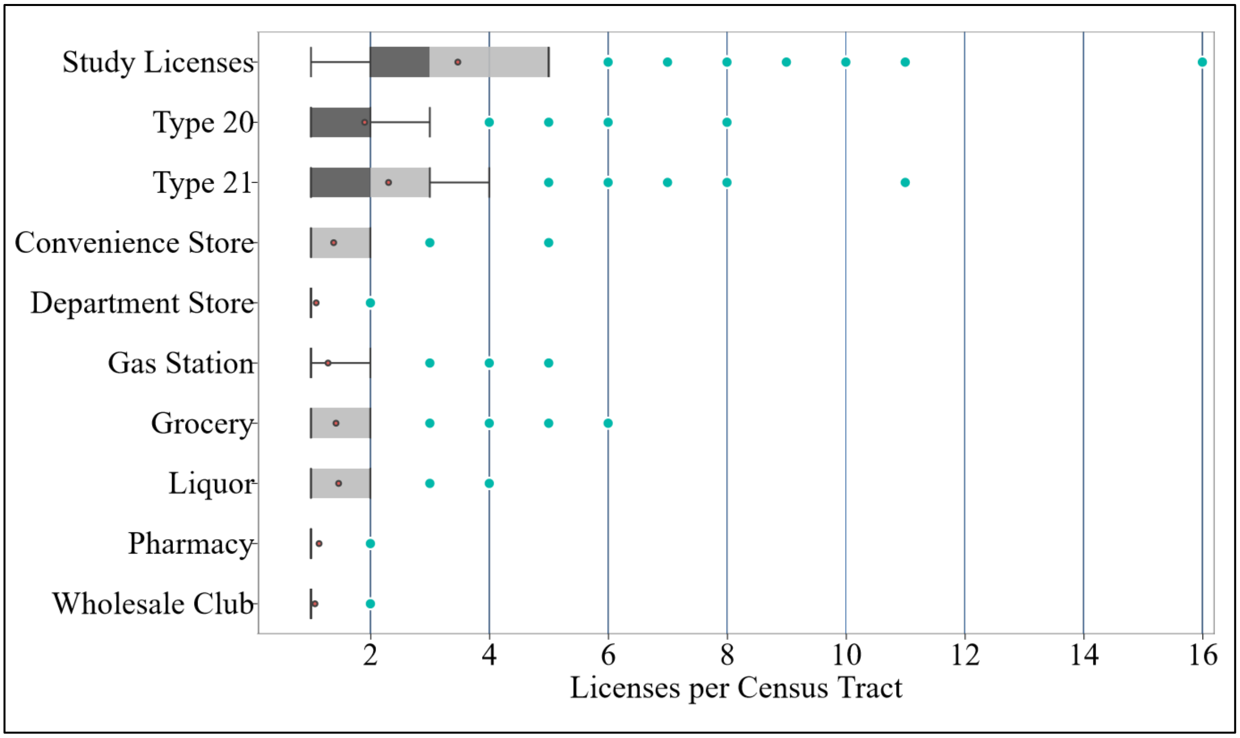


Figure 8 OC Alcohol Licenses by Type and Retailer per Census Tract

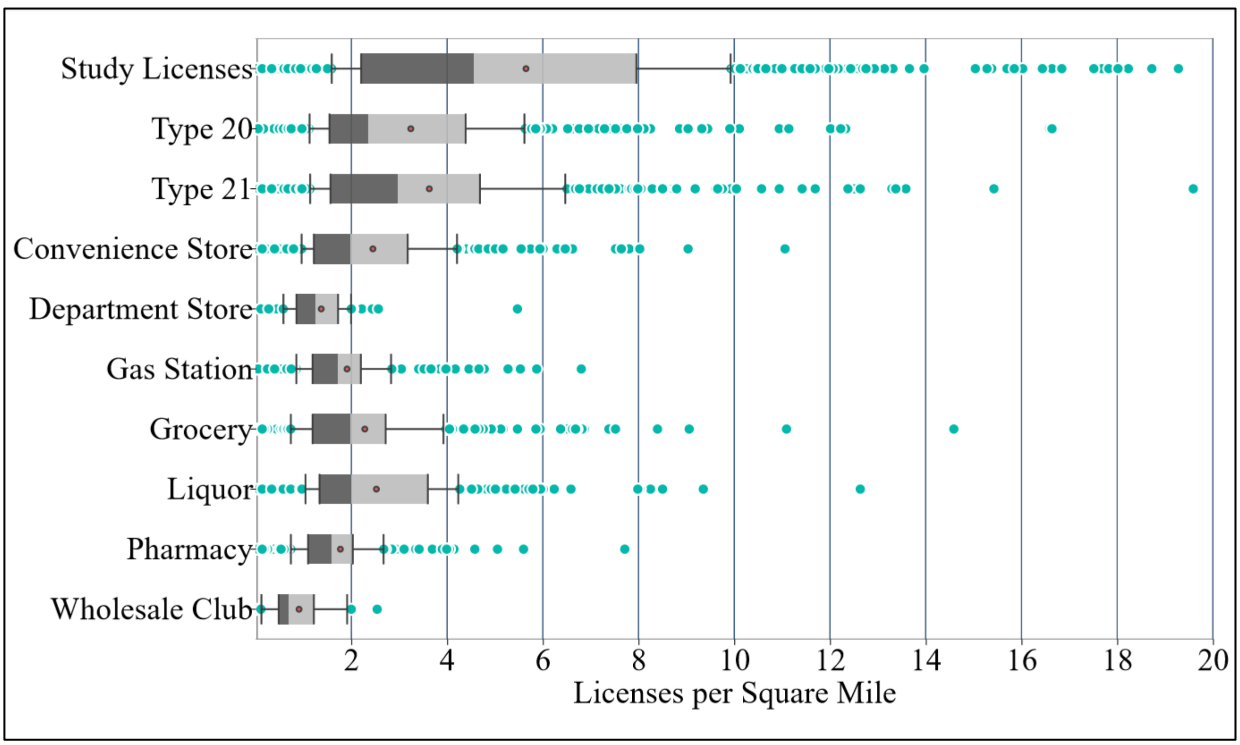


Figure 9 OC Alcohol Licenses by Type and Retailer per Square Mile per Census Tract

Next, a Nearest Neighbor analysis was performed to determine if the distributions of the licenses were spatially clustered, dispersed, or random. The test was performed for all retailer licenses in Orange County as a single group, the Type 20 licenses, the Type 21 licenses, and then all licenses by each category of retailer. Each Nearest Neighbor test was repeated twice, first using Euclidean distance and then Manhattan distance (see Table 6).

Table 6 License Nearest Neighbor Statistics

	Licenses	**Expected Mean**	**Method**	**Mean**	**z score**	**p value**	**Spatial Distribution**
All	1672	1,825	Euclidean	790	-44.33	0.00	Clustered[1]
			Manhattan	967	-36.77	0.00	Clustered[1]
Type 20	695	2,831	Euclidean	1,521	-23.34	0.00	Clustered[1]
			Manhattan	1,839	-17.67	0.00	Clustered[1]
Type 21	977	2,387	Euclidean	1,213	-29.4	0.00	Clustered[1]
			Manhattan	1,488	-22.52	0.00	Clustered[1]
Liquor Stores	418	3,650	Euclidean	2,360	-13.82	0.00	Clustered[1]
			Manhattan	2,878	-8.27	0.00	Clustered[1]
Convenience Stores	347	4,006	Euclidean	2,813	-10.61	0.00	Clustered[1]
			Manhattan	3,476	-4.72	0.00	Clustered[1]
Gas Stations	270	4,541	Euclidean	3,118	-9.85	0.00	Clustered[1]
			Manhattan	3,755	-5.44	0.00	Clustered[1]
Department Stores	50	10,553	Euclidean	8,440	-2.71	0.006	Clustered[1]
			Manhattan	10,900	0.44	0.66	Random
Pharmacies	159	5,918	Euclidean	4,539	-5.62	0.00	Clustered[1]
			Manhattan	5,396	-2.13	0.03	Clustered[2]
Wholesale Clubs	16	18,656	Euclidean	17,048	-0.65	0.65	Random
			Manhattan	20,769	0.87	0.03	Random
Grocers	412	3,676	Euclidean	2,328	-14.24	0.00	Clustered[1]
			Manhattan	2,867	-8.55	0.00	Clustered[1]

[1] Less than 1% likelihood that pattern could be result of random chance

[2] Less than 5% likelihood that pattern could be result of random chance

The results of the Nearest Neighbor tests supported the general premise that alcohol licenses are not randomly distributed in the built environment, especially in the case of all licenses. One reason for spatial clustering is that retailer site selection is generally confined to the commercial and business zones of the built environment. On the other hand, the distribution of licenses categorized as Department Stores (i.e. Target and K-Mart) and Wholesale Clubs (i.e. Costco and Walmart) suggested different distribution functions operated based on the type of retailer as these two categories produced random (Euclidean) and dispersed (Manhattan) distributions. Alternatively, these distributions could simply have been the result of the smaller number of retailers (Dept Stores: N=50 and Wholesale Clubs: N=16) in these two categories.

3.2 Spatial Analysis: Two Areal Aggregation Units

An integral data requirement for exploring structural racism is the relevant demographic data of the population under study. For this study, race/ethnicity population estimates at the census tract level and the administrative boundaries for OC and OC census tracts meet that requirement. Also, in order to mitigate MAUP and spillover issues, this study utilized the Oak Ridge National Laboratory's LandScan Global 2018 population dataset to create a scaled population grid. The following sections describe these data sources in greater detail.

3.2.1. ACS Race/Ethnicity Estimates and Margins of Error

The U.S. Census, through the American Community Survey (ACS), maintains demographic summaries and statistics for multiple administrative units, including counties and census tracts; these demographic summaries are available in table format as text files. ACS 2017 5-Year Estimates Table DP05 Demographic and Housing Estimates contained the relevant race and ethnicity data required for this study (U.S. Census Bureau 2017). This study utilized the ACS race/ethnicity classification that included a Hispanic/Latino category to accommodate the significant portion of OC population that identifies as Hispanic or Latino (see Table 7). Likewise, there are significant OC population segments that racially identify as Asian or White, which are provided as single race estimates in Table DP05. While Table DP05 estimates that the

OC Black population is exceedingly small (1.6% of the population), it was included as a category for analysis in this study, while the remaining racial categories in Table DP05 were small fractions of a percent of the population and were combined as a single Other category for analysis.

Table 7 Orange County Race/Ethnicity Summary

2017 ACS Table DP05	Estimate	Margin of Error	Percent
Total Population	3,155,816	*	100%
Hispanic (of any race)	1,079,172	*	34.2%
White alone	1,306,398	+/- 790	41.4%
Asian alone	615,659	+/- 2,831	19.5%
Black alone	49,590	+/- 1,181	1.6%
Other (some other race alone or two or more races)	105,027	+/- 3,580	3.3%

*Estimate is controlled, margin of error treated as zero

Moreover, the ACS race/ethnicity values are estimates based on survey data, and each estimate has a corresponding margin of error. Aggregating ACS data, and transforming it to new spatial scales, requires additional processing to derive new margins of error. These new margins of error were calculated from original ACS county and census tract margins of error using guidelines and formulas published by the U.S. Census (U.S. Census Bureau 2018).

3.2.2. Scale 1: Census Tracts

For this study, the necessary administrative units (counties and census tracts) and their boundaries were all available from the U.S. Census as TIGER/Line shapefiles. Figure 10 shows the TIGER/Line county boundaries for the study area and four surrounding counties (Los

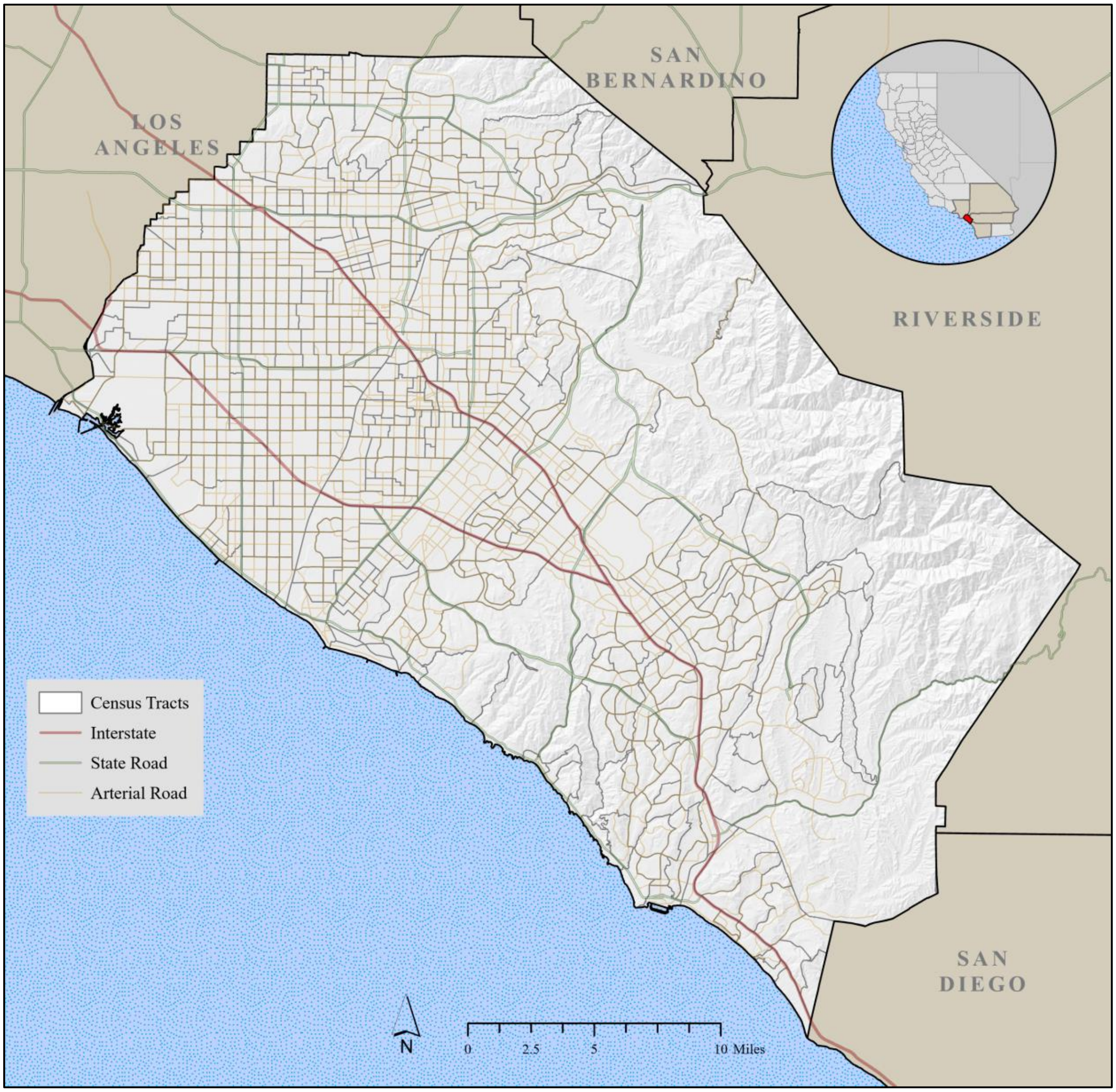


Figure 10 OC and Surrounding Counties

Angeles, San Bernardino, Riverside, and San Diego). Notably, the north-western part of the county was composed primarily of small regularly shaped census tracts with significant roadway infrastructure, while the south-eastern part of the county was composed of irregularly shaped large census tracts with less infrastructure. Frequently, census tract boundaries followed the transportation infrastructure creating the regular grid patterns in the north and the irregular shapes in the south.

The ACS 2017 5-Year race/ethnicity estimates in Table DP05 were linked to the OC census tracts. OC has a total of 583 census tracts; however, one census tract was removed before analysis in this study. Census tract 9901 was removed because it has no land area and zero population. On the other hand, census tract 9800—with an estimated population of only 27 Hispanics and a margin of error of +/-18—was retained even though it covers the Disneyland resort complex which is an area that is mostly compromised of theme parks, restaurants, and commercial and hotel properties related to the tourism industry. Figure 11 depicts census tract dominant race and ethnicity with diversity indicated by applying shading based upon a diversity index.

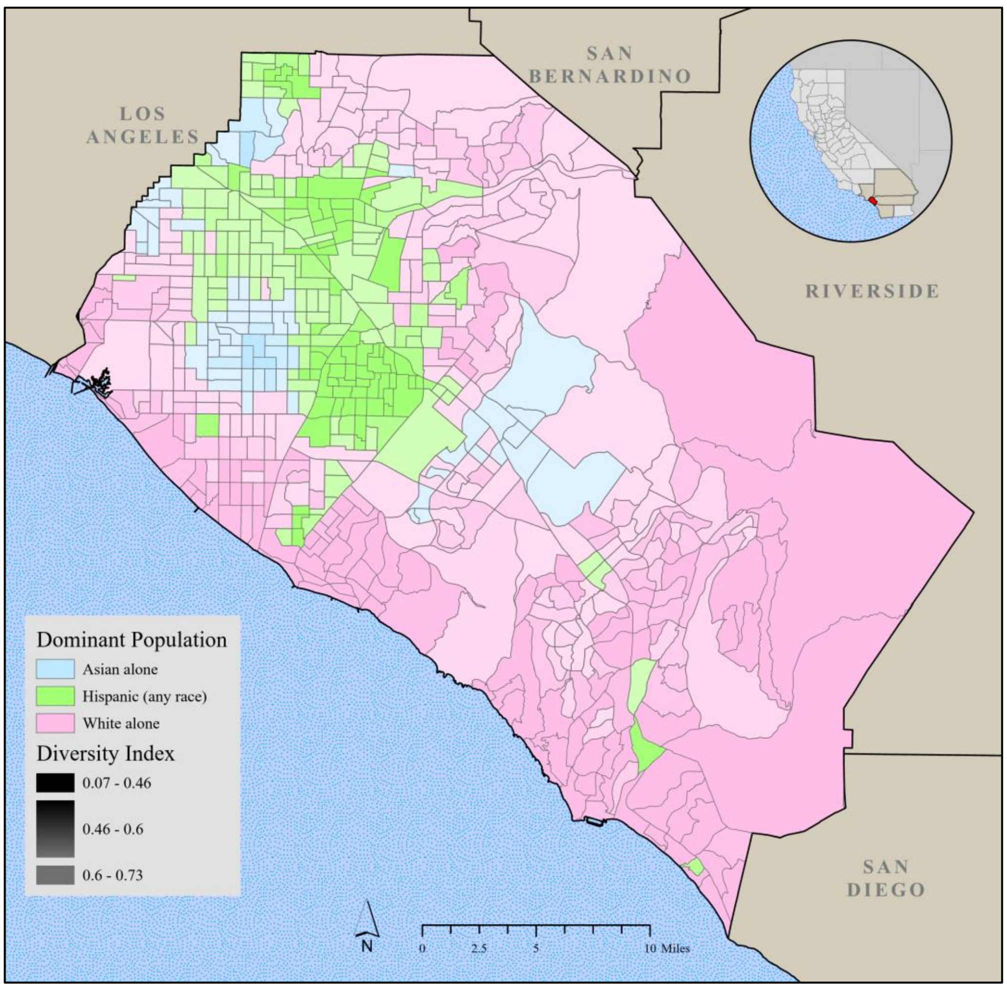


Figure 11 OC Race and Ethniciy with Diversity Index Shading

The shading algorithm is based on Simpson's Diversity Index—a method to quantify whether a community is dominated by a single group versus having multiple groups with similar populations—as an aid for visualizing census tract diversity (Barcelona Field Studies Centre 2020). In general terms, the diversity index produces a range of values from 0 to 1, where 0 represents no diversity and 1 represents infinite diversity. For OC, the index ranged from 0.072 (almost no diversity, darker shades) to 0.725 (fairly diverse, lighter shades), with 0.52 being the average index value across the census tracts. Figure 12 provides an alternative representation of density and diversity based upon ACS census tract data where each dot represents 500 people.

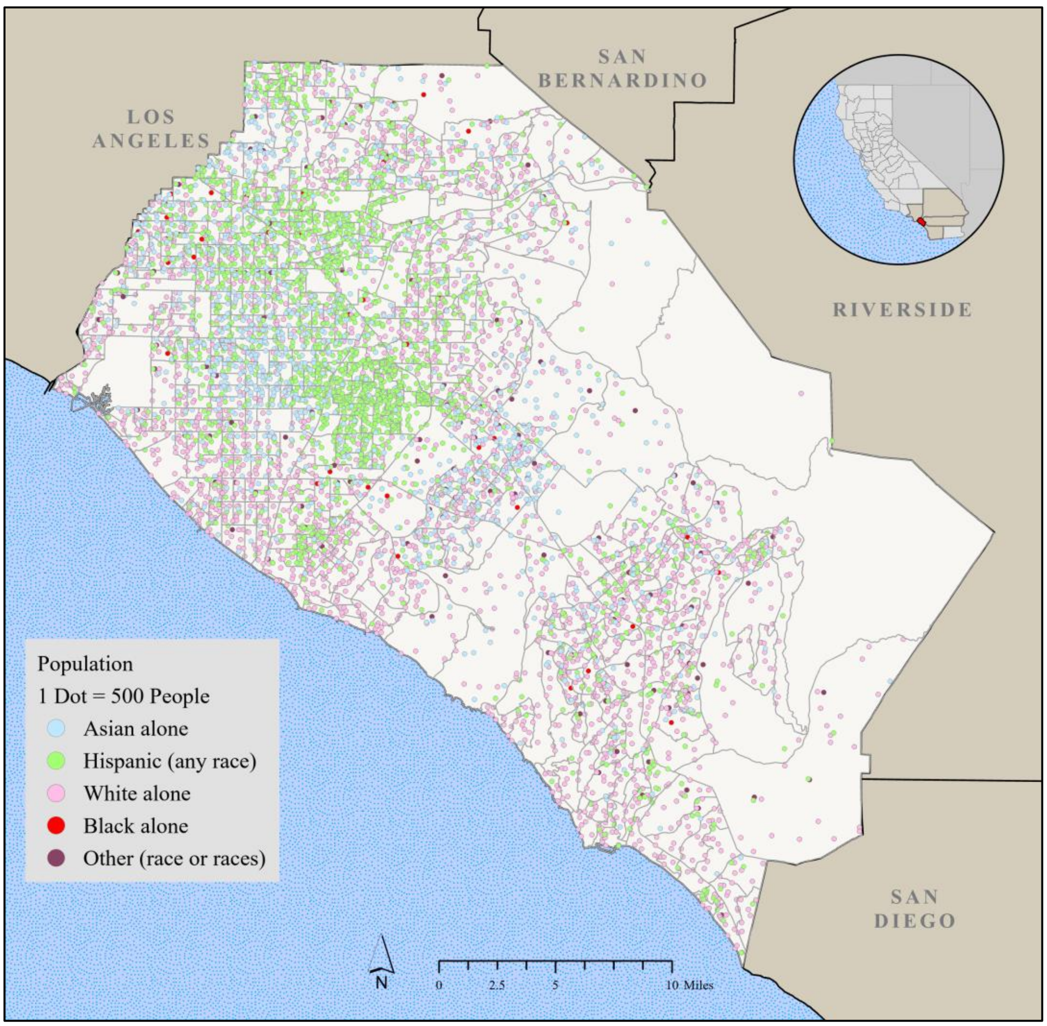
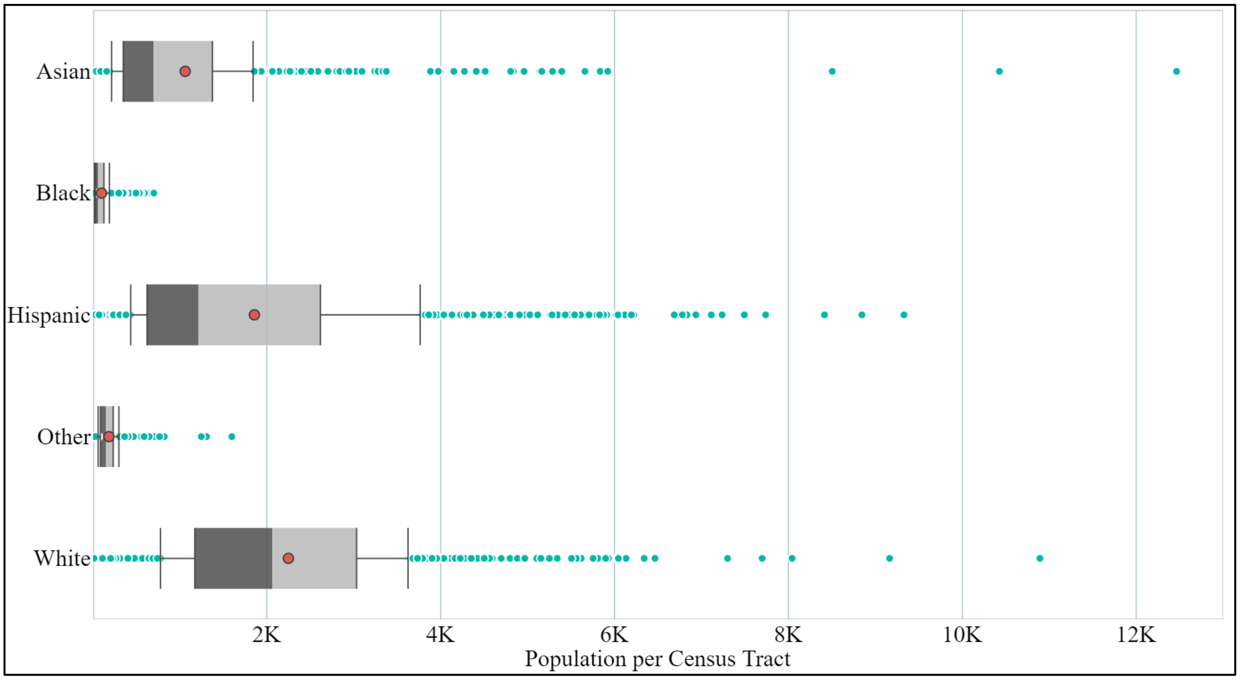


Figure 12 OC Census Tract Population Dot Map

Figure 13 provides a box plot summary of the racial/ethnic population estimates for OC census tracts while Figure 14 normalizes the data by square mile per census tract.



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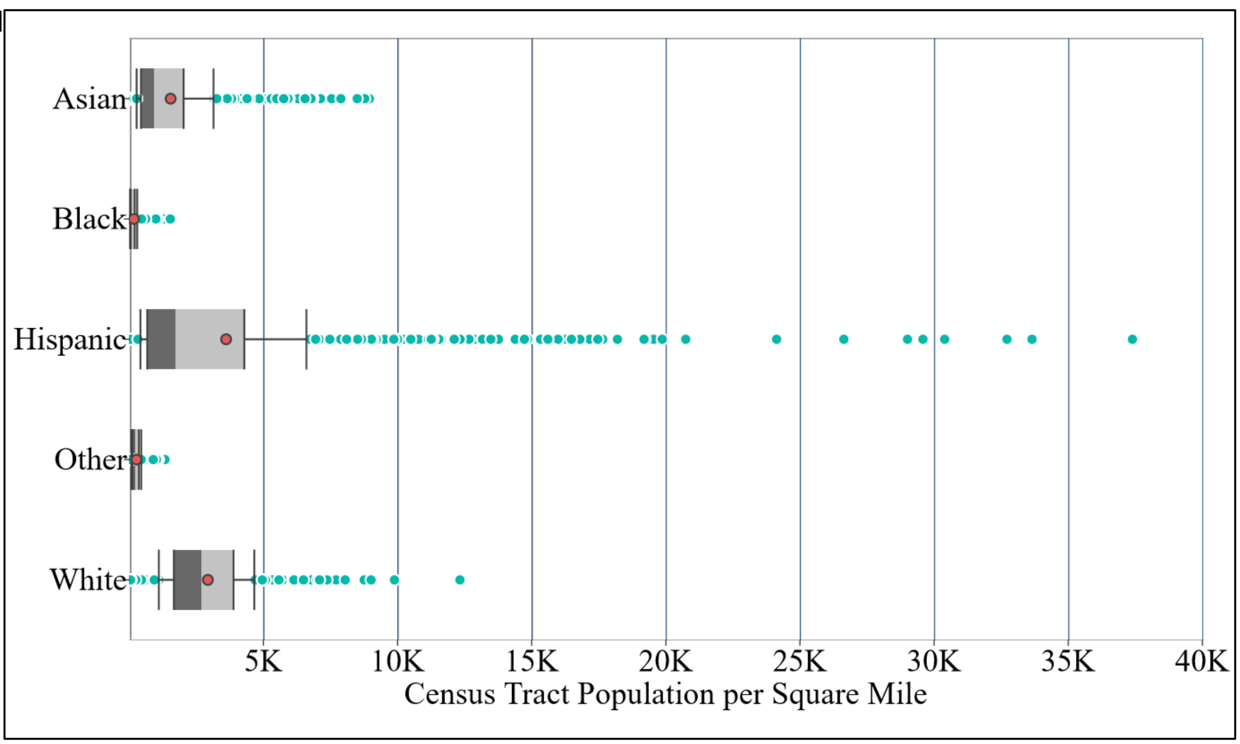

Figure 14 2017 ACS Table DP05 Estimates of Population Race/Ethnicity by Square Mile

3.2.3. Scale 2: Scaled Population Grid

The spatial distribution of humans in OC presents potential issues with using census tracts directly for spatial analysis. For example, the northern part of the county was densely populated with small areal census tracts, compared to the southern portion where there were large areal but sparsely populated census tracts (Figure 15). Moreover, there were multiple census tracts with large areas that were completely devoid of housing; these areas include

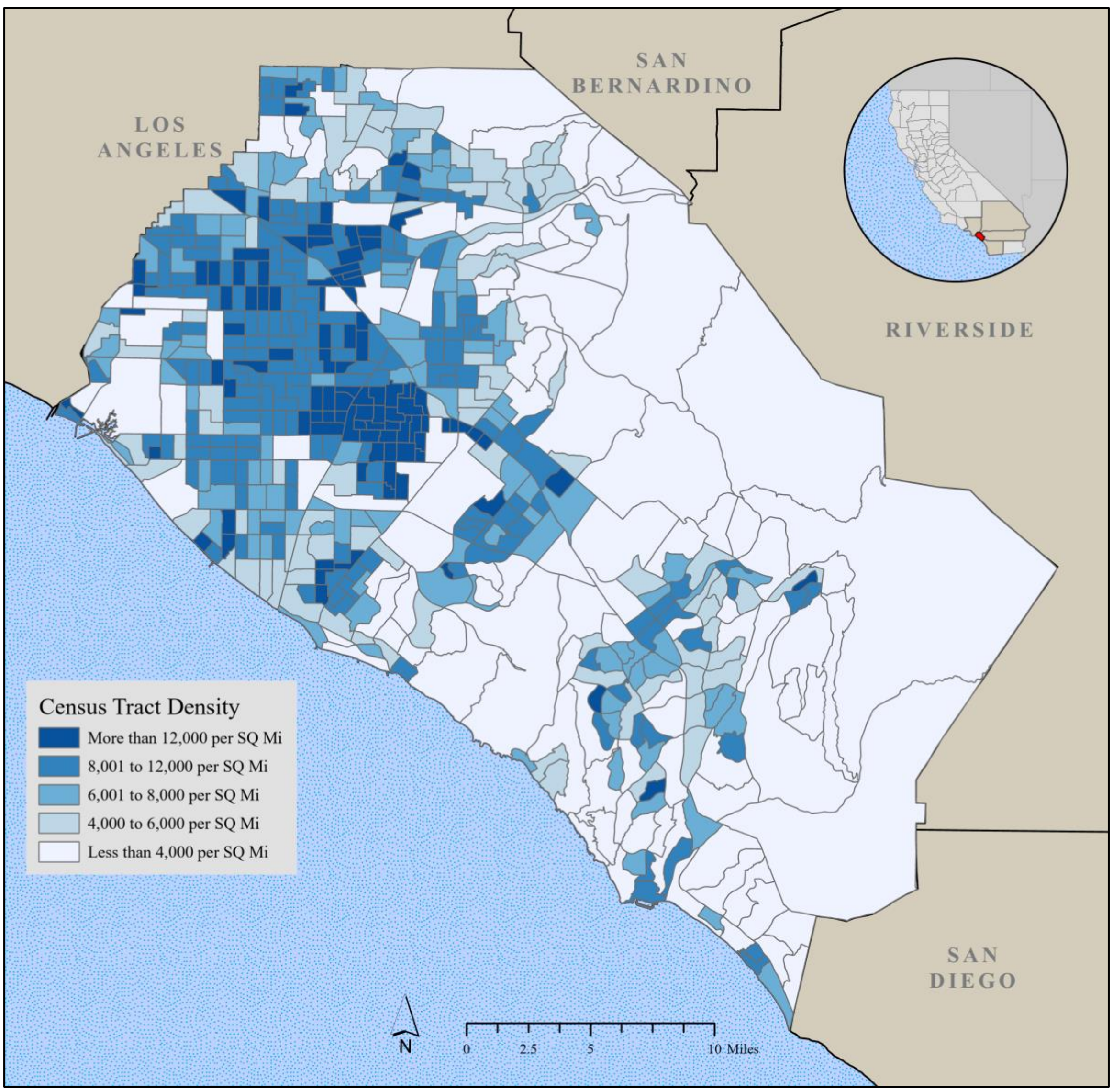

Figure 15 OC Census Tract Population Density

Disneyland, Naval Weapons Station Seal Beach, and numerous city, county, state, and national parks.

To address these population variation issues, this study utilized the ORNL LandScan Global 2018 (LG18) dataset, which provided an ambient population distribution raster with approximately 30 arcsecond (~ 0.5 mile) resolution. Figure 16 shows the LG18 raster superimposed over the study area. In the figure, the darker squares indicate higher population, whereas the white and tan areas indicate zero population. For this study, the LG18 raster was used as both a grid to spatially redistribute the census tract population counts into 30 arcsecond grid cells and to scale the underlying census tract populations.

This was necessary for three reasons. First, the LG18 dataset does not have any racial data, and second, some portions of the census tracts have areas with no population. Second, by scaling the census tract data areally to the LG18 population counts, the overall census tract racial populations remain the same, while the areal population distribution more closely resembles the built environment. Third, the cell samples the local population effectively no further than approximately a half mile from an alcohol license street address.

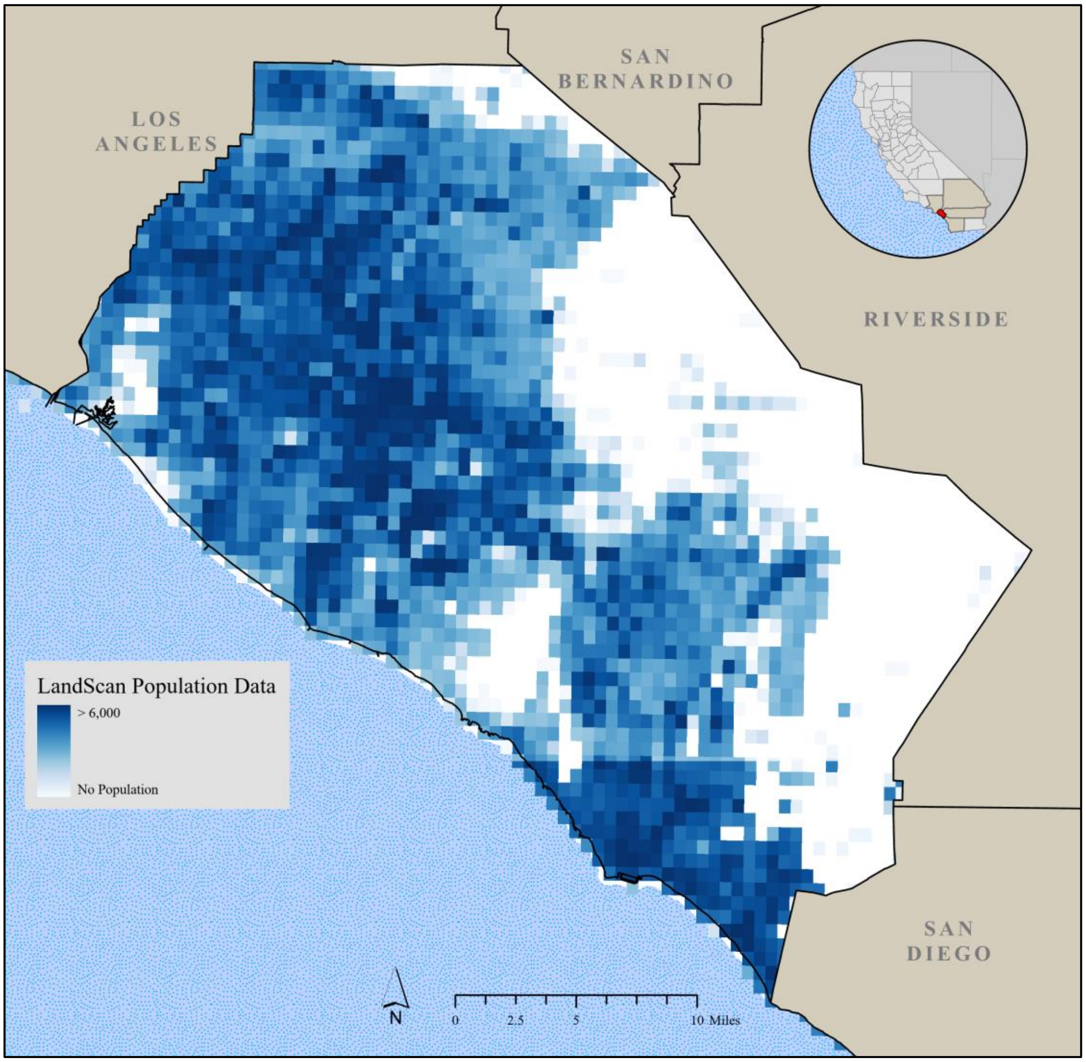

Figure 16 LandScan Population Surface, 2018

An areally weighted interpolation process was used to scale and redistribute the census tract population estimates into the grid cells. While the scaling and redistribution process required multiple steps, the process can be summarized simply. Where an LG18 cell intersects more than one census tract, split the LG18 population into each census tract by proportion of the LG18 cell covered by each census tract. Next, divide the census tract populations proportionally by area into a new grid LG18 based grid (scalar 1). Where multiple census tracts intersect a cell, divide the census tract populations proportionally by their proportional area within the cell, then split the new LG18 cells by the census tract boundaries and calculate areal differences (scalar 2). Next scale the total and racial population values using scalar 1, scalar 2, and the original LG18 cell population values (scalar 3). Finally, create the final grid by summarizing all the scaled population values from step Four into an LG18 based grid.

The result was a scaled population grid with 3,097 cells with each cell approximately 0.28 square miles in size and 0.57 miles on a side. Moreover, of the 3,097 cells, 2,172 were identified as having some population. Figure 17 presents the final redistributed population grid for OC.

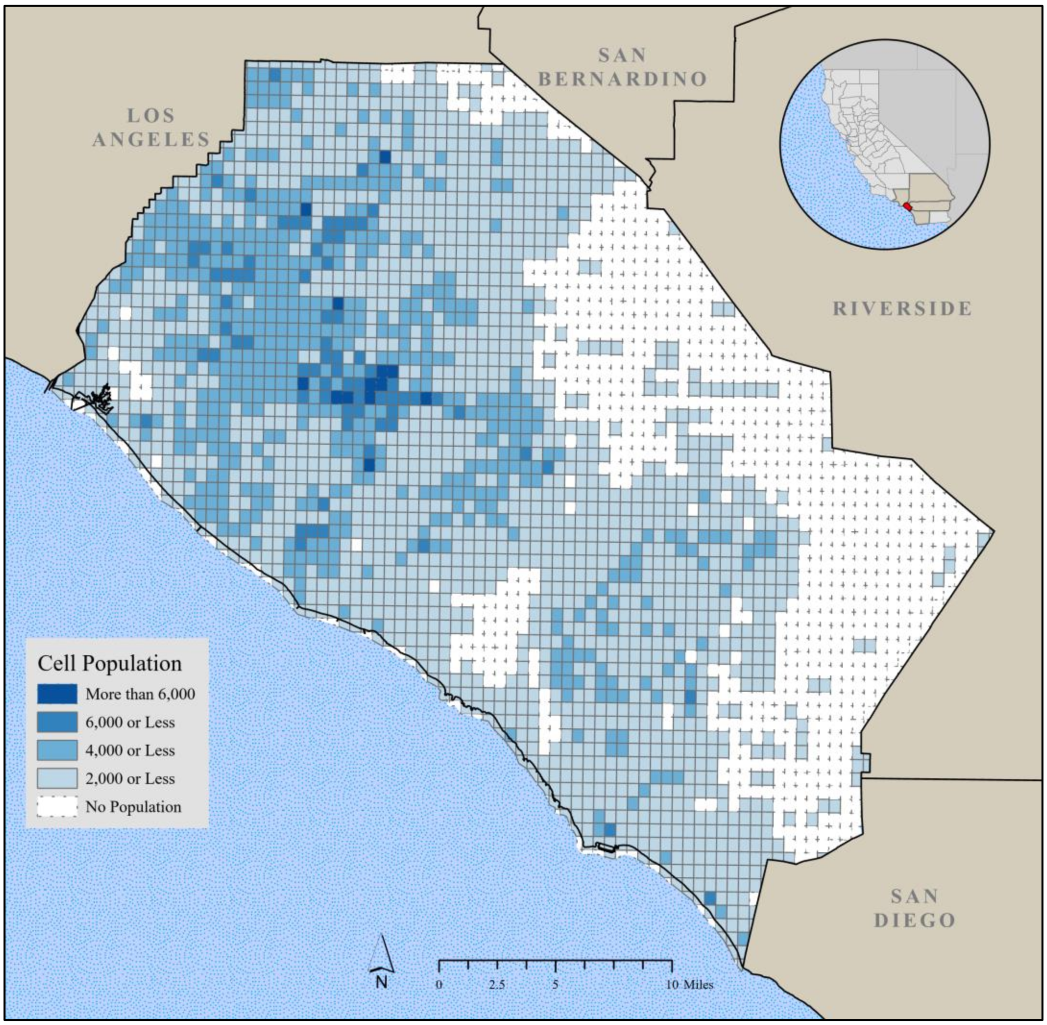

Figure 17 OC Scaled Population Grid

Furthermore, each cell has the ACS racial populations based upon the underlying census tracts scaled locally by the census tract composite values of the LG18 cells (see Figure 18). However, while the grid provided higher population fidelity for areas with minimum and maximum local population distributions, the allocation of the racial populations to each grid cell is a proportional (fractional) distribution across the landscape—a potentially unlikely scenario in the real world, especially in large areal census tracts. While this did introduce a question as to whether the race/ethnicity dynamics in the census tracts were amenable to proportional allocation in the cells, there are two factors that suggest those concerns were minimal in Orange County.

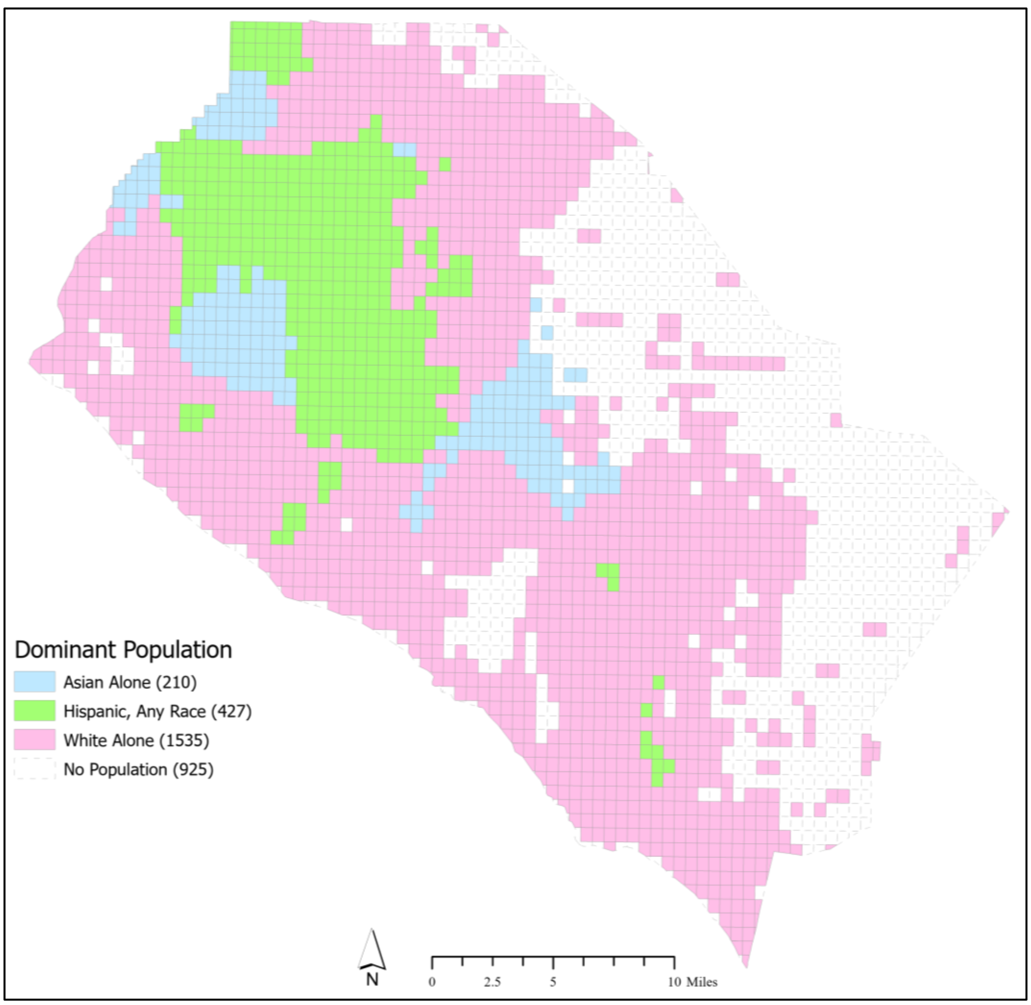

Figure 18 OC Scaled Population Grid with Dominant Race/Ethnicity

First, the denser areas of Orange County have smaller areal census tracts which were scaled into similarly sized LandScan cells covering the same general area. Thus, any localized race/ethnicity dynamics would likely be dispersed or concentrated in no more than two to four scaled cells within close proximity to the origin census tracts. Second, the larger census tracts in Orange County tended to have less racial diversity while also having significant open space where there was little to no population. Overall, the previously inaccurate areal dispersal of the census tract population was more accurately concentrated in cells that had been identified by the LandScan data as having discernible populated areas.

3.3 Quantifying Race Neutral and Disparate Distributions

While this study's premise that race-neutral regulations should result in distributions of retailers where the populations near the retailers are representative of county-wide populations is straightforward, observing such distributions in the spatial reality of the built environment is more complicated. First, individual census tracts or other areal units are unlikely to have population proportions matching the county-wide proportions. Second, no single sampling scheme or analytic method can prove the absence or presence of race-neutrality under all conditions arising in and from the built environment.

Thus, multiple complimentary analytical methods applied to both census tracts and the scaled population grid cells ensured that there were sufficient robust observations to support the study's conclusions. One set of methods analyzed summary statistics regarding the presence and absence of licenses and retailers in the aggregate, while a second set used simple linear regressions to analyze license densities versus population proportions. After each analysis, nonvalid results were discarded and additional thresholds applied to account for margins of error and other dynamic variations in the built environment.

For the first method, summary population proportions were created for both the presence and absence of all licenses, each license type, and all retailers based on the aggregate race/ethnicity populations of census tracts and scaled population grid cells. Population proportions were similarly created for each bin of Getis Ord Gi* hot spot analyses performed on both the census tract and scaled population grid cell data. The differences between the observed population proportions from county-wide proportions were then calculated and adjusted using margins of error values (from both the county-wide and observed variables) that would produce the least difference between the county-wide and observed proportions. The least difference adjustment was chosen in order to bias the results towards an outcome inline with a best-case scenario of the ACS estimates being accurate, whereas a greatest difference adjustment would have biased the results towards a worst-case scenario of the ACS estimates being inaccurate. Thereafter, differences within the margin of error (designated "E" in *Dist* columns in summary tables) were excluded from further evaluation.

Finally, the remaining differences were evaluated for disparate distributions using tiered cutoffs to account for dynamic built environment variations; these evaluations were captured in *Dist* columns of summary tables. If there was a difference of less than 5%, the observation was deemed a race-neutral distribution ("N"). If the difference was between 5% and 10%, the observation was deemed a race-correlated distribution ("C"). Finally, if the difference was 10% or greater, the observation was deemed a disparate distribution ("D"). These cutoffs were chosen to account for random population variations while recognizing that to qualify as a disparate distribution needed to be more than a nominal difference from the county-wide average.

For the second method, the license/retailer density per square mile per census tract and density per 1,000 people per census tract were analyzed using a simple linear regression:

$$Y_l = b_0 + \ b_1 X_p \tag{2}$$

Where independent variable X_p is the Asian/Hispanic/White percent of population per tract and dependent variable Y_l is the license or retailer density per tract. Similar regressions were performed on the scaled population grid cells.

If a regression result p-value was greater than 0.05, the result was discarded as not statistically significant; otherwise, the trend line polarities (signs) of the race/ethnicity populations were compared. Results where polarities were the same were deemed race neutral distributions (“N”), while opposite polarities were deemed race-correlated distributions (“C”). The slope polarity provides a simple metric that indicates a positive or negative correlation between the dependent and independent variables, with the assumption that a race neutral distribution would occur when all races/ethnicities exhibit the same slope polarity. Arguably, comparing the slope magnitudes would provide greater certainty, but there are currently no benchmarks for analyzing what magnitudes would be significant for each set of race/ethnicity and license/retailer density scenarios.

After performing the analyses outlined above, the totality of the results for the Asian, Hispanic, and White populations for each scenario was assessed. An occurrence of two or more D’s was deemed a disparate distribution, while a single D or the occurrence of two or more C’s was deemed a race-correlated distribution. Any other combination was deemed race neutral; these assessments were documented in summary tables in *Dist* columns. This provided a consistent framework for evaluating whether race-neutral or disparate distributions were occurring for all combinations of race/ethnicities and licenses/retailers at both the census tract and scaled population grid cell level. Additionally, the results for the Black and Other populations were also generated and included for anecdotal review, but were not factors in the final distribution assessments.

Chapter 4 Results

As the works cited in Chapter 2 suggests, excessive access to alcohol has been associated with negative outcomes for individuals and communities. Moreover, minority communities tend to experience greater negative environmental burdens compared to nearby white majority neighborhoods. Yet, as a general premise, the concentration of retail outlets selling package alcoholic beverages in a community should be largely uniform and not correlated with the racial composition of the community. In California, legislation has existed since the early 1990's that mandates just such a race neutral alcohol retailer licensing scheme. This study set out to determine if the race neutral licensing scheme has resulted in a race neutral distribution of alcohol retailers in Orange County, California.

Analyzing the spatial distribution of alcohol licenses in Orange County, California entailed a multi-step process. First, the license data was obtained from the ABC and geocoded to geographic coordinates. Next the license data was matched against a business analytics database to facilitate classifying the licenses into retailer type (liquor store, grocery store, gas station, etc.) for analysis. Finally, the spatial distributions of the licenses were analyzed at two scales—census tract and a scaled population grid of ~ 0.25 square mile cells—using multiple analytical techniques. This chapter details the results.

4.1 Scale 1: Census Tract Analytical Results

The distributions of alcohol licenses at the census tract level were analyzed using summary statistics, simple linear regression trend line slope analysis, and Getis Ord Gi* hot spot analysis. The following sections examine the results of those analyses at the census tract level.

4.1.1. Census Tract Alcohol License Summary Statistics

If a race-neutral function controls the distribution of alcohol retailers in Orange County census tracts, then both the presence and absence of alcohol retailers should generally follow the demographic profiles of the census tracts. Thus, the first step in analyzing the distribution of alcohol licenses at the census tract level was to explore the percentage of the Orange County census tract populations that do and do not have alcohol licenses (see Figure 19).

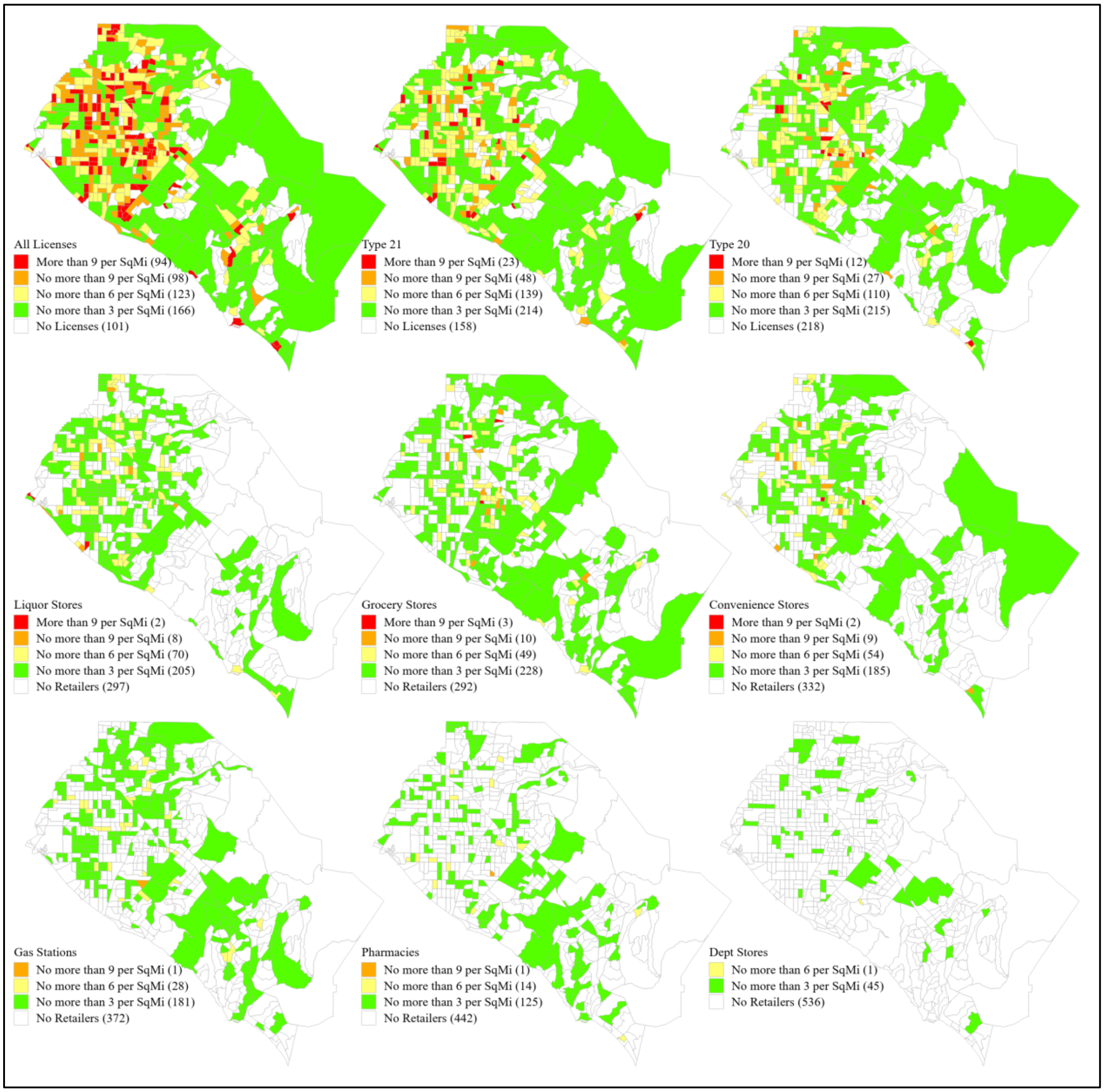

Figure 19 OC Census Tracts with Alcohol Licenses

Out of 582 census tracts, 101 did not have any licensed alcohol licenses. These 101 census tracts represented 15.3% of the OC population. As Table 8 illustrates, an expected population distribution (*% Expected* column) was created by scaling the county census tract population percentages by 15.3% to allow comparison with the actual aggregated population percentages (*% Actual* column) of those census tracts with no licenses. Next, the differences between the county (*Pop % County* column) and tract (*Pop % Tracts* column) percentages and the differences between the expected and actual population distributions were evaluated to determine if there were any disparate distributions (*Dist* columns).

Table 8 Orange County Summary Statistics of Census Tracts with Zero License

Tracts with Zero Alcohol Licenses: 101 / 15.3% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	20.55% (±0.48)	**C**	2.98%	3.14% (±0.07)	**N**
Hispanic (any race**)**	34.2% (*)	18.75% (±0.56)	**D**	5.22%	2.86% (±0.08)	**D**
White Alone	41.4% (±.1)	55.18% (±0.67)	**D**	6.32%	8.43% (±0.1)	**D**
Black Alone	1.6% (±.1)	1.51% (±0.23)	*D*	0.24%	0.23% (±0.04)	*E*
All Other Race(s)	3.3% (±.1)	4.01% (±0.26)	*D*	0.51%	0.61% (±0.04)	*D*
Totals	100%	100%		15.3%	15.3%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

However, when comparing the census tract actual percentages to the expected values, it must be kept in mind that the actual values are not linear, but rather aggregations of discrete values determined by the population of each individual census tract. For example, the census tract with the highest population in Orange County contributes 0.76% to the total population of

Orange County while the second most populated census tract contributes 0.62%. Anecdotally, both these census tracts also happen to have majority Asian populations. While inclusion or exclusion of highly populated census tracts like these could bias the aggregated percentages to a particular race/ethnicity, the assumption is that the aggregation of more than twenty census tracts will sufficiently render that particular bias small enough to be considered negligible.

The results in Table 8 suggest that Asians and Whites tended to have greater representation in no alcohol licenses census tracts than expected, even accounting for ACS margins of error. On the other hand, Hispanics tended to be underrepresented in those census tracts. These results were further bolstered by examining the population distribution within the target no alcohol census tracts (*Pop % Tracts* column) and comparing it with the general county distribution (*Pop % County*). Again, Whites and Asians had greater representation in no alcohol retailer census tracts compared to their county-wide populations, while Hispanics were significantly less represented compared to their county-wide population.

Moreover, the quantity of D values in the *Dist* columns suggested disparate distributions were occurring at multiple evaluation points. While these results were not conclusive of racial disparity in the distribution of alcohol licenses, they suggested a disparate distribution for the absence of alcohol licenses in those census tracts.

A similar approach was applied to analyze the census tracts with alcohol licenses. Out of 582 census tracts, 481 had one or more licensed alcohol retailers within their boundaries. Moreover, these 481 census tracts represented 84.7% of the OC population. As Table 9 illustrates, an expected population distribution (*% Expected* column) was created by scaling the county census tract totals by 84.7% to allow comparison with the actual aggregated population percentages (*% Actual* column) of those census tracts with retailers. Next, the differences between the county (*Pop % County* column) and tract (*Pop % Tracts* column) percentages and the differences between the expected and actual population distributions were evaluated to determine if there were any disparate distributions (*Dist* columns).

Table 9 Orange County Summary Statistics of Census Tracts with Alcohol Licenses

Tracts with Alcohol Licenses: 481 / 84.7% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.32% (±0.23)	**E**	19.75% (±0.13)	**E**	16.53%	16.37% (±0.19)	**E**
Hispanic (any race)	34.2% (*)	36.98% (±0.34)	**C**	39.07% (±0.2)	**D**	28.98%	31.33% (±0.29)	**C**
White Alone	41.4% (±.1)	38.91% (±0.28)	**C**	36.35% (±0.15)	**D**	35.08%	32.97% (±0.24)	**C**
Black Alone	1.6% (±.1)	1.58% (±0.1)	*D*	1.65% (±0.05)	*C*	1.33%	1.34% (±0.08)	*E*
All Other Race(s)	3.3% (±.1)	3.21% (±0.13)	*N*	3.18% (±0.07)	*E*	2.82%	2.72% (±0.11)	*E*
Totals	100%	100%		100%		84.7%	84.7%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

The results in Table 9 suggested that Whites tend to have lower representation in alcohol retailer census tracts than expected, even accounting for ACS margins of error. On the other hand, Hispanics tended to be overrepresented in those census tracts and the expected percentage of Asians was within the ACS margin of error to their actual percentage. These results were further bolstered by examining the population distribution within the aggregated census tracts (*Pop % Tracts* column) and comparing it with the general county distribution (*Pop % County* column). Again, Whites were underrepresented compared to their county-wide populations, while Hispanics were significantly overrepresented and Asians were within the margin of error.

However, as Figure 19 indicated, most census tracts had more than two alcohol licenses and this initial analysis did not account for the number of alcohol licenses in the census tracts. To evaluate the impact of multiple licenses in the census tracts, each census tract population value was multiplied by the number of licenses in the census tract and the resulting values were then aggregated to calculate new population proportions. this license scaled population proportion is displayed in the *(Pop x L) % Tracts* column.

As this column shows, after scaling the census populations by the number of alcohol licenses, the Hispanic population's overrepresentation had increased; suggesting that majority Hispanic census tracts had more retailers than would have occurred if a race neutral function was in operation. On the other hand, the White population showed greater underrepresentation after scaling compared to the White county-wide population suggesting the opposite, while the Asian population was still within the margin of error of its county-wide proportion. Finally, the combination of results in the three *Dist* columns suggests the absence of a race-neutral function in the distribution of alcohol licenses in Orange County.

As the above two tables indicate, the majority White population was both overrepresented in census tracts without alcohol retailers and underrepresented in census tracts with alcohol retailers. Likewise, the Hispanic population was both overrepresented in census tracts with alcohol retailers and underrepresented in census tracts without alcohol retailers. Moreover, while the Asian population somewhat tracked the White population in both categories, its over/underrepresentation was much closer to, if not within, the margins of error.

Next, of the 582 census tracts, 218 did not have any Type 20 licensed alcohol retailers. These 218 census tracts represented 35% of the OC population. Table 10 compared the expected 35% population estimates with the county-level percentages in those census tracts with No Type

20 licenses. The No Type-20 licenses statistics closely tracked the no licenses of any type statistics, with Hispanics underrepresented, White overrepresented, and Asian within the margins of error.

Table 10 OC Summary Statistics of Census Tracts with Zero Type 20 Licenses

Tracts with Zero Type 20 Alcohol Licenses: 218 / 35.0% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.21% (±0.33)	**N**	6.84%	6.73% (±0.12)	**E**
Hispanic (any race**)**	34.2% (*)	23.66% (±0.43)	**D**	11.98%	8.29% (±0.15)	**D**
White Alone	41.4% (±.1)	51.78% (±0.46)	**D**	14.5%	18.14% (±0.16)	**D**
Black Alone	1.6% (±.1)	1.5% (±0.15)	*D*	0.55%	0.53% (±0.05)	*E*
All Other Race(s)	3.3% (±.1)	3.83% (±0.19)	*D*	1.17%	1.34% (±0.06)	*C*
Totals	100%	100%		35.0%	35.0%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Turning to Type 20 licenses, these licenses occurred in 364 census tracts, representing 65% of the OC population. Table 11 presents the Type 20 licenses, which followed the same pattern as all Alcohol Licenses: Hispanics overrepresented, Whites underrepresented, and Asians nearly within the margins of error. Moreover, comparing the values in the *% Actual* and *Pop % Tracts* columns suggested that Type 20 licenses tended to be more prevalent in Hispanic dominant census tracts. Overall, multiple observations surpassed the 10% threshold for the difference between county-wide values and observations to be deemed disparate distributions.

Table 11 OC Summary Statistics of Census Tracts with Type 20 Licenses

Tracts with Type 20 Alcohol Licenses: 364 / 65.0% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.67% (±0.26)	**E**	18.99% (±0.19)	**N**	12.67%	12.78% (±0.17)	**E**
Hispanic (any race**)**	34.2% (*)	39.87% (±0.41)	**D**	43.04% (±0.31)	**D**	22.22%	25.9% (±0.26)	**D**
White Alone	41.4% (±.1)	35.79% (±0.31)	**D**	33.38% (±0.22)	**D**	26.9%	23.25% (±0.2)	**D**
Black Alone	1.6% (±.1)	1.61% (±0.11)	*D*	1.66% (±0.08)	*A*	1.02%	1.04% (±0.07)	*E*
All Other Race(s)	3.3% (±.1)	3.06% (±0.14)	*E*	2.93% (±0.1)	*N*	2.16%	1.99% (±0.09)	*E*
Totals	100%	100%		100%		65.0%	65.0%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Type 21 licenses were found in 424 census tracts and represented 76.3% of the population; the remaining 158 census tracts do not have Type 21 licenses and represent 23.7% population. Table 12 provides the summary statistics for census tracts with no Type 21 licenses and Table 13 the summary for census tracts with Type 21 licenses. These two tables show that while the Hispanic population was underrepresented in census tracts with zero Type 21 licenses, they appeared nominally race neutral unless license scaling was factored. On the other hand, the majority White population continued to manifest overrepresentation in the zero Type 21 license tracts and nominally race neutral representation in the Type 21 tracts. These values showed a different distribution profile than that which occurred in the Type 20 White and Hispanic populations.

Table 12 OC Summary Statistics of Census Tracts with Zero Type 21 Licenses

Tracts with Zero Type 21 Alcohol Licenses: 158 / 23.7% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.21% (±0.33)	**N**	4.63%	4.38% (±0.09)	**N**
Hispanic (any race**)**	34.2% (*)	23.66% (±0.43)	**D**	8.12%	7.23% (±0.12)	**C**
White Alone	41.4% (±.1)	51.78% (±0.46)	**D**	9.83%	10.95% (±0.12)	**D**
Black Alone	1.6% (±.1)	1.5% (±0.15)	*D*	0.37%	0.35% (±0.04)	*E*
All Other Race(s)	3.3% (±.1)	3.83% (±0.19)	*D*	0.79%	0.83% (±0.05)	*E*
Totals	100%	100%		23.7%	23.7%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 13 OC Summary Statistics of Census Tracts with Type 21 Licenses

Tracts with Type 21 Alcohol Licenses: 424 / 76.3% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.84% (±0.25)	**E**	20.28% (±0.17)	**N**	14.88%	15.13% (±0.19)	**E**
Hispanic (any race**)**	34.2% (*)	35.36% (±0.37)	**N**	36.34% (±0.26)	**C**	26.08%	26.96% (±0.28)	**N**
White Alone	41.4% (±.1)	39.93% (±0.3)	**N**	38.39% (±0.2)	**C**	31.57%	30.45% (±0.23)	**N**
Black Alone	1.6% (±.1)	1.6% (±0.1)	*D*	1.65% (±0.07)	*C*	1.2%	1.22% (±0.08)	*E*
All Other Race(s)	3.3% (±.1)	3.27% (±0.13)	*C*	3.34% (±0.09)	*N*	2.54%	2.5% (±0.1)	*E*
Totals	100%	100%		100%		76.3%	76.3%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Moreover, comparing the values in the *Pop % Tracts* and the *(Pop x L) % Tracts* columns between this and the Type 20 scenario suggested that Type 21 licenses tended to be more prevalent in White dominant census tracts whereas Type 20 licenses were more prevalent in Hispanic dominant census tracts. On the other hand, the Asian population values were close to expected for a race neutral function or too close to the margins of errors. Overall, the values of the *(Pop x L) % Tracts* made the distribution more than race neutral, but also did not pass the disparate threshold.

The next step was to analyze each type of retailer, starting with the Liquor Store category. First, there were more tracts without liquor stores (N=297) than tracts with liquor stores (N=285). However, the percent of the population living in tracts without liquor stores was 48.5% compared to 51.5% living in tracts with liquor stores. Moreover, this category presented a unique case since it had the greatest number of retailers (N=418), and all Liquor Store retailers only had Type 21 licenses. Table 14 presents the no Liquor Store license summary statistics and Table 15 the Liquor Store summary statistics.

Table 14 OC Summary Statistics of Census Tracts with Zero Liquor Stores

Tracts with Zero Liquor Store Retailers: 297 / 48.5% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	20.45% (±0.3)	**C**	9.46%	9.92% (±0.14)	**N**
Hispanic (any race**)**	34.2% (*)	27.76% (±0.36)	**D**	16.59%	13.46% (±0.18)	**D**
White Alone	41.4% (±.1)	46.67% (±0.37)	**D**	20.08%	22.64% (±0.18)	**D**
Black Alone	1.6% (±.1)	1.49% (±0.13)	*D*	0.76%	0.72% (±0.07)	*E*
All Other Race(s)	3.3% (±.1)	3.64% (±0.18)	*D*	1.62%	1.76% (±0.09)	*E*
Totals	100%	100%		48.5%	48.5%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 15 OC Summary Statistics of Census Tracts with Liquor Stores

Tracts with Liquor Store Retailers: 285 / 51.5% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	18.62% (±0.29)	**N**	18.03% (±0.23)	**C**	10.05%	9.59% (±0.15)	**N**
Hispanic (any race**)**	34.2% (*)	40.26% (±0.48)	**D**	40.87% (±0.39)	**D**	17.61%	20.73% (±0.25)	**D**
White Alone	41.4% (±.1)	36.43% (±0.35)	**D**	36.45% (±0.29)	**D**	21.32%	18.76% (±0.18)	**D**
Black Alone	1.6% (±.1)	1.65% (±0.12)	*D*	1.64% (±0.1)	*A*	0.81%	0.85% (±0.06)	*E*
All Other Race(s)	3.3% (±.1)	3.04% (±0.14)	*E*	3.01% (±0.12)	*E*	1.71%	1.56% (±0.07)	*N*
Totals	100%	100%		100%		51.5%	51.5%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Hispanics fared worse with liquor stores compared to their Type 21 statistics. They were even more underrepresented in no liquor census tracts (27.76%: liquor vs 30.46%: Type 21) and likewise further overrepresented with regards to population scaled by the number of Type 21 licenses compared to number of liquor stores (40.87%: liquor vs 36.34%: Type 21). Whites were nearly unchanged in census tracts without liquor stores compared to Type 21 licenses, but Asian have increased representation (20.45% liquor vs 18.43% Type 21). On the other hand, both Whites and Asians each represented nearly 2% less population for liquor stores compared to the Type 21 licenses. These statistics suggested that liquor stores may be more concentrated in Hispanic dominated census tracts compared to the other Type 21 retailers. The significant quantity of Ds in the *Dist* columns of both tables further suggested Liquor Stores were disparately distributed.

One other retailer category, Wholesale Clubs (i.e. Costco and Sam's Club), was comprised solely of retailers with Type 21 licenses. However, because only 2.8% of the county population was present in the fifteen census tracts where those retailers (N=16) were located, this sample was deemed too small to make a meaningful assessment and the results were excluded from distribution assessment (see Table 17). On the other hand, 567 census tracts do not have a Wholesale Club with an alcohol license and those tracts represent 97.2% of the county; this large sample size did allow for an inference of a race-neutral function operating for their absence (see Table 16).

Table 16 OC Summary Statistics of Census Tracts with Zero Wholesale Clubs

Tracts with Zero Wholesale Club Retailers: 567 / 97.2% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.28% (±0.21)	**N**	18.96%	18.74% (±0.2)	**E**
Hispanic (any race**)**	34.2% (*)	34.32% (±0.3)	**N**	33.24%	33.36% (±0.29)	**E**
White Alone	41.4% (±.1)	41.53% (±0.26)	**N**	40.24%	40.36% (±0.25)	**E**
Black Alone	1.6% (±.1)	1.56% (±0.09)	*D*	1.53%	1.51% (±0.09)	*E*
All Other Race(s)	3.3% (±.1)	3.32% (±0.12)	*C*	3.24%	3.22% (±0.11)	*E*
Totals	100%	100%		97.2%	97.2%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 17 OC Summary Statistics of Census Tracts with Wholesale Clubs

Tracts with Wholesale Club Retailers: 15 / 2.8% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	27.53% (±1.77)	**D**	26.19% (±1.68)	**D**	0.55%	0.77% (±0.05)	**D**
Hispanic (any race**)**	34.2% (*)	29.82% (±2.76)	**E**	32.51% (±2.65)	**E**	0.96%	0.84% (±0.08)	**E**
White Alone	41.4% (±.1)	36.88% (±1.83)	**C**	35.65% (±1.74)	**C**	1.16%	1.03% (±0.05)	**C**
Black Alone	1.6% (±.1)	2.08% (±0.77)	*E*	2.09% (±0.73)	*E*	0.04%	0.06% (±0.02)	*E*
All Other Race(s)	3.3% (±.1)	3.69% (±0.7)	*E*	3.56% (±0.66)	*E*	0.09%	0.1% (±0.02)	*E*
Totals	100%	100%		100%		2.8%	2.8%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Grocery Stores (N=412) represented the second largest retailer category behind Liquor Stores (N=418) in the OC built environment. Although Grocery Stores may hold either a Type 20 or Type 21 license, the majority (N=300) operated with a Type 21 license like Liquor Stores. In Orange County, there were 292 census tracts with 45.5% of the population that did not have a grocery store with an alcohol license compared to 290 tracts with 54.5% of the population that did (see Table 18 and Table 19). Table 18 shows that the Hispanic population is underrepresented in census tracts without grocery stores holding an alcohol license, but overall, the table *Dist* values did not cross the threshold for disparate distribution. Table 19 *Dist* column values, on the other hand, suggested disparate distributions were occurring in the census tracts with grocery stores.

Table 18 OC Summary Statistics of Census Tracts with Zero Grocery Stores

Tracts with Zero Grocery Store Retailers: 292 / 45.5% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.04% (±0.28)	**N**	8.88%	8.67% (±0.13)	**E**
Hispanic (any race**)**	34.2% (*)	31.09% (±0.42)	**D**	15.57%	14.16% (±0.19)	**C**
White Alone	41.4% (±.1)	44.86% (±0.37)	**C**	18.85%	20.43% (±0.17)	**C**
Black Alone	1.6% (±.1)	1.58% (±0.13)	*D*	0.71%	0.72% (±0.06)	*E*
All Other Race(s)	3.3% (±.1)	3.43% (±0.15)	*D*	1.52%	1.56% (±0.07)	*E*
Totals	100%	100%		45.5%	45.5%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 19 OC Summary Statistics of Census Tracts with Grocery Stores

Tracts with Grocery Store Retailers: 290 / 54.5% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.9% (±0.3)	**E**	20.5% (±0.26)	**N**	10.63%	10.84% (±0.16)	**E**
Hispanic (any race**)**	34.2% (*)	36.79% (±0.43)	**C**	38.3% (±0.39)	**D**	18.63%	20.04% (±0.23)	**C**
White Alone	41.4% (±.1)	38.5% (±0.36)	**C**	36.41% (±0.3)	**D**	22.55%	20.97% (±0.19)	**C**
Black Alone	1.6% (±.1)	1.56% (±0.13)	*D*	1.54% (±0.1)	*C*	0.86%	0.85% (±0.07)	*E*
All Other Race(s)	3.3% (±.1)	3.24% (±0.17)	*C*	3.24% (±0.14)	*C*	1.81%	1.77% (±0.09)	*E*
Totals	100%	100%		100%		54.5%	54.5%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Like, retailers in the Grocery Store category, retailers in the remaining categories may hold either a Type 20 or Type 21 license. The third most prevalent retailer category was Convenience Store (N=347). The majority of retailers in this category held a Type 20 license (N=296), while the rest held a Type 21 (N=51). There were 332 census tracts representing 54.4% of the population that did not have a retailer in the Convenience Store category (see Table 20), while 250 tracts with 45.6% of the population did (see Table 21).

Table 20 OC Summary Statistics of Census Tracts with Zero Convenience Stores

Tracts with Zero Convenience Store Retailers: 332 / 54.4% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	20.9% (±0.28)	**C**	10.6%	11.36% (±0.15)	**C**
Hispanic (any race**)**	34.2% (*)	26.25% (±0.36)	**D**	18.59%	14.27% (±0.2)	**D**
White Alone	41.4% (±.1)	47.73% (±0.36)	**D**	22.5%	25.94% (±0.2)	**D**
Black Alone	1.6% (±.1)	1.43% (±0.11)	*D*	0.85%	0.78% (±0.06)	*E*
All Other Race(s)	3.3% (±.1)	3.7% (±0.17)	*D*	1.81%	2.01% (±0.09)	*C*
Totals	100%	100%		54.4%	54.4%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 21 OC Summary Statistics of Census Tracts with Convenience Stores

Tracts with Convenience Store Retailers: 250 / 45.6% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	17.85% (±0.31)	**C**	17.8% (±0.26)	**C**	8.91%	8.15% (±0.14)	**C**
Hispanic (any race**)**	34.2% (*)	43.66% (±0.51)	**D**	45.54% (±0.43)	**D**	15.61%	19.93% (±0.23)	**D**
White Alone	41.4% (±.1)	33.86% (±0.37)	**D**	32.2% (±0.3)	**D**	18.9%	15.45% (±0.17)	**D**
Black Alone	1.6% (±.1)	1.74% (±0.15)	*E*	1.7% (±0.12)	*E*	0.72%	0.8% (±0.07)	*E*
All Other Race(s)	3.3% (±.1)	2.89% (±0.15)	*N*	2.76% (±0.13)	*C*	1.52%	1.32% (±0.07)	*C*
Totals	100%	100%		100%		45.7%	45.6%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

The values in the tables indicated that a large percentage of the Hispanic population had access to convenience stores and are overrepresented compared to Whites and Asians. On the other hand, the Asian values were slightly outside the margins of error and more closely track the White population than the previously examined categories. Finally, *Dist* column values in both tables suggested disparate distributions were occurring.

The fourth most prevalent retailer category was Gas Stations (N=270). Like Convenience Stores, the majority of retailers in this category held a Type 20 license (N=255), while the rest held a Type 21 (N=15). There were 372 census tracts representing 62.0% of the population that did not have a retailer in the Gas Station category (see Table 22), while 210 tracts with 38.0% of the population did (see Table 23). As the values in the *Dist* columns in both tables show, there appeared to be a mix of race-neutral and absence of race-neutral distributions occurring with Gas Stations. The Zero Gas Stations scenario appeared to be nearly race-neutral.

Table 22 OC Summary Statistics of Census Tracts with Zero Gas Stations

Tracts with Zero Gas Station Retailers: 372 / 62.0% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	18.47% (±0.24)	**C**	12.1%	11.45% (±0.15)	**N**
Hispanic (any race**)**	34.2% (*)	33.29% (±0.36)	**N**	21.21%	20.65% (±0.22)	**N**
White Alone	41.4% (±.1)	43.45% (±0.32)	**C**	25.68%	26.95% (±0.2)	**N**
Black Alone	1.6% (±.1)	1.48% (±0.12)	*D*	0.97%	0.92% (±0.07)	*E*
All Other Race(s)	3.3% (±.1)	3.32% (±0.13)	*C*	2.07%	2.06% (±0.08)	*E*
Totals	100%	100%		62.0%	62.0%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 23 OC Summary Statistics of Census Tracts with Gas Stations

Tracts with Gas Station Retailers: 210 / 38.0% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	21.21% (±0.54)	**C**	22.19% (±0.35)	**D**	7.41%	8.05% (±0.14)	**C**
Hispanic (any race**)**	34.2% (*)	35.68% (±0.42)	**N**	34.88% (±0.5)	**E**	12.99%	13.55% (±0.21)	**N**
White Alone	41.4% (±.1)	38.04% (±0.14)	**C**	37.73% (±0.38)	**C**	15.72%	14.45% (±0.16)	**C**
Black Alone	1.6% (±.1)	1.72% (±0.21)	*E*	1.79% (±0.13)	*E*	0.6%	0.65% (±0.05)	*E*
All Other Race(s)	3.3% (±.1)	3.34% (±0.21)	*C*	3.41% (±0.2)	*E*	1.26%	1.27% (±0.08)	*E*
Totals	100%	100%		100%		38.0%	38.0%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

There were 159 Pharmacies licensed to sell alcohol in Orange County; the majority of which had Type 21 licenses (N=135). The pharmacies were spread among 140 census tracts containing 26.1% of the population leaving 442 census tracts with 73.9% of the population without pharmacies (see Table 24 and Table 25). Notably, Pharmacy was the only retailer category where, although within the race neutral threshold, the White population was overrepresented in the census tracts with the retailer.

Table 24 OC Summary Statistics of Census Tracts with Zero Pharmacies

Tracts with Zero Pharmacy Retailers: 442 / 73.9% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.4% (±0.23)	**N**	14.41%	14.33% (±0.17)	**E**
Hispanic (any race**)**	34.2% (*)	35.21% (±0.35)	**N**	25.26%	26.01% (±0.26)	**N**
White Alone	41.4% (±.1)	40.61% (±0.29)	**N**	30.58%	30.0% (±0.21)	**N**
Black Alone	1.6% (±.1)	1.57% (±0.1)	*D*	1.16%	1.16% (±0.07)	*E*
All Other Race(s)	3.3% (±.1)	3.21% (±0.12)	*C*	2.46%	2.37% (±0.09)	*E*
Totals	100%	100%		73.9%	73.9%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 25 OC Summary Statistics of Census Tracts with Pharmacies

Tracts with Pharmacy Retailers: 140 / 26.1% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.83% (±0.63)	**E**	19.52% (±0.43)	**N**	5.1%	5.18% (±0.12)	**E**
Hispanic (any race**)**	34.2% (*)	31.33% (±0.56)	**C**	32.63% (±0.59)	**N**	8.94%	8.19% (±0.16)	**C**
White Alone	41.4% (±.1)	43.61% (±0.2)	**N**	42.53% (±0.52)	**E**	10.82%	11.4% (±0.15)	**N**
Black Alone	1.6% (±.1)	1.58% (±0.27)	*D*	1.58% (±0.18)	*D*	0.41%	0.41% (±0.05)	*E*
All Other Race(s)	3.3% (±.1)	3.65% (±0.27)	*E*	3.74% (±0.28)	*E*	0.87%	0.96% (±0.07)	*E*
Totals	100%	100%		100%		26.1%	26.1%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Overall, the Pharmacy category *Dist* column values, like the Wholesale Club category, suggested that a race neutral function operated for the absence of pharmacies in the built environment. On the other hand, where pharmacies occurred barely passed the threshold for the absence of a race neutral distribution.

Department Stores was the final category. As Table 26 shows, Department Stores (N=50) were absent in 536 census tracts and the *Dist* column values showed a race-neutral distribution. Likewise, Table 27 indicates they were present in 46 census tracts and the *Dist* column values show a disparate distribution; moreover, the Asian population appeared overrepresented in the census tracts where department stores were present.

Table 26 OC Summary Statistics of Census Tracts with Zero Department Stores

Tracts with Zero Department Store Retailers: 536 / 91.0% of OC Population						
	Pop % County	**Pop % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	18.91% (±0.21)	**N**	17.75%	17.21% (±0.19)	**N**
Hispanic (any race**)**	34.2% (*)	34.19% (±0.31)	**N**	31.12%	31.11% (±0.28)	**E**
White Alone	41.4% (±.1)	42.04% (±0.27)	**N**	37.67%	38.25% (±0.25)	**N**
Black Alone	1.6% (±.1)	1.55% (±0.09)	*D*	1.43%	1.41% (±0.09)	*E*
All Other Race(s)	3.3% (±.1)	3.31% (±0.11)	*C*	3.03%	3.01% (±0.1)	*E*
Totals	100%	100%		91.0%	91.0%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 27 OC Summary Statistics of Census Tracts with Department Stores

Tracts with Department Store Retailers: 46 / 9.0% of OC Population								
	Pop % County	**Pop % Tracts**	**Dist**	**(Pop x L) % Tracts**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	25.54% (±1.26)	**D**	25.31% (±0.9)	**D**	1.76%	2.3% (±0.08)	**D**
Hispanic (any race**)**	34.2% (*)	34.28% (±0.85)	**E**	33.51% (±1.28)	**E**	3.08%	3.09% (±0.11)	**E**
White Alone	41.4% (±.1)	34.89% (±0.31)	**D**	35.83% (±0.83)	**D**	3.73%	3.15% (±0.08)	**D**
Black Alone	1.6% (±.1)	1.74% (±0.4)	*E*	1.74% (±0.31)	*E*	0.14%	0.16% (±0.03)	*E*
All Other Race(s)	3.3% (±.1)	3.54% (±0.4)	*E*	3.61% (±0.38)	*E*	0.3%	0.32% (±0.04)	*E*
Totals	100%	100%		100%		9.0%	9.0%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 28 summarizes the *(Pop x L) % Tracts* column values and overall distribution assessments of the license/retailers for all the census tract scenarios. As the table indicates, the Hispanic-dominated communities had the most overrepresentation scenarios. Also, the majority of scenarios exceeded the disparate distribution threshold for the Hispanic population. Two anecdotal observations were also made, first although the Black population accounted for less than 2% of the Orange County total population and was not part of the distribution assessments, there was a positive correlation for the Black population with all but two of the scenarios, Pharmacies and Grocery Stores. Second, there did not appear to be a consistent positive or negative correlation between the Other population and the presence of alcohol licenses or retailers; this was likely due to the fact that the Other population was made up of multiple small sub-populations.

Table 28 OC Census Tracts with Licenses Population Summary

	Asian	**Hispanic**	**White**	**Black**	**Other**	**Dist**
Orange County	19.5% (±0.1)	34.2% *	41.4% (±0.1)	1.6% (±0.1)	3.3% (±0.1)	N/A
All	19.75% (±0.13)	**39.07% (±0.2)**	36.35% (±0.15)	1.65% (±0.05)	3.18% (±0.07)	**D**
Type 21	20.28% (±0.17)	**36.34% (±0.26)**	38.39% (±0.2)	1.65% (±0.07)	3.34% (±0.09)	**C**
Type 20	18.99% (±0.19)	**43.04% (±0.31)**	33.38% (±0.22)	1.66% (±0.08)	2.93% (±0.1)	**D**
Liquor Stores	18.03% (±0.23)	**40.87% (±0.39)**	36.45% (±0.29)	1.64% (±0.1)	3.01% (±0.12)	**D**
Grocery Stores	20.5% (±0.26)	**38.3% (±0.39)**	36.41% (±0.3)	1.54% (±0.1)	3.24% (±0.14)	**D**
Convenience Stores	17.8% (±0.26)	**45.54% (±0.43)**	32.2% (±0.3)	1.7% (±0.12)	2.76% (±0.13)	**D**
Gas Stations	**22.19% (±0.35)**	34.88% (±0.5)	37.73% (±0.38)	1.79% (±0.13)	3.41% (±0.2)	**C**
Pharmacies	19.52% (±0.43)	32.63% (±0.59)	**42.53% (±0.52)**	1.58% (±0.18)	3.74% (±0.28)	**C**
Department Stores	**25.31% (±0.9)**	33.51% (±1.28)	35.83% (±0.83)	1.74% (±0.31)	3.61% (±0.38)	**D**
Wholesale Clubs	**26.19% (±1.68)**	32.51% (±2.65)	35.65% (±1.74)	2.09% (±0.73)	3.56% (±0.66)	**X**

*Estimate is controlled, margin of error treated as zero

C: Race Correlated | D: Disparate Distribution | N/A: Not Applicable | X: Exclude

Table 29 summarizes the *Pop % Tracts* values and overall distribution assessments of the zero license/retailers for all the census tract scenarios. As the table indicates, the Hispanic population was underrepresented in the census tracts without licenses, while the White population was overrepresented in nearly every census tract without licenses, except for the Pharmacies scenario.

Table 29 OC Census Tracts with Zero Licenses Population Summary

	Asian	**Hispanic**	**White**	**Black**	**Other**	**Dist**
Orange County	19.5% (±0.1)	34.2% *	41.4% (±0.1)	1.6% (±0.1)	3.3% (±0.1)	N/A
All	20.55% (±0.48)	18.75% (±0.56)	**55.18% (±0.67)**	1.51% (±0.23)	4.01% (±0.26)	**D**
Type 21	18.43% (±0.37)	30.46% (±0.5)	**46.12% (±0.49)**	1.48% (±0.18)	3.5% (±0.21)	**D**
Type 20	19.21% (±0.33)	23.66% (±0.43)	**51.78% (±0.46)**	1.5% (±0.15)	3.83% (±0.19)	**D**
Liquor Stores	20.45% (±0.3)	27.76% (±0.36)	**46.67% (±0.37)**	1.49% (±0.13)	3.64% (±0.18)	**D**
Grocery Stores	19.04% (±0.28)	31.09% (±0.42)	**44.86% (±0.37)**	1.58% (±0.13)	3.43% (±0.15)	**C**
Convenience Stores	20.9% (±0.28)	26.25% (±0.36)	**47.73% (±0.36)**	1.43% (±0.11)	3.7% (±0.17)	**D**
Gas Stations	18.47% (±0.24)	33.29% (±0.36)	**43.45% (±0.32)**	1.48% (±0.12)	3.32% (±0.13)	**C**
Pharmacies	19.4% (±0.23)	**35.21% (±0.35)**	40.61% (±0.29)	1.57% (±0.1)	3.21% (±0.12)	**N**
Department Stores	18.91% (±0.21)	34.19% (±0.31)	**42.04% (±0.27)**	1.55% (±0.09)	3.31% (±0.11)	**N**
Wholesale Clubs	19.28% (±0.21)	34.32% (±0.3)	41.53% (±0.26)	1.56% (±0.09)	3.32% (±0.12)	**N**

*Estimate is controlled, margin of error treated as zero

C: Race Correlated | D: Disparate Distribution | N/A: Not Applicable | X: Exclude

Individually, these various results suggested that multiple factors and functions influenced both the presence and absence of licenses and retailers in the built environment. However, there did appear to be support for correlations between race and the density of alcohol licenses, which suggested disparate distributions. For example, the overrepresentation of

Hispanic populations in census tracts with alcohol licenses, or the overrepresentation of White populations in census tracts without alcohol licenses. But a conclusion beyond those generalized observations would not be supported by the data and analysis of this study.

4.1.2. Census Tract Alcohol License Density

The next step in analyzing the likelihood of race-neutral distributions of alcohol licenses at the census tract level was to assess how race/ethnicity correlated with the license density per square mile in each census tract. Figure 20 provides a visual representation of the census tract license density per square mile for Orange County. The slope polarity (sign) of a linear regression trend line was used to indicate a positive or negative correlation between a dependent variable (licenses per square mile per census tract) and an independent variable (race/ethnicity percent population per census tract).

First, scatter plots were generated for each race/ethnicity census tract percentage versus the census tract licenses or retailers per square mile. Next, linear regressions were performed with the licenses and retailers per square mile as the dependent variable for each scatter plot and the resulting trend lines were coded red if the race/ethnicity indicated a positive correlation with increasing population percentage and green if the race/ethnicity indicated a negative correlation with increasing population percentage. Finally, a regression result was rejected for further analysis if the p-value was greater than 0.05. Out of ten regression scenarios, the Department Stores and Wholesale Club categories were rejected for further analysis since their regression p-values were greater than 0.05.

For the regressions with p-values less than 0.05, if the slope polarities between two or more populations were inconsistent, then the likelihood of a race-neutral distribution function was rejected and assumed to be a race-correlated distribution. To be clear, only the differences in

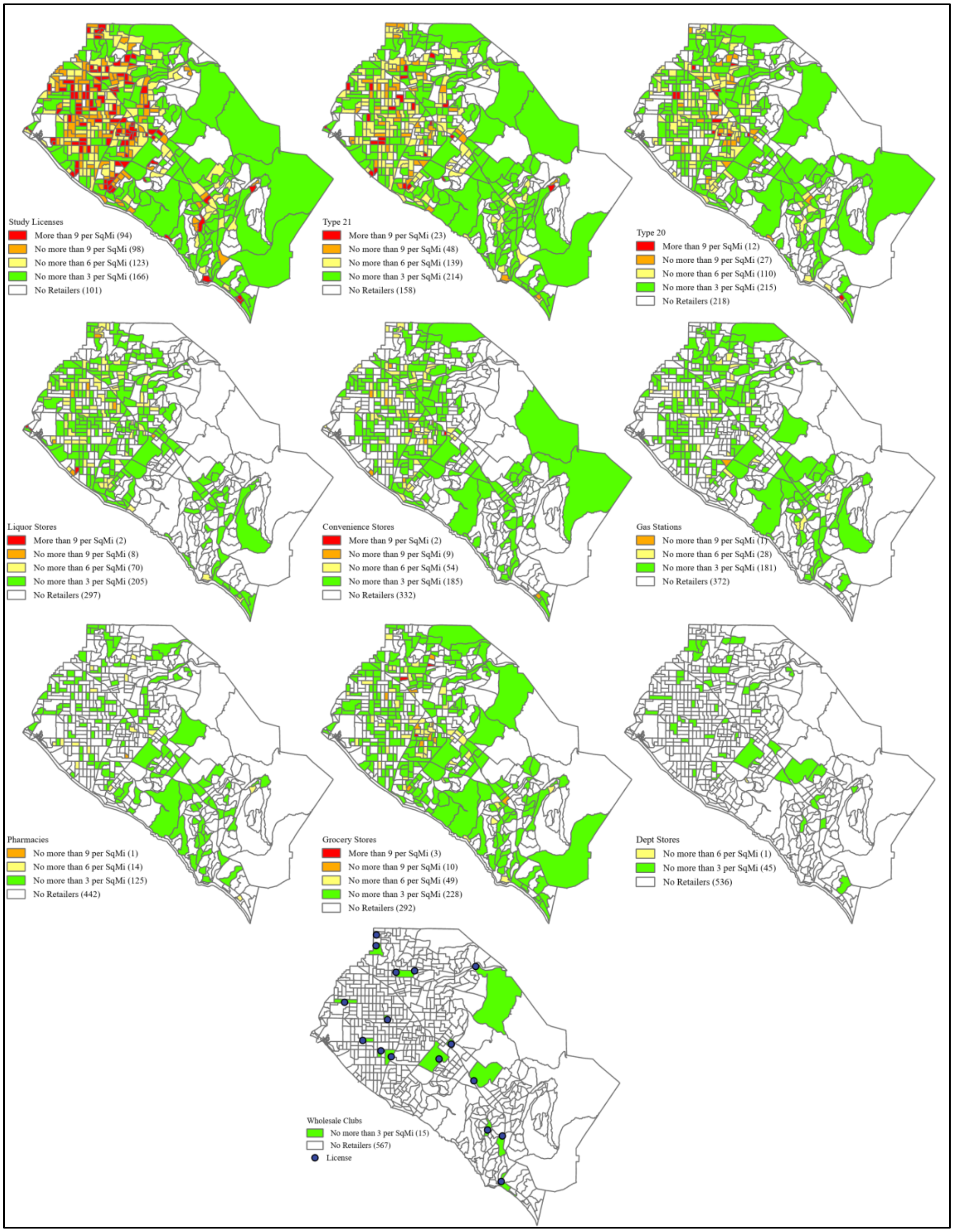

Figure 20 OC Licenses/Retailers per Square Mile

the slope polarities between the populations were assessed. This methodology allowed for a quick visual inspection to determine the potential existence of race-neutral versus race-correlated distributions in the distributions per square mile per census tract of the licenses/retailers.

Figure 21 shows the scatter plots and trend lines for All Licenses per square mile per census tract. This figure presented a positive slope with increasing Hispanic population percentage and increasing areal alcohol license density correlation, while the White and Asian populations manifested a negative slope and decreasing population percentage correlations. This result was interpreted as a race-correlated distribution. Similar results occurred for the Type 20 licenses (see Figure 22).

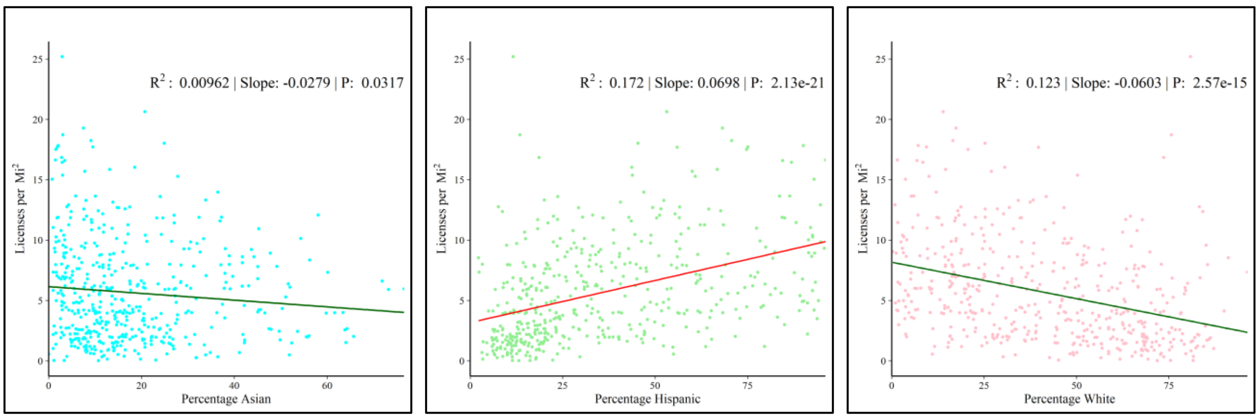

Figure 21 OC Linear Regressions on All Licenses per Square Mile

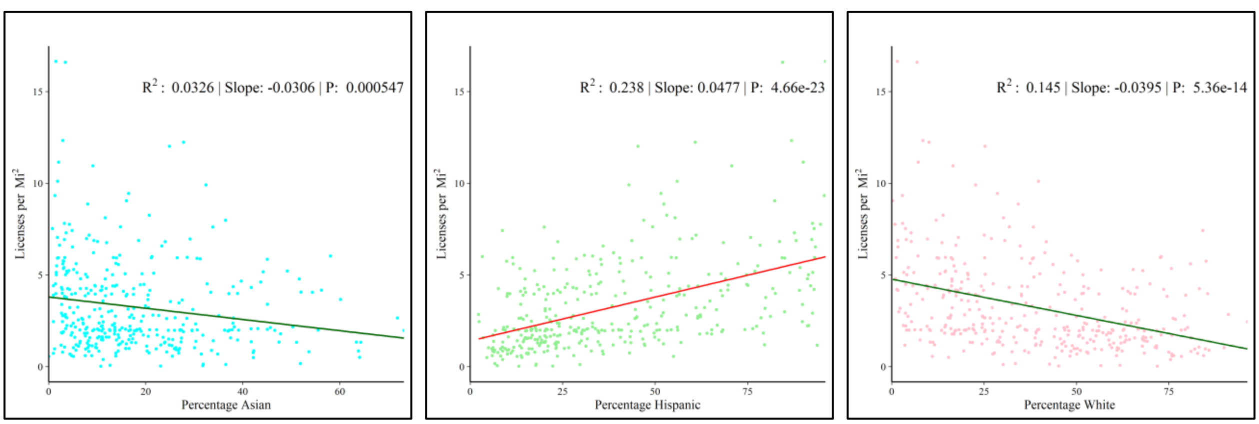

Figure 22 OC Linear Regressions on Type 20 Licenses per Square Mile

Before assessing correlations for the Type 21 licenses and Liquor Stores, the Asian regressions had to be rejected for p-values greater than 0.05 (see Figure 23 and Figure 24). . Notwithstanding rejected of the Asian results, both these scenarios produced opposite slope polarities between the Hispanic and White populations, this study's criteria for a race-correlated distribution.

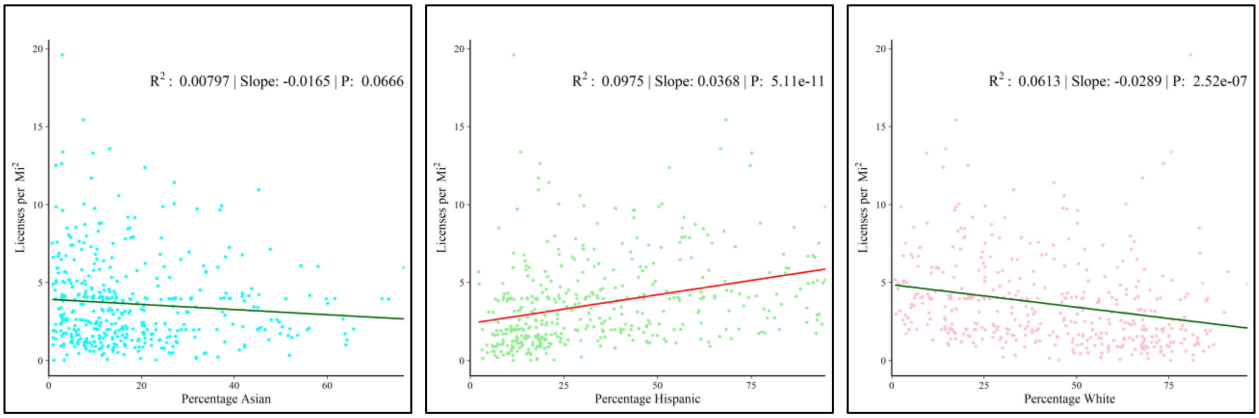

Figure 23 OC Linear Regressions on Type 21 Licenses per Square Mile

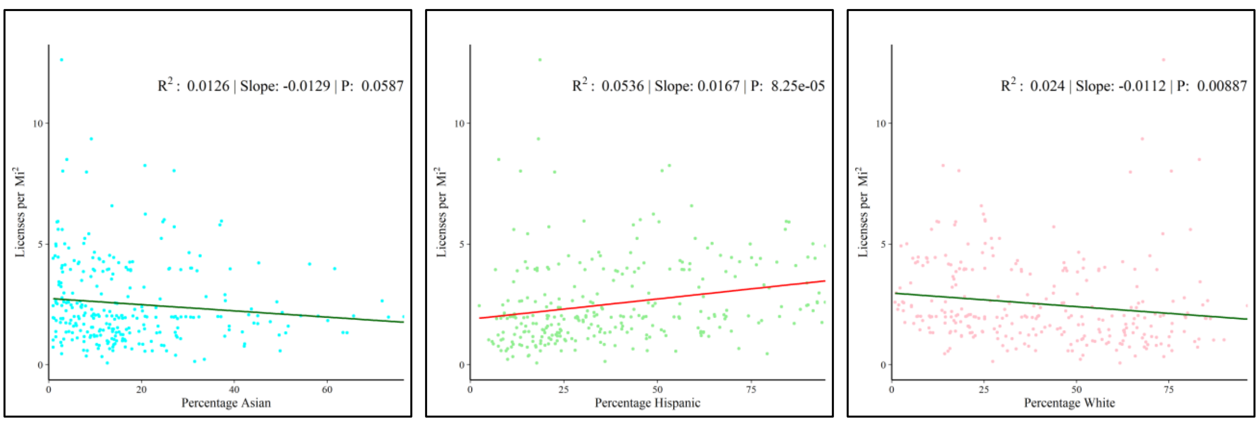

Figure 24 OC Linear Regressions on Liquor Stores per Square Mile

Grocery Stores and Convenience Stores were the next categories to be analyzed. The Grocery Store category was the second largest retailer category (N=412) and the majority of retailers (N=300) held Type 21 licenses, while Convenience Stores was the third largest (N=347) with a majority of retailers (N=296) holding Type 20 licenses (see Figure 25 and Figure 26). Both scenarios presented one race with opposite trend line polarities to the other two races and were deemed race-correlated distributions.

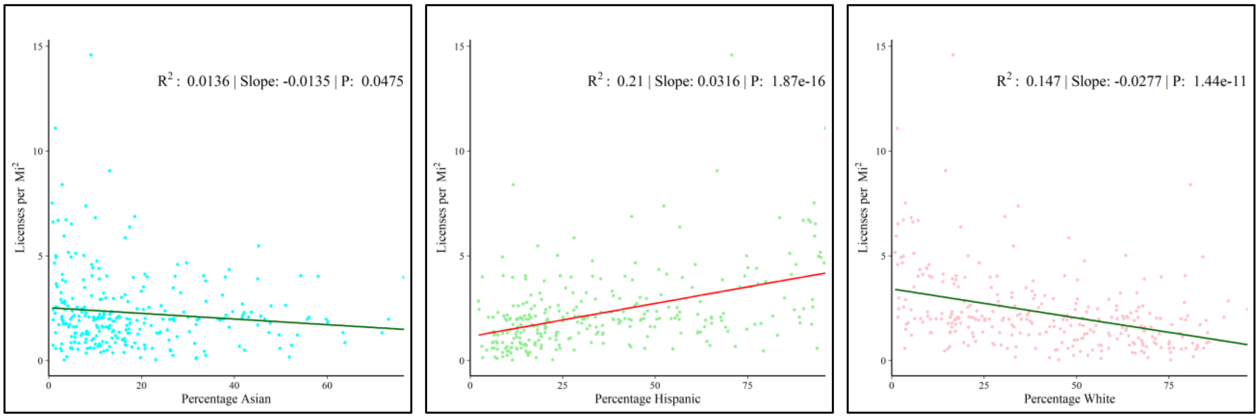

Figure 25 OC Linear Regressions on Grocery Stores per Square Mile

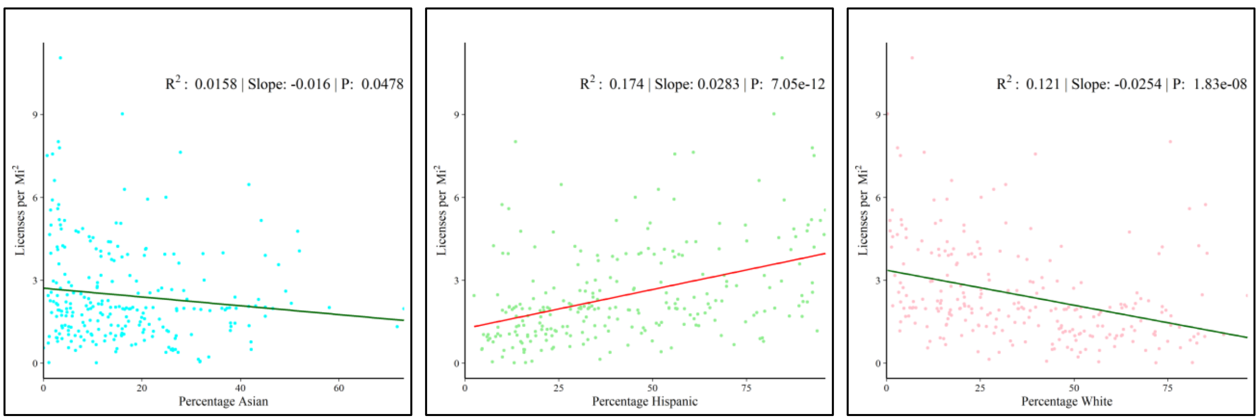

Figure 26 OC Linear Regressions on Convenience Stores per Square Mile

Gas Stations and Pharmacies were the last two categories that were analyzed. Gas Stations (N=270) were composed primarily of Type 20 license holders (N=255), while Pharmacies (N=159) were primarily Type 21 licenses (N=135). Before observing the trend line polarities, the Asian regressions were rejected for having p-values greater than 0.05. The non-rejected trend lines had opposite polarities, meeting the criteria for race-correlated distributions.

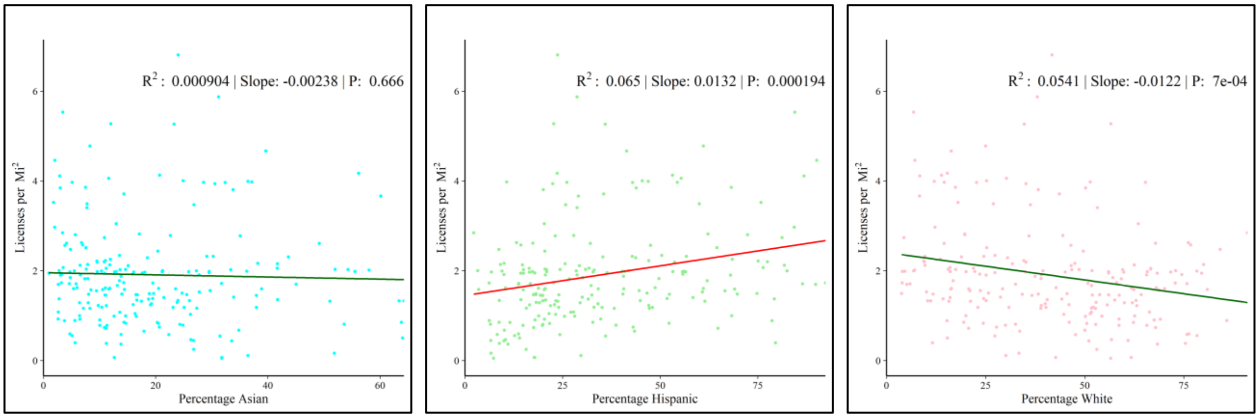

Figure 27 OC Linear Regressions on Gas Stations Stores per Square Mile

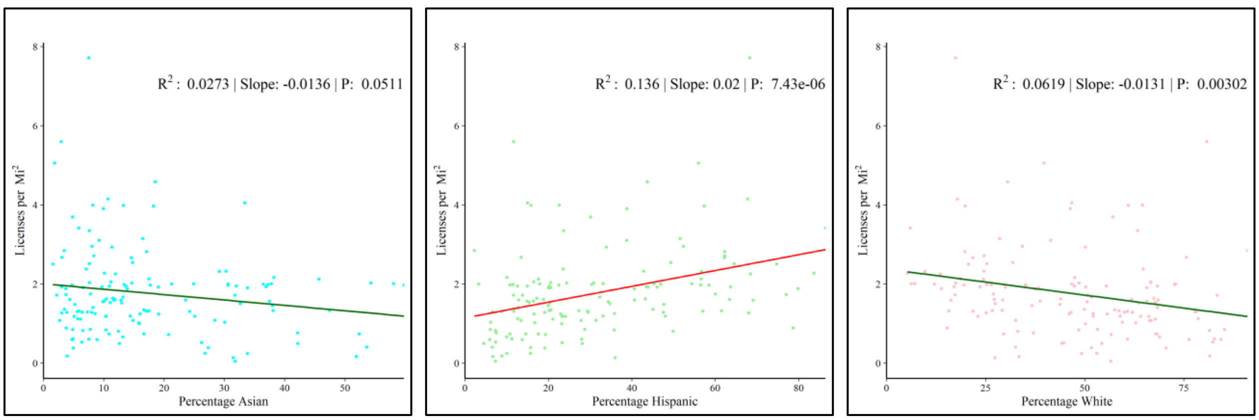

Figure 28 OC Linear Regressions on Pharmacies per Square Mile

Table 30 summarizes the results for the percent population versus licenses per square mile regressions. For all the non-rejected results, the trend line slope polarities for the Hispanic population were always opposite to the White population. These results met the study’s threshold for the presence of race-correlated distribution functions in the built environment, at least as between White and Hispanic populations. A similar result appeared likely as between Asian and Hispanic populations, although six Asian observations had to be rejected as inconclusive due to p-values greater than 0.05.

Table 30 Census Tract Linear Regressions per Square Mile Trend Line Summary

	Asian	Hispanic	White	Black	Other	Dist
All	—	+	—	X	—	**C**
Type 21	X	+	—	X	—	**C**
Type 20	—	+	—	X	—	**C**
Liquor Stores	X	+	—	X	X	**C**
Grocery Stores	—	+	—	X	—	**C**
Convenience Stores	—	+	—	X	—	**C**
Gas Stations	X	+	—	X	—	**C**
Pharmacies	X	+	—	X	X	**C**
Department Stores	X	X	X	X	X	**X**
Wholesale Clubs	X	X	X	X	X	**X**

— Negative Slope +Positive Slope X: Excluded C: Race Correlated

Another metric evaluated for race/ethnicity correlation was the distribution of alcohol licenses based on the density of licenses per 1,000 people (see Figure 29). This metric was concerned with the population density where alcohol licenses are present, whereas licenses per square mile evaluated the areal density of those licenses.

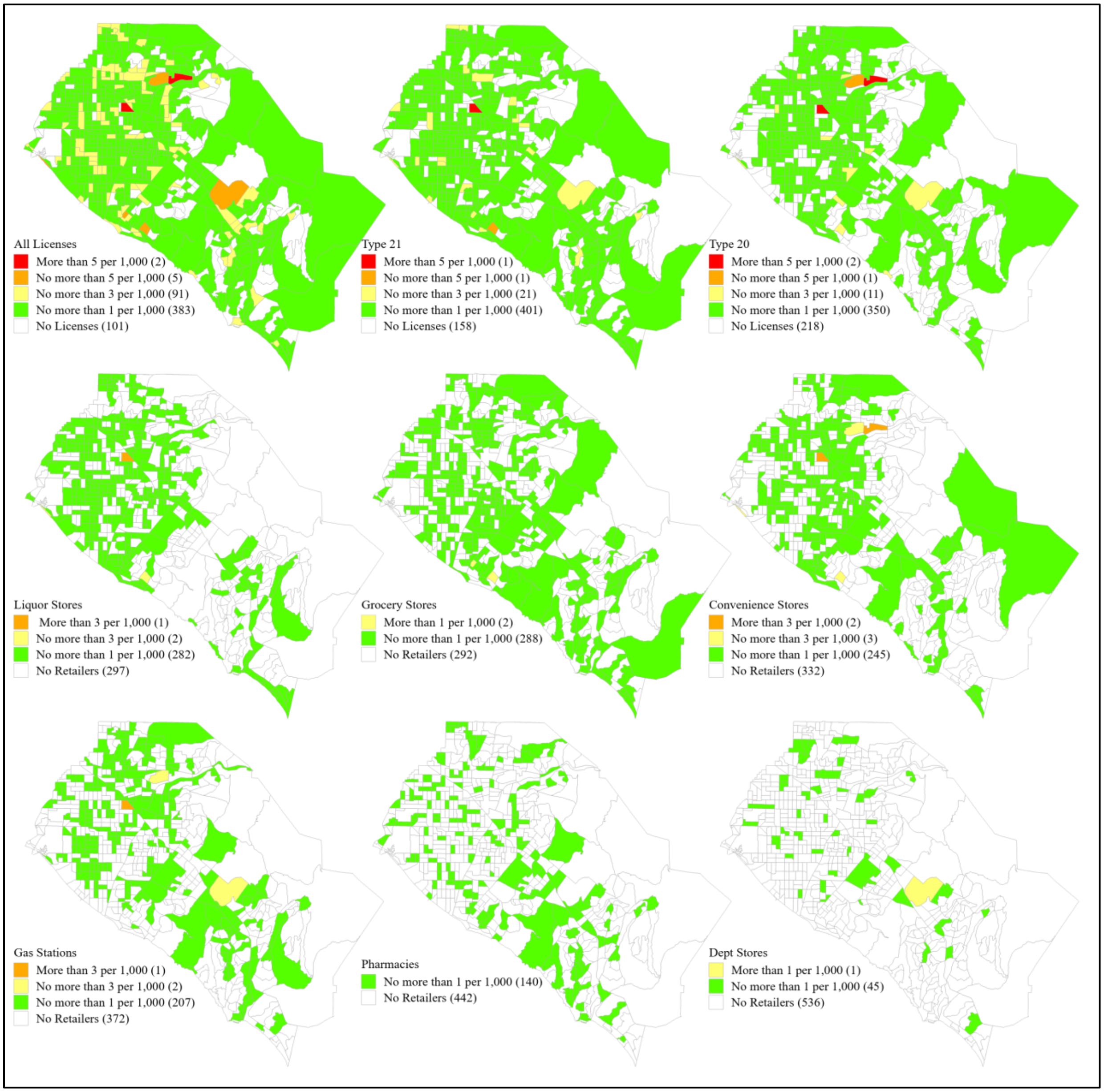

Figure 29 OC Licenses and Retailers per 1,000 People per Census Tract

First, scatter plots were generated for each race/ethnicity census tract percentage versus the census tract for each license type and all the retailer categories per 1,000 people in each census tract. Next, linear regressions were performed with the licenses/retailers per 1,000 people as the dependent variable for each scatter plot. Again, the resulting trend lines were coded red if the race/ethnicity indicated a positive correlation with increasing population percentage and green if the race/ethnicity indicated a negative correlation with increasing population percentage. Finally, regression results with p-values greater than 0.05 were rejected for further analysis. As a result, six of the ten license/retailer scenarios were rejected for having two or more p-values greater than 0.05: All Licenses, Type 20 licenses, Convenience Stores, Gas Stations, Department Stores, and Wholesale Clubs. For the regressions with p-values less than 0.05, if the slope polarities between two or more populations were inconsistent, then the likelihood of a race-neutral distribution function was rejected and assumed to be a race-correlated distribution.

Figure 30 shows the regression results for Type 21 scenario and Figure 31 the results for Liquor Stores which was also composed entirely of retailers with Type 21 licenses While the Type 21 Hispanic regression result was rejected for its p-value being too large, the Asian and White regressions p-values were under 0.05 and the exhibited opposite polarity slopes. The Liquor Store regressions were all valid, and the Asian and Hispanic trend lines exhibited opposite slope polarities to the White trend line. Thus, these scenarios met the criteria for race-correlated distributions

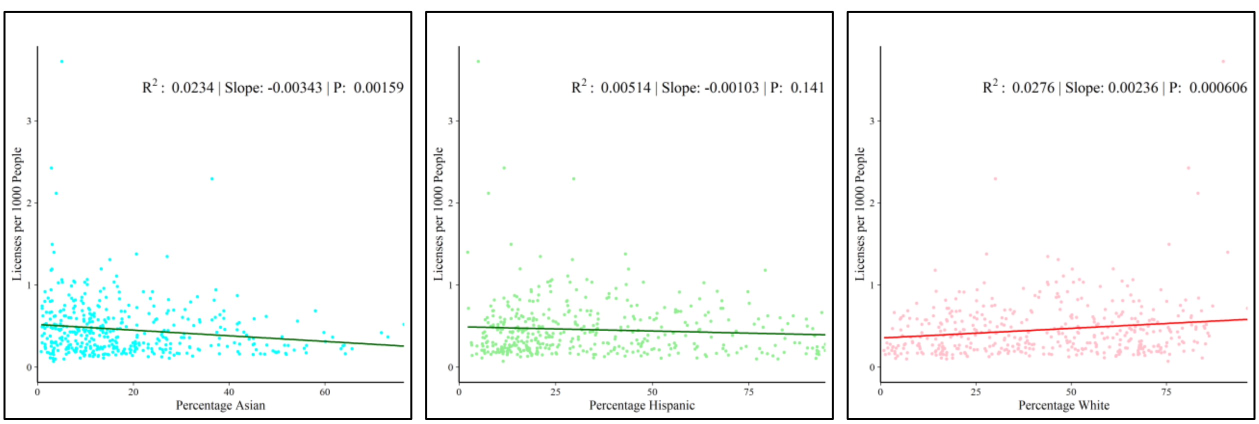

Figure 30 OC Linear Regressions on Type 21 Licenses per 1,000 People

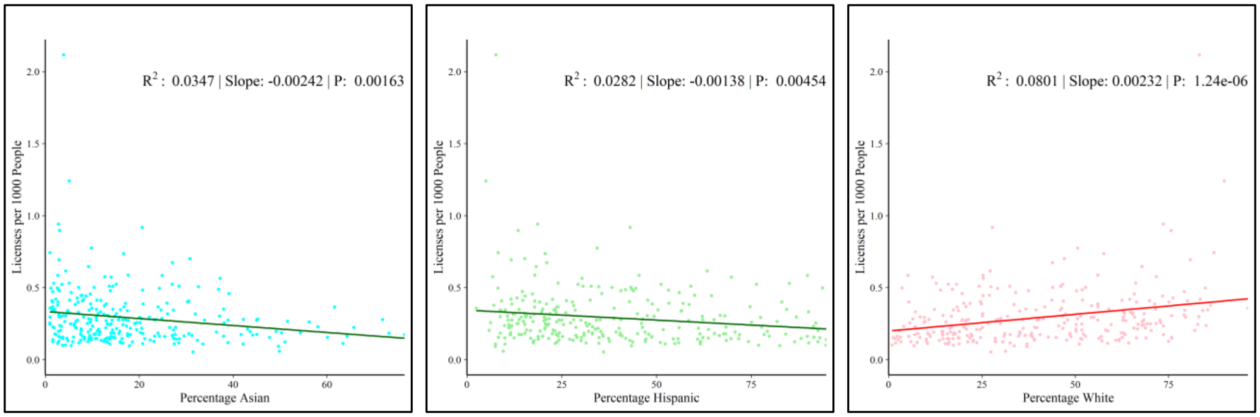

Figure 31 OC Linear Regressions on Liquor Stores per 1,000 People

The Hispanic regression results in the remaining two categories, Grocery Store (Figure 32) and Pharmacy (Figure 33), were also rejected for having p-values greater than 0.05. However, the White and Asian p-values were below 0.05 and manifested opposite polarity slopes, satisfying the criteria for race-correlated distributions.

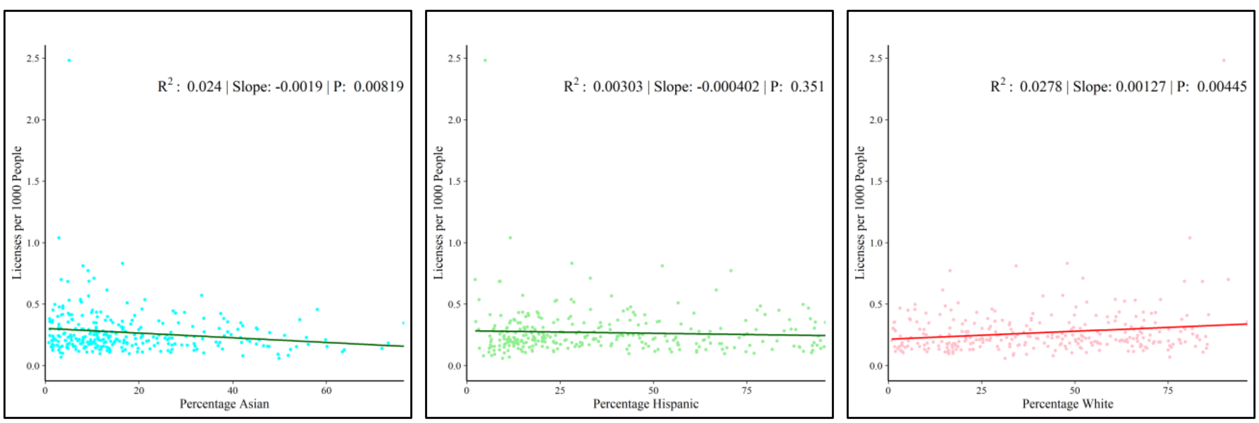

Figure 32 OC Linear Regressions on Grocery Stores per 1,000 People

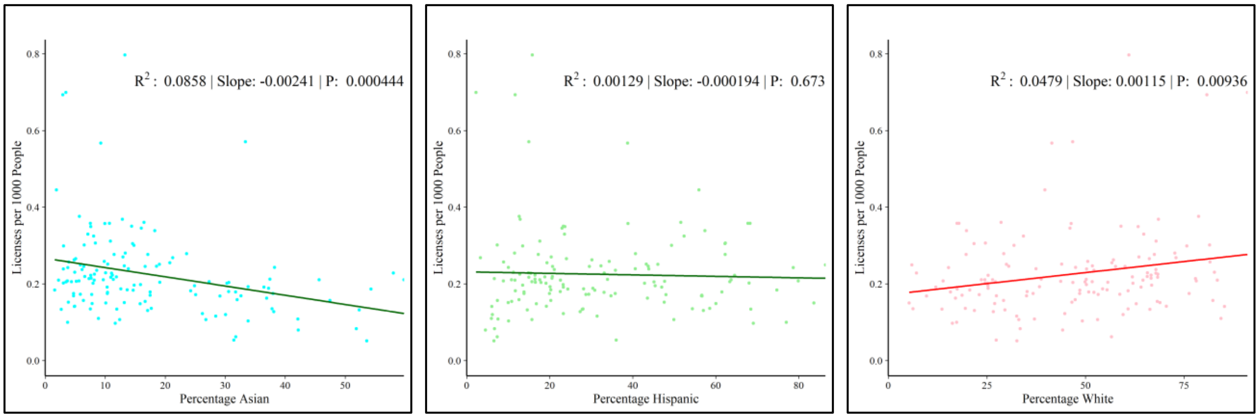

Figure 33 OC Linear Regressions on Pharmacies per 1,000 People

Table 31 summarizes the results for the percent population versus licenses per 1,000 people regressions. Overall, there were a number of rejected results, however, for non-rejected results the slope polarities for the Asian population were opposite to the White population. These results met the study's threshold for the presence of race-correlated distribution functions in the built environment, at least as between White and Asian populations. A similar result appeared likely as between White and Hispanic populations, although nine Hispanic observations had to be rejected as inconclusive due to p-values greater than 0.05.

Table 31 Census Tract Linear Regressions per 1,000 People Trend Line Summary

	Asian	Hispanic	White	Black	Other	Dist
All	—	X	X	X	+	**X**
Type 21	—	X	+	X	X	**C**
Type 20	—	X	X	X	+	**X**
Liquor Stores	—	—	+	X	X	**C**
Grocery Stores	—	X	+	X	X	**C**
Convenience Stores	X	X	+	X	X	**X**
Gas Stations	X	X	+	+	X	**X**
Pharmacies	—	X	+	X	X	**C**
Department Stores	X	X	X	X	X	**X**
Wholesale Clubs	X	X	X	X	X	**X**

— Negative Slope +Positive Slope X: Excluded C: Race Correlated

4.1.3. Census Tract Alcohol License Hot Spots: Getis-Ord Gi Statistic*

A Getis-Ord Gi* statistic was utilized to determine the presence of statistically significant clustering of alcohol licenses. Specifically, the Optimized Hot Spot Analysis tool in ArcGIS Pro was configured to assess the optimal parameters for aggregating all study area licenses into bounding polygons defined by the census tract boundaries in OC. The tools output was then reviewed to identify the neighborhood distance that was identified by the run (~6.4 miles). The statistic was then run for all retailer licenses in Orange County as a single group, the Type 21 licenses, the Type 20 licenses, and for licenses by each category of retailer using the same parameter for each run to create the Optimized Hot Spot Analysis. However, the Hot Spot Analysis failed to provide results for Wholesale Clubs (N=16) because the statistic requires a minimum of 30 data points to generate valid results. Figure 34 shows the Optimized Hot Spots results.

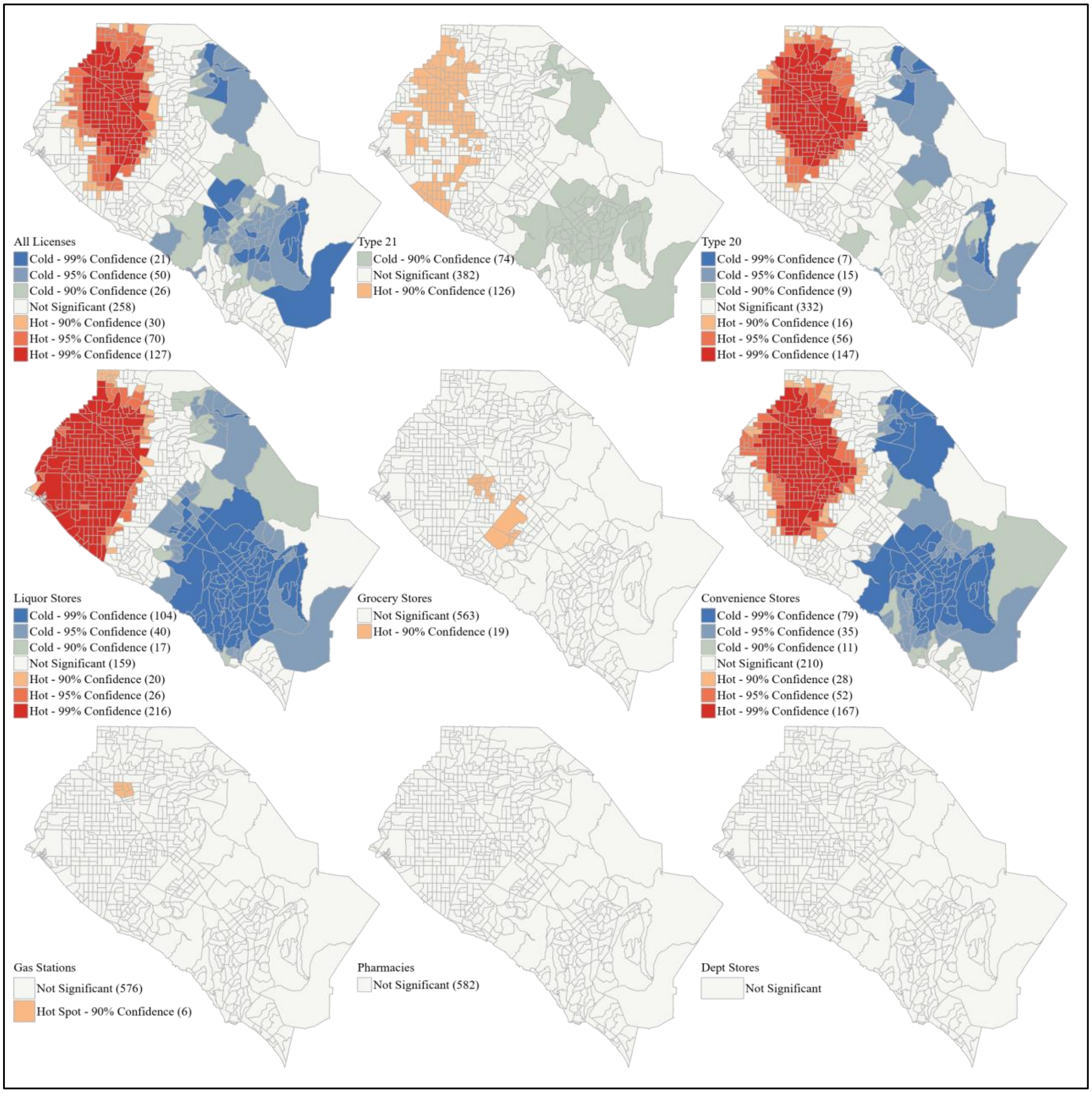

Figure 34 OC Optimized Hot Spots Based Upon Census Tract Boundaries

As Figure 34 reveals, there appeared to be a consistent distribution bias of license hot spots for the northern portion of the county and license cold spots for the southern portion. Surprisingly, the Type 21 licenses hot and cold spot distributions were attenuated in distribution and statistical confidence. Moreover, the Optimized Hot Spot analysis for Grocery Stores and Gas Stations registered just a few hot spots, while Pharmacies and Department Stores showed no statistically significant hot or cold spots. Thus, those categories were excluded from further analysis.

After generating the Optimized Hot Spots statistics, the race/ethnicity summary statistics were generated for the confidence levels for All Licenses, Type21, Type 20, Liquor Stores, and Convenience Stores. As previously discussed, inclusion or exclusion of highly populated census tracts could bias estimates made with small numbers of census tracts; however, the assumption in this study is that the aggregation of more than twenty census tracts would sufficiently render that bias negligible. That is not to say that aggregations of less than twenty tracts cannot produce valid and meaningful results, only that those results were not evaluated for disparate distributions.

Table 32 shows the summary statistics for the All Licenses Optimized Hot Spot Analysis; there appeared to be converse racial representations in each confidence level of the hot and cold spot populations between Hispanic and White populations. On the other hand, the Asian population was overrepresented in two of the three Hot bins and underrepresented in all the Cold bins. Table 33 shows that while the Type 21 Licenses manifested only two statistically significant bins—Hot 90% Confidence and Cold 90% Confidence—the Asian and Hispanic populations were aligned in overrepresentation in Hot and underrepresentation in Cold, with the

White population produced the opposite representations. Finally, the Type 20 Licenses (Table 34) also showed converse representations between Hispanic and White populations.

Table 32 OC All Licenses Optimized Hot Spots Summary Statistics

	Tracts	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	127	24.95% (±0.11)	**D**	52.91% (±0.18)	**D**	18.34% (±0.09)	**D**	1.67% (±0.04)	E	2.13% (±0.04)	D
Hot 95% Confidence	70	23.42% (±0.07)	**D**	41.53% (±0.11)	**D**	30.61% (±0.08)	**D**	1.76% (±0.03)	D	2.68% (±0.03)	D
Hot 90% Confidence	30	15.63% (±0.04)	**D**	43.98% (±0.07)	**D**	35.45% (±0.05)	**D**	1.41% (±0.02)	D	3.53% (±0.02)	C
Cold 90% Confidence	26	17.03% (±0.05)	**D**	21.14% (±0.06)	**D**	56.06% (±0.07)	**D**	1.75% (±0.03)	D	4.01% (±0.03)	D
Cold 95% Confidence	50	13.95% (±0.05)	**D**	16.94% (±0.06)	**D**	63.37% (±0.08)	**D**	1.44% (±0.03)	A	4.29% (±0.03)	D
Cold 99% Confidence	21	11.99% (±0.03)	**D**	15.4% (±0.05)	**D**	66.05% (±0.06)	**D**	1.52% (±0.02)	E	5.05% (±0.03)	D

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Table 33 OC Type 21 Licenses Optimized Hot Spots Summary Statistics

	Tracts	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 90% Confidence	126	23.64% (±0.1)	**D**	41.84% (±0.16)	**D**	29.62% (±0.11)	**D**	1.94% (±0.04)	D	2.97% (±0.05)	D
Cold 90% Confidence	74	13.58% (±0.07)	**D**	18.05% (±0.08)	**D**	62.39% (±0.11)	**D**	1.54% (±0.03)	E	4.44% (±0.05)	D

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Table 34 OC Type 20 Licenses Optimized Hot Spots Summary Statistics

	Tracts	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	147	21.86% (±0.11)	**D**	54.49% (±0.19)	**D**	20.06% (±0.1)	**D**	1.58% (±0.04)	E	2.02% (±0.04)	D
Hot 95% Confidence	56	22.06% (±0.07)	**D**	43.96% (±0.11)	**D**	29.36% (±0.07)	**D**	1.73% (±0.03)	D	2.89% (±0.03)	D
Hot 90% Confidence	16	18.21% (±0.03)	**X**	47.54% (±0.05)	**X**	29.77% (±0.04)	**X**	1.81% (±0.01)	X	2.67% (±0.02)	X
Cold 90% Confidence	9	14.7% (±0.03)	**X**	18.35% (±0.03)	**X**	60.43% (±0.04)	**X**	1.37% (±0.02)	X	5.15% (±0.02)	X
Cold 95% Confidence	15	16.04% (±0.03)	**X**	16.54% (±0.04)	**X**	61.06% (±0.05)	**X**	1.3% (±0.02)	X	5.06% (±0.03)	X
Cold 99% Confidence	7	14.89% (±0.01)	**X**	13.44% (±0.02)	**X**	66.44% (±0.03)	**X**	1.89% (±0.01)	X	3.35% (±0.01)	X

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Overall, the *Dist* columns of the tables indicated that the majority of the bins manifested distributions that exceeded this study's disparate distribution threshold of 10% difference from the county-wide proportions. However, four bins from Type 20 licenses, although statistically significant, were excluded from the disparate distribution analysis for having less than 20 census tracts represented in the results.

Liquor Stores and Convenience Stores were the only retailer categories with at least one bin containing more than 20 census tracts. The Liquor Store category, Table 35, indicated a strong overrepresentation of the Hispanic population in hot spots and a strong overrepresentation of the White population in cold spots. However, the Asian population had mixed over and under representation in both hot and cold spots. Likewise, the Convenience Store category, Table 36, also manifested overrepresentation of Hispanic populations in hot spots and overrepresentation of White populations in cold spots.

Table 35 OC Liquor Stores Optimized Hot Spots Summary Statistics

	Tracts	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	216	26.31% (±0.13)	**D**	38.05% (±0.2)	**D**	30.76% (±0.14)	**D**	1.79% (±0.05)	D	3.1% (±0.06)	C
Hot 95% Confidence	26	16.28% (±0.04)	**D**	52.1% (±0.06)	**D**	27.82% (±0.04)	**D**	1.86% (±0.02)	D	1.95% (±0.01)	D
Hot 90% Confidence	20	10.91% (±0.03)	**D**	52.73% (±0.06)	**D**	32.4% (±0.04)	**D**	1.82% (±0.01)	D	2.15% (±0.01)	D
Cold 90% Confidence	17	27.58% (±0.05)	**X**	20.71% (±0.04)	**X**	45.79% (±0.06)	**X**	1.69% (±0.02)	X	4.23% (±0.05)	X
Cold 95% Confidence	40	23.24% (±0.07)	**D**	16.63% (±0.09)	**D**	53.94% (±0.09)	**D**	1.17% (±0.02)	D	5.02% (±0.04)	D
Cold 99% Confidence	104	18.41% (±0.1)	**C**	16.67% (±0.1)	**D**	58.71% (±0.13)	**D**	1.78% (±0.05)	D	4.42% (±0.05)	D

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Table 36 OC Convenience Stores Optimized Hot Spots Summary Statistics

	Tracts	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	167	24.34% (±0.12)	**D**	50.91% (±0.2)	**D**	20.9% (±0.11)	**D**	1.65% (±0.05)	E	2.19% (±0.05)	D
Hot 95% Confidence	52	23.28% (±0.06)	**D**	37.72% (±0.09)	**D**	33.79% (±0.06)	**D**	2.04% (±0.03)	D	3.16% (±0.03)	C
Hot 90% Confidence	28	16.86% (±0.04)	**D**	48.19% (±0.07)	**D**	30.06% (±0.05)	**D**	1.56% (±0.02)	E	3.33% (±0.02)	E
Cold 90% Confidence	11	24.96% (±0.04)	**X**	10.34% (±0.03)	**X**	58.62% (±0.05)	**X**	1.21% (±0.01)	X	4.87% (±0.04)	X
Cold 95% Confidence	35	14.13% (±0.04)	**D**	17.65% (±0.06)	**D**	62.13% (±0.07)	**D**	1.39% (±0.02)	D	4.69% (±0.04)	D
Cold 99% Confidence	79	14.27% (±0.07)	**D**	18.07% (±0.09)	**D**	61.85% (±0.11)	**D**	1.59% (±0.04)	E	4.21% (±0.04)	D

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Overall, the majority of Optimized Hot Spot bins provided strong support for the conclusion that the alcohol license and race/ethnicity population ratios in the hot/cold census tracts exhibited environmental clustering differing significantly from the county norm. Moreover, the *Dist* column values in the tables likewise exceeded this study's disparate distribution threshold of differences between observed and county-wide population proportions greater than 10%.

The Hot Spot Analysis was also performed using a 3-mile distance band in order to observe whether clustering also occurred at finer scale (see Figure 35). Three miles was chosen to represent a reasonable distance an OC resident would travel to a retailer on a regular basis. As Figure 35 reveals, there continued to be a distribution bias of license hot spots in the northern portion of the county and a lesser distribution of cold spots in the southern portion. However, while this observational method attenuated some of the hot and cold spot distributions in both quantity and statistical confidence for several scenarios, new hot and cold spots were also identified.

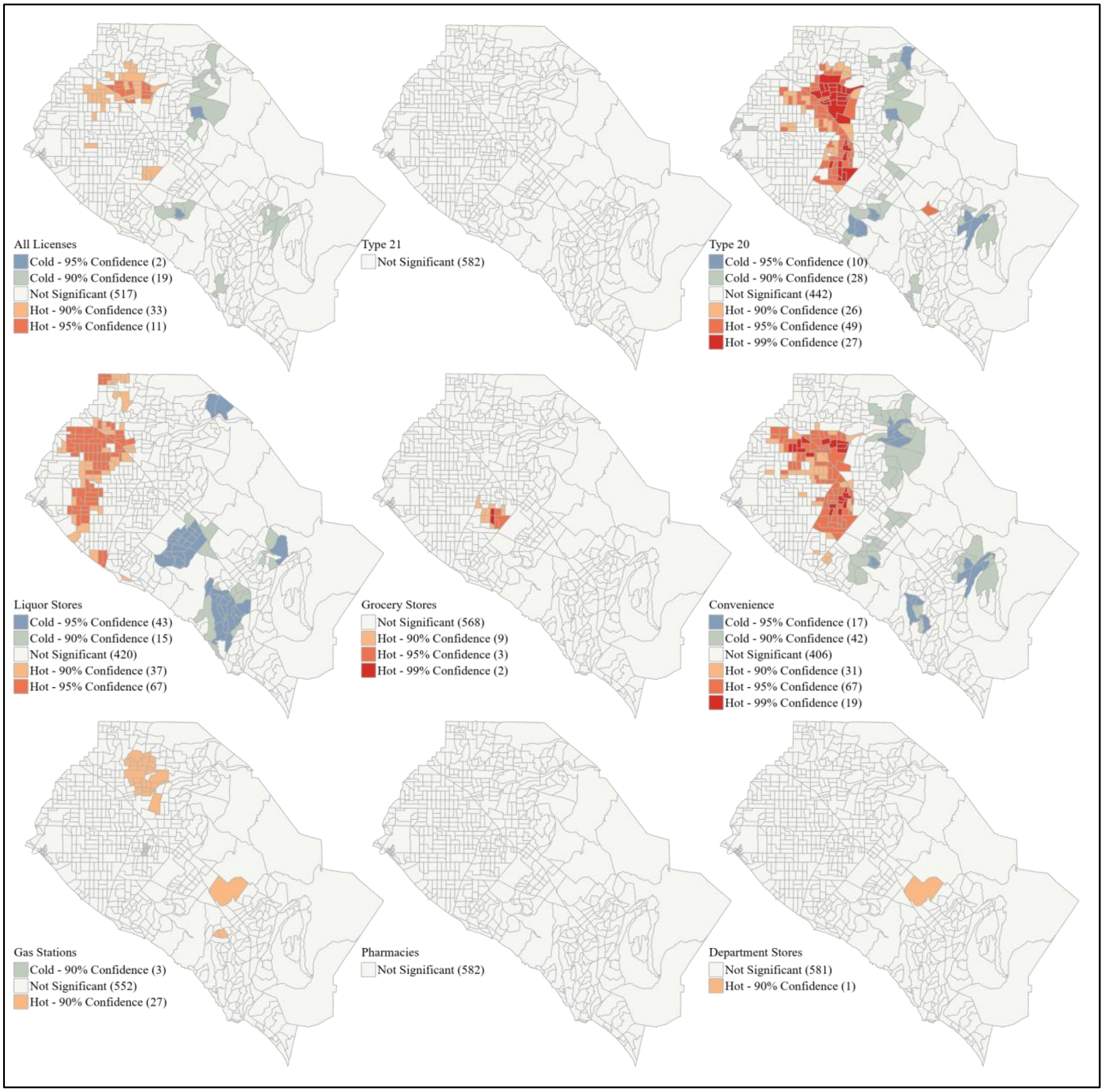

Figure 35 OC Three Mile Observational Hot Spots Based Upon Census Tract Boundaries

Table 37 exhibits the Observational Hot Spots summary statistics for All Licenses. Examining the scenario, the number of hot and cold spots had diminished significantly, with only one bin—Hot 90% Confidence—having a sufficiently large sample size (N=33) for disparate analysis. That bin, Hot 90% Confidence, showed both significant overrepresentation for the Hispanic population and underrepresentation of the White and Asian populations. Moreover, the *Dist* column values exceeded the disparate distribution threshold.

Table 37 OC All Licenses Observational Hot Spots Summary Statistics

	Tracts	**Asian**	**Dist**	**Hispanic**	**Dist**	**White**	**Dist**	**Black**	**Dist**	**Other**	**Dist**
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 95% Confidence	11	9.46% (±0.02)	**X**	70.1% (±0.06)	**X**	16.33% (±0.02)	**X**	2.15% (±0.02)	X	1.97% (±0.01)	X
Hot 90% Confidence	33	17.1% (±0.05)	**D**	58.8% (±0.1)	**D**	19.32% (±0.05)	**D**	2.3% (±0.02)	D	2.47% (±0.02)	D
Cold 90% Confidence	19	19.44% (±0.03)	**X**	15.87% (±0.03)	**X**	59.44% (±0.04)	**X**	1.75% (±0.01)	X	3.5% (±0.02)	X
Cold 95% Confidence	2	17.21% (±0.01)	**X**	8.61% (±0.0)	**X**	68.13% (±0.01)	**X**	0.33% (±0.0)	X	5.72% (±0.01)	X

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Table 38 provides the summary statistics for Type 20 licenses (there were no hot or cold spots for Type 21 licenses). The number of hot and cold bins and census tracts increased compared to the combined licenses scenario, indicating that much of the attenuation of the All Licenses Observational Hot Spots from the All Licenses Optimized was attributable to the Type 21 license distributions. For Type 20 licenses, four bins showed both significant overrepresentation for the Hispanic population and underrepresentation of the White population and mixed representations for the Asian population. Overall, the majority of bins surpassed this study's disparate distribution threshold.

Table 38 OC Type 20 Licenses Observational Hot Spots Summary Statistics

	Tracts	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	27	9.75% (±0.04)	**D**	70.77% (±0.1)	**D**	16.12% (±0.04)	**D**	1.52% (±0.02)	E	1.83% (±0.02)	D
Hot 95% Confidence	49	11.74% (±0.05)	**D**	69.11% (±0.11)	**D**	15.52% (±0.05)	**D**	1.8% (±0.03)	D	1.83% (±0.02)	D
Hot 90% Confidence	26	20.63% (±0.05)	**C**	53.11% (±0.08)	**D**	22.74% (±0.05)	**D**	1.53% (±0.02)	E	1.98% (±0.02)	D
Cold 90% Confidence	28	23.03% (±0.06)	**D**	15.1% (±0.05)	**D**	56.46% (±0.06)	**D**	1.08% (±0.01)	D	4.33% (±0.03)	D
Cold 95% Confidence	10	13.64% (±0.02)	**X**	10.38% (±0.02)	**X**	71.78% (±0.04)	**X**	1.52% (±0.01)	X	2.67% (±0.01)	X

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Moreover, there was an interesting difference in the Type 20 Observational Hot Spots from the Type 20 Optimized Hot Spots: the occurrence of a hot spot located at census tract 524.08 (see Figure 36). This hot spot illustrated the importance of carefully reviewing and understanding Hot Spot parameters and results. Specifically, census tract 524.08 had zero Type 20 licenses while most of the surrounding census tracts within three miles of census tract 540.08 contained at least one. Thus, census tract 524.08 was like a Type 20 license free island in a sea of census tracts with Type 20 licenses.

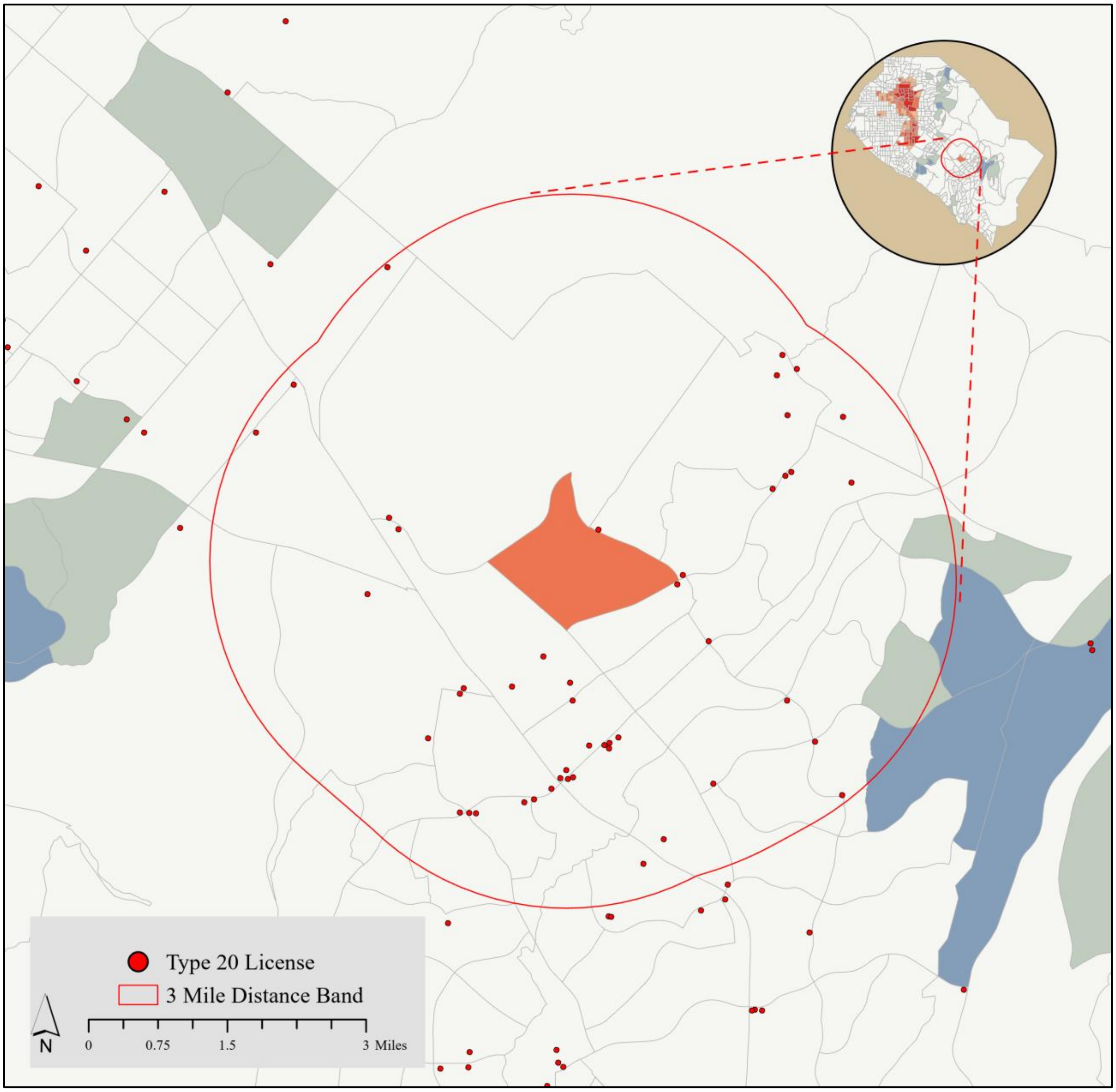

Figure 36 Observational Hot Spot of Type 20 Licenses Occurring at Census Tract 524.08

Even though census tract 524.08 did not have any Type 20 licenses, it was presumed that the race/ethnicity population dynamics were representative of its neighbors within the distance band value (3 miles). Table 39 provides the summary statistics for census tract 524.08, from which it can be inferred that the tracts within three miles also likely have a greater proportion of White population than the county-wide statistics. Moreover, this hot spot illustrated how the hot spot analysis indirectly accounts for spillover effects because the Getis-Ord Gi* statistic takes into account licenses occurring in nearby census tracts within the distance band value.

Table 39 Census Tract 524.08 Type 20 Hot Spots Summary Statistics

	Tracts	**Asian**	**Hispanic**	**White**	**Black**	**Other**
County Statistics	582	19.5% (±0.1)	34.2% *	41.4% (±0.1)	1.6% (±0.1)	3.3% (±0.1)
Hot 95% Confidence	1	13.16% (±0.01)	9.99% (±0.01)	68.93% (±0.01)	0.63% (±0.0)	7.28% (±0.01)

*Estimate is controlled, margin of error treated as zero

As mentioned, the observational Hot Spot analysis was performed using a three-mile distance band; however, at some smaller value there would not have been a hot spot at census tract 524.08. On the other hand, the hot spot may have grown or moved to the two or three census tracts south of 524.08 where multiple Type 20 licenses occur if a larger band value was used. Further increasing the distance band value would eventually result in the area becoming a cold spot or not statistically significant (see Figure 34 where the distance band was ~6.4 miles).

Table 40 provides the summary statistics on Observational Hot Spots for Liquor Stores, which are a subset of Type 21 licenses. The fact that there were hot spots with Liquor Stores and not Type 21 licenses suggested that the other retailers with Type 21 licenses were more diffusively distributed compared to Liquor Stores. Moreover, Table 40 shows that Liquor Store Observational Hot Spots continued to trend heavily Hispanic while the local Cold Spots trended heavily White. Overall, the majority of bins surpassed this study’s disparate distribution threshold.

Table 40 OC Liquor Stores Observational Hot Spots Summary Statistics

	Tracts	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 95% Confidence	67	24.2% (±0.08)	**D**	43.71% (±0.13)	**D**	26.69% (±0.08)	**D**	2.16% (±0.03)	D	3.24% (±0.04)	E
Hot 90% Confidence	37	23.06% (±0.05)	**D**	43.37% (±0.08)	**D**	29.69% (±0.05)	**D**	1.66% (±0.02)	E	2.21% (±0.02)	D
Cold 90% Confidence	15	24.58% (±0.04)	**X**	12.68% (±0.03)	**X**	55.81% (±0.05)	**X**	2.17% (±0.02)	X	4.76% (±0.02)	X
Cold 95% Confidence	43	26.85% (±0.07)	**D**	13.13% (±0.06)	**D**	53.14% (±0.08)	**D**	1.86% (±0.03)	D	5.03% (±0.03)	D

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Convenience Stores and Gas Stations were the only two categories remaining with at least one bin containing sufficient samples for disparate distribution analysis. Table 41 indicates overrepresentation of Hispanic populations in Hot Spots and overrepresentation of White populations in Cold Spots for Convenience Stores. Likewise, Table 42 shows a Hispanic overrepresentation in the Hot 90% Confidence bin for Gas Stations. Overall, the majority of bins surpassed this study's disparate distribution threshold, although the Gas Stations scenario was close to being excluded for having only 27 census tracts.

Table 41 OC Convenience Stores Observational Hot Spots Summary Statistics

	Tracts	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	19	10.89% (±0.03)	**X**	72.76% (±0.08)	**X**	13.35% (±0.03)	**X**	1.44% (±0.01)	X	1.56% (±0.01)	X
Hot 95% Confidence	67	14.61% (±0.07)	**D**	65.97% (±0.14)	**D**	16.05% (±0.07)	**D**	1.61% (±0.03)	E	1.76% (±0.03)	D
Hot 90% Confidence	31	23.41% (±0.05)	**D**	49.77% (±0.08)	**D**	22.59% (±0.05)	**D**	1.38% (±0.02)	D	2.85% (±0.03)	D
Cold 90% Confidence	42	24.82% (±0.07)	**D**	14.29% (±0.06)	**D**	54.95% (±0.08)	**D**	1.48% (±0.02)	E	4.46% (±0.03)	D
Cold 95% Confidence	17	15.6% (±0.02)	**X**	16.28% (±0.03)	**X**	62.91% (±0.04)	**X**	1.27% (±0.01)	X	3.93% (±0.02)	X

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Table 42 OC Gas Stations Observational Hot Spots Summary Statistics

	Tracts	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	582	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 90% Confidence	27	13.14% (±0.03)	**D**	54.2% (±0.07)	**D**	28.32% (±0.04)	**D**	1.94% (±0.02)	D	2.4% (±0.02)	D
Cold 90% Confidence	3	2.96% (±0.0)	**X**	94.45% (±0.03)	**X**	2.27% (±0.01)	**X**	0.08% (±0.0)	X	0.24% (±0.0)	X

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Overall, whether OC census tracts were analyzed by license count, license per square mile, license per 1,000 population, by Optimized Hot Spots, or by Observational Hot Spots, the Hispanic population appeared to be overrepresented at the census tract level more often than would be expected based upon the county-wide population statistics for nearly all license types and retailer categories. The Asian population, on the other hand, showed mixed representation results, with overrepresentation in some scenarios and underrepresentation in others. Furthermore, the White population showed consistent overrepresentation in census tracts that do not have alcohol licenses and often had many indicators suggesting underrepresentation in census tracts with alcohol licenses, with possibly the exception of Pharmacy retailers. Finally, the majority of scenario results exceeded this study's disparate distribution thresholds.

4.2 Scale 2: Scaled Population Grid Analytical Results

The census tract level analysis of alcohol license distributions suggested that race/ethnicity biases were in operation in Orange County. However, there was concern with using census tracts as the basis for spatial analysis because of the potential introduction of unknown issues in the form of modifiable areal unit problems (MAUP) due to the variable nature of census tract boundaries. There was also the issue of spillover effects—unmeasured impacts in adjacent census tracts—due to the fact that many retailers were right next to census tract boundaries because census tract boundaries often run down the centerline of streets. While some of these concerns were partially addressed by the Census Tract Hot Spot Analyses, another way to address these concerns was to replace the random areas defined by census tract boundaries with a consistently applied scaled population grid.

After creating the scaled population grid, the cells with no population were removed in order to aggregate the distributions of alcohol licenses to cells with identified populations. These scaled population cells were then used to perform the same simple summary statistics, linear regression trend line slope analysis, and Getis Ord Gi* hot spot analysis performed in the previous sections. The following sections examine the results of those analyses.

4.2.1. Scaled Population Grid Alcohol License Summary Statistics

If a race-neutral function controls the distribution of alcohol retailers in Orange County built environment, then both the presence and absence of alcohol retailers should generally follow the demographic profile of the county. Thus, the first step in analyzing the distribution of alcohol licenses at the cell level was to explore the percentage of the cell populations that do and do not have alcohol licenses for all the various licenses and retailer scenarios. The maps in Figure 37 present the cell counts for all the license and retailer scenarios for Orange County, except for Wholesale Clubs which was excluded due to the small sample size (N=16).

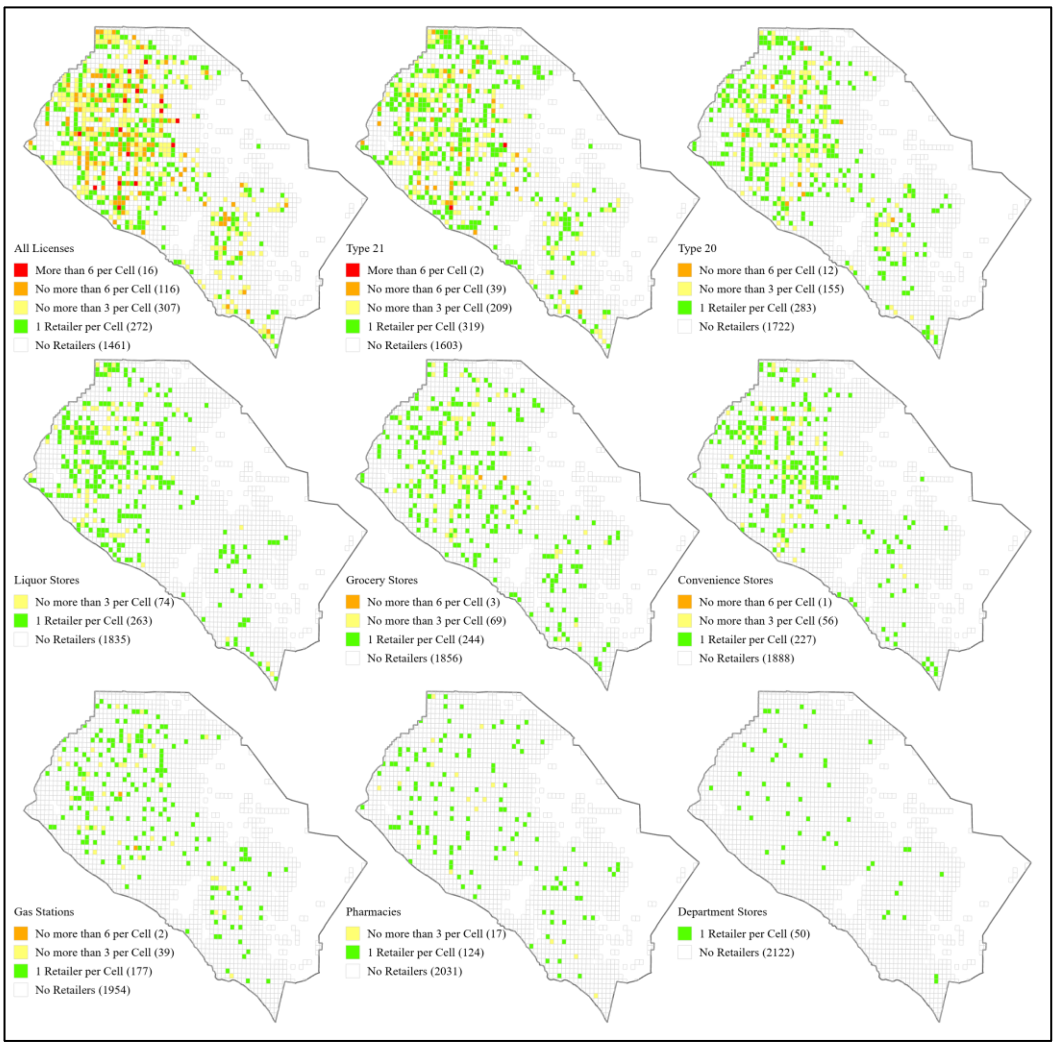

Figure 37 OC Licenses and Retailers Per Cell

Table 43 shows the zero licenses summary statistics, while Table 44 shows the summary statistics for cells that contain licenses. These tables, with different county-wide population denominators compared to the census tract zero licenses tables (cells: 47.8% and 52.2% vs tracts: 15.3% and 84.7%) still manifested very similar race/ethnicity dynamics to the census tract versions. Moreover, because the cell sizes are approximately 0.28 square miles, they represented the populations within roughly 0.5 miles of the alcohol retailers, compared to the random range of distances when using census tracts.

Table 43 OC Summary Statistics of Cells with Zero Licenses

Cells with Zero Alcohol Licenses: 1,461 / 47.8% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	20.47% (±0.31)	**C**	9.33%	9.79% (±0.15)	**N**
Hispanic (any race**)**	34.2% (*)	25.81% (±0.39)	**D**	16.36%	12.35% (±0.19)	**D**
White Alone	41.4% (±.1)	48.49% (±0.4)	**D**	19.8%	23.19% (±0.19)	**D**
Black Alone	1.6% (±.1)	1.52% (±0.14)	*D*	0.75%	0.73% (±0.07)	*E*
All Other Race(s)	3.3% (±.1)	3.7% (±0.18)	*D*	1.59%	1.77% (±0.09)	*C*
Totals	100%	100%		47.8%	47.8%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 44 OC Summary Statistics of Cells with Alcohol Licenses

Cells with Alcohol Licenses: 711 / 52.2% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	18.63% (±0.27)	**N**	17.86% (±0.17)	**C**	10.18%	9.72% (±0.14)	**N**
Hispanic (any race**)**	34.2% (*)	41.88% (±0.46)	**D**	44.37% (±0.29)	**D**	17.84%	21.85% (±0.24)	**D**
White Alone	41.4% (±.1)	34.89% (±0.33)	**D**	33.26% (±0.2)	**D**	21.6%	18.2% (±0.17)	**D**
Black Alone	1.6% (±.1)	1.62% (±0.12)	*D*	1.62% (±0.07)	*C*	0.82%	0.84% (±0.06)	*E*
All Other Race(s)	3.3% (±.1)	2.98% (±0.14)	*E*	2.89% (±0.09)	*C*	1.74%	1.56% (±0.08)	*C*
Totals	100%	100%		100%		52.2%	52.2%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

In this scenario, the Hispanic population continued to be overrepresented in cells with alcohol licenses and underrepresented in cells that did not have licenses. Likewise, the White population continued to be overrepresented in cells without licenses and underrepresented in cells with licenses. On the other hand, the Cells with Licenses scenario showed the Asian population with underrepresentation compared to the census tract scenario Asian population. Overall, while some race-neutral distribution was observed for the Asian population in this scenario, the majority of evaluation points surpassed the disparate distribution threshold for this study.

There were 1,603 cells containing Type 21 licenses representing 57.3% of the OC population with no Type 21 licenses (Table 45). On the other hand, there were 569 cells containing 42.7% of the OC population with Type 21 licenses (see Table 46). These tables also had different county-wide population denominators compared to the census tract versions (cells: 57.3% and 42.7% vs tracts: 23.7% and 76.3%), and also manifested the race/ethnicity dynamics of overrepresentation of Hispanics in cells with Type 21 licenses compared to the underrepresentation of Whites found in the census tract versions. However, in these cells, the overrepresentation of Hispanics increased from 36.34% to 41.26%. Overall, while some race-neutral distribution was observed for the Asian population in this scenario, the majority of evaluation points exceeded the disparate distribution threshold for this study.

Table 45 OC Summary Statistics of Cells with Zero Type 21 Licenses

Cells with Zero Type 21 Alcohol Licenses: 1,603 / 57.3% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.96% (±0.24)	**N**	11.17%	11.43% (±0.16)	**E**
Hispanic (any race**)**	34.2% (*)	29.39% (±0.33)	**D**	19.58%	16.83% (±0.21)	**D**
White Alone	41.4% (±.1)	45.6% (±0.31)	**D**	23.7%	26.11% (±0.2)	**C**
Black Alone	1.6% (±.1)	1.52% (±0.11)	*D*	0.9%	0.87% (±0.07)	*E*
All Other Race(s)	3.3% (±.1)	3.52% (±0.14)	*D*	1.91%	2.02% (±0.09)	*E*
Totals	100%	100%		57.3%	57.3%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 46 OC Summary Statistics of Cells with Type 21 Licenses

Cells with Type 21 Alcohol Licenses: 569 / 42.7% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	18.9% (±0.31)	**E**	18.42% (±0.22)	**N**	8.34%	8.08% (±0.13)	**E**
Hispanic (any race**)**	34.2% (*)	40.63% (±0.5)	**D**	41.26% (±0.38)	**D**	14.62%	17.37% (±0.22)	**D**
White Alone	41.4% (±.1)	35.76% (±0.37)	**D**	35.6% (±0.28)	**D**	17.7%	15.29% (±0.16)	**D**
Black Alone	1.6% (±.1)	1.63% (±0.13)	*D*	1.64% (±0.1)	*C*	0.67%	0.7% (±0.06)	*E*
All Other Race(s)	3.3% (±.1)	3.07% (±0.16)	*E*	3.08% (±0.12)	*E*	1.42%	1.31% (±0.07)	*E*
Totals	100%	100%		100%		42.7%	42.7%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Next, Type 20 licenses were analyzed; as Table 47 indicates, 65.6% of the OC population occurred within 1,722 cells, and Table 48 shows that 34.4% of the population occurred within 450 cells. These tables also had different population denominators than their census tract counter parts (cells: 65.6% and 34.4% vs tracts: 35% and 65%), but followed the same basic trends for Hispanics and Whites. Hispanics again were overrepresented in cells with licenses and underrepresented in cells without them, while Whites were the converse of the Hispanic population. Overall, the majority of evaluation points exceeded the disparate distribution threshold for this study.

Table 47 OC Summary Statistics of Cells with Zero Type 20 Licenses

Cells with Zero Type 20 Alcohol Licenses: 1,722 / 65.6% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	20.41% (±0.26)	**C**	12.8%	13.39% (±0.17)	**N**
Hispanic (any race**)**	34.2% (*)	28.44% (±0.35)	**D**	22.43%	18.66% (±0.23)	**D**
White Alone	41.4% (±.1)	46.01% (±0.33)	**D**	27.15%	30.18% (±0.22)	**D**
Black Alone	1.6% (±.1)	1.53% (±0.11)	*D*	1.03%	1.% (±0.07)	*E*
All Other Race(s)	3.3% (±.1)	3.6% (±0.15)	*D*	2.18%	2.36% (±0.1)	*E*
Totals	100%	100%		65.6%	65.6%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 48 OC Summary Statistics of Cells with Type 20 Licenses

Cells with Type 20 Alcohol Licenses: 450 / 34.4% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	17.79% (±0.33)	**C**	17.08% (±0.25)	**D**	6.71%	6.12% (±0.11)	**C**
Hispanic (any race**)**	34.2% (*)	45.16% (±0.58)	**D**	48.63% (±0.47)	**D**	11.77%	15.54% (±0.2)	**D**
White Alone	41.4% (±.1)	32.6% (±0.39)	**D**	30.03% (±0.3)	**D**	14.25%	11.22% (±0.14)	**D**
Black Alone	1.6% (±.1)	1.65% (±0.15)	*D*	1.58% (±0.11)	*D*	0.54%	0.57% (±0.05)	*E*
All Other Race(s)	3.3% (±.1)	2.81% (±0.17)	*C*	2.67% (±0.13)	*D*	1.15%	0.97% (±0.06)	*D*
Totals	100%	100%		100%		34.4%	34.4%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

The Liquor Store category had the most licenses (N=418) in Orange County. As Table 49 and Table 50 show, Liquor Stores followed the trend of the previous scenarios where Hispanics were underrepresented in the absence of Liquor Stores and overrepresented in their presence and the White population the converse. Moreover, the cell version of the statistics showed greater correlation with the Hispanic population in the presence of Liquor Stores than the census tract version. Overall, the absence of Liquor Stores did not surpass the disparate distribution threshold, but was more than race-neutral. On the other hand, the presence of Liquor stores surpassed the disparate distribution threshold, particularly between Hispanic and White populations.

Table 49 OC Summary Statistics of Cells with Zero Liquor Stores

Cells with Zero Liquor Store Retailers: 1,835 / 73.4% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.7% (±0.27)	**N**	14.31%	14.45% (±0.18)	**E**
Hispanic (any race**)**	34.2% (*)	31.3% (±0.38)	**C**	25.09%	22.97% (±0.25)	**C**
White Alone	41.4% (±.1)	44.01% (±0.34)	**C**	30.37%	32.29% (±0.22)	**C**
Black Alone	1.6% (±.1)	1.53% (±0.12)	*D*	1.15%	1.12% (±0.08)	*E*
All Other Race(s)	3.3% (±.1)	3.46% (±0.15)	*D*	2.44%	2.54% (±0.1)	*E*
Totals	100%	100%		73.4%	73.4%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 50 OC Summary Statistics of Cells with Liquor Stores

Cells with Liquor Store Retailers: 337 / 26.6% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	18.99% (±0.38)	**E**	17.97% (±0.33)	**C**	5.2%	5.06% (±0.1)	**E**
Hispanic (any race**)**	34.2% (*)	42.16% (±0.65)	**D**	43.64% (±0.59)	**D**	9.11%	11.23% (±0.17)	**D**
White Alone	41.4% (±.1)	34.19% (±0.47)	**D**	33.78% (±0.41)	**D**	11.03%	9.11% (±0.12)	**D**
Black Alone	1.6% (±.1)	1.69% (±0.17)	*D*	1.69% (±0.15)	*D*	0.42%	0.45% (±0.05)	*E*
All Other Race(s)	3.3% (±.1)	2.96% (±0.2)	*E*	2.92% (±0.17)	*E*	0.89%	0.79% (±0.05)	*E*
Totals	100%	100%		100%		26.6%	26.6%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

There were 412 Grocery Stores with alcohol licenses in Orange County, second only to Liquor Stores with 418. Moreover, Grocery Stores may hold either a Type 20 or Type 21 license, but the majority (N=300) operated with a Type 21. Table 51 shows the sample size of cells with zero Grocery Stores was quite large (N=1,856 out of 2172 cells) and produced a very similar absence of retailer profile where Hispanics are underrepresented and Whites are overrepresented. Table 52 summarized the cells containing Grocery Stores with alcohol licenses, which closely tracked the Liquor Store scenario with Hispanics significantly overrepresented and Whites underrepresented.

Table 51 OC Summary Statistics of Cells with Zero Grocery Stores

Cells with Zero Grocery Store Retailers: 1,856 / 74.7% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	20.06% (±0.28)	**N**	14.57%	14.98% (±0.18)	**N**
Hispanic (any race**)**	34.2% (*)	31.46% (±0.39)	**C**	25.53%	23.49% (±0.25)	**C**
White Alone	41.4% (±.1)	43.46% (±0.35)	**C**	30.91%	32.44% (±0.23)	**N**
Black Alone	1.6% (±.1)	1.57% (±0.12)	*D*	1.17%	1.17% (±0.08)	*E*
All Other Race(s)	3.3% (±.1)	3.45% (±0.15)	*D*	2.49%	2.57% (±0.1)	*E*
Totals	100%	100%		74.7%	74.7%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 52 OC Summary Statistics of Cells with Grocery Stores

Cells with Grocery Store Retailers: 316 / 25.3% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	17.87% (±0.39)	**C**	17.22% (±0.33)	**C**	4.94%	4.53% (±0.1)	**C**
Hispanic (any race**)**	34.2% (*)	42.26% (±0.66)	**D**	46.07% (±0.58)	**D**	8.67%	10.71% (±0.17)	**D**
White Alone	41.4% (±.1)	35.33% (±0.48)	**D**	32.36% (±0.39)	**D**	10.49%	8.95% (±0.12)	**D**
Black Alone	1.6% (±.1)	1.57% (±0.17)	*D*	1.52% (±0.14)	*C*	0.4%	0.4% (±0.04)	*E*
All Other Race(s)	3.3% (±.1)	2.98% (±0.21)	*E*	2.83% (±0.18)	*C*	0.84%	0.75% (±0.05)	*E*
Totals	100%	100%		100%		25.3%	25.3%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Overall, the cells with licenses surpassed the disparate distribution threshold. On the other hand, the zero-retailer scenario manifested a distribution that was slightly more than race neutral. Although this was to be expected because as the number of cells with zero licenses/retailers increases towards the county-wide total, the population dynamics will approach the county-wide profile.

Convenience Stores (N=347) rank third by number of licenses in the list of retailer categories. Moreover, as Table 53 indicates, the number cells without Convenience Stores (N=1,888) was greater than scenarios with Liquor Stores (N=1,835) and Grocery Stores (N=1,856). However, even though the sample size continued to approach the county-wide value (N=2,172), this scenario surpassed the disparate distribution threshold. This suggested a race-biased function at least in part operated for the absence of convenience stores in the built environment between Hispanic and White populations. One potential factor related to this distribution could be that the majority of Convenience Stores had Type 20 licenses (N=296) while the rest had Type 21 (N=51), unlike Liquor Stores and Grocery Stores which primarily had Type 21 licenses.

Table 53 OC Summary Statistics of Cells with Zero Convenience Stores

Cells with Zero Convenience Store Retailers: 1,888 / 76.9% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	20.04% (±0.28)	**N**	15.01%	15.42% (±0.19)	**N**
Hispanic (any race**)**	34.2% (*)	29.86% (±0.39)	**D**	26.32%	22.97% (±0.25)	**D**
White Alone	41.4% (±.1)	45.03% (±0.36)	**C**	31.86%	34.65% (±0.23)	**C**
Black Alone	1.6% (±.1)	1.54% (±0.12)	*D*	1.21%	1.18% (±0.08)	*E*
All Other Race(s)	3.3% (±.1)	3.53% (±0.16)	*D*	2.56%	2.72% (±0.1)	*E*
Totals	100%	100%		77.0%	76.9%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 54 covers the cells with Convenience Stores scenario. Here again, both overrepresentation of Hispanic populations and underrepresentation of White and Asian populations were observed. Moreover, seven out of ten evaluation points exceeded the disparate distribution threshold.

Table 54 OC Summary Statistics of Cells with Convenience Stores

Cells with Convenience Store Retailers: 284 / 23.1% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	17.73% (±0.39)	**C**	17.11% (±0.34)	**D**	4.5%	4.09% (±0.09)	**C**
Hispanic (any race)	34.2% (*)	48.68% (±0.72)	**D**	50.08% (±0.65)	**D**	7.88%	11.22% (±0.17)	**D**
White Alone	41.4% (±.1)	29.26% (±0.46)	**D**	28.6% (±0.41)	**D**	9.54%	6.75% (±0.11)	**D**
Black Alone	1.6% (±.1)	1.68% (±0.18)	*D*	1.64% (±0.16)	*D*	0.36%	0.39% (±0.04)	*E*
All Other Race(s)	3.3% (±.1)	2.65% (±0.2)	*D*	2.58% (±0.18)	*D*	0.77%	0.61% (±0.05)	*D*
Totals	100%	100%		100%		23.1%	23.1%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Gas Stations (N=270) followed Convenience Stores in the list of retailer categories by license count. Like Convenience Stores, Gas Stations primarily held Type 20 licenses (N=255), but there were a small number with Type 21 licenses (N=15). Table 55 confirmed that as the number of cells with absence of retailers (Gas Stations) approaches the full county-wide cell count, bias attenuates into the margin of errors and becomes race neutral.

Table 55 OC Summary Statistics of Cells with Zero Gas Stations

Cells with Zero Gas Station Retailers: 1,954 / 84.7% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.52% (±0.29)	**N**	16.53%	16.53% (±0.19)	**E**
Hispanic (any race**)**	34.2% (*)	33.17% (±0.42)	**N**	28.97%	28.1% (±0.27)	**N**
White Alone	41.4% (±.1)	42.41% (±0.36)	**N**	35.07%	35.93% (±0.24)	**N**
Black Alone	1.6% (±.1)	1.54% (±0.13)	*D*	1.33%	1.3% (±0.08)	*E*
All Other Race(s)	3.3% (±.1)	3.37% (±0.16)	*C*	2.82%	2.85% (±0.11)	*E*
Totals	100%	100%		84.7%	84.7%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 56, on the other hand, manifested a nearly symmetrical 5% difference of over/under representation between Hispanics and White Populations. Moreover, the other minority populations are nearly all within the margins of error for the expected and observed percentages. Overall, the disparate distribution threshold was exceeded between Hispanics and Whites, but the Asian population impact was effectively race neutral.

Table 56 OC Summary Statistics of Cells with Gas Stations

Cells with Gas Stations Retailers: 218 / 15.3% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.47% (±0.53)	**N**	19.7% (±0.48)	**E**	2.98%	2.98% (±0.08)	**E**
Hispanic (any race)	34.2% (*)	39.89% (±0.86)	**D**	39.69% (±0.78)	**D**	5.23%	6.1% (±0.13)	**D**
White Alone	41.4% (±.1)	35.77% (±0.62)	**D**	35.69% (±0.56)	**D**	6.33%	5.47% (±0.09)	**D**
Black Alone	1.6% (±.1)	1.75% (±0.22)	*E*	1.74% (±0.2)	*E*	0.24%	0.27% (±0.03)	*E*
All Other Race(s)	3.3% (±.1)	3.12% (±0.29)	*E*	3.17% (±0.25)	*E*	0.51%	0.48% (±0.04)	*E*
Totals	100%	100%		100%		15.3%	15.3%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Orange County had 159 Pharmacies with either a Type 21 (N=135) or Type 20 (N=24) alcohol license. As Table 57 indicates, the absence of retailer sample size (N=2,031) for this category was even closer to the county-wide cell count (N=2,172) than previous categories. As expected, the population dynamics with such a large sample was approaching the county-wide percentages. As such, the absence of pharmacies appeared to be a race neutral function.

Table 57 OC Summary Statistics of Cells with Zero Pharmacies

Cells with Zero Pharmacy Retailers: 2,031 / 89.2% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.68% (±0.3)	**N**	17.4%	17.54% (±0.2)	**E**
Hispanic (any race**)**	34.2% (*)	34.06% (±0.44)	**N**	30.49%	30.37% (±0.29)	**E**
White Alone	41.4% (±.1)	41.37% (±0.37)	**N**	36.91%	36.88% (±0.24)	**E**
Black Alone	1.6% (±.1)	1.58% (±0.13)	*D*	1.4%	1.41% (±0.09)	*E*
All Other Race(s)	3.3% (±.1)	3.32% (±0.16)	*C*	2.97%	2.96% (±0.11)	*E*
Totals	100%	100%		89.2%	89.2%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 58, on the other hand, presented a new population distribution dynamic. Although there still appeared to be an overrepresentation bias with the Hispanic population, the White population was effectively race neutral, being neither over nor under represented. This was a departure from the census tract version where the Hispanic population manifested an underrepresentation and the White population indicated a slight overrepresentation. These differences were most likely related to MAUP issues in the census tract analysis. Overall, this scenario narrowly manifested some absence of race neutral distribution, but only where multiple pharmacies in a cell were a factor.

Table 58 OC Summary Statistics of Cells with Pharmacies

Cells with Pharmacy Retailers: 141 / 10.8% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	18.14% (±0.59)	**N**	16.96% (±0.54)	**C**	2.11%	1.97% (±0.06)	**N**
Hispanic (any race**)**	34.2% (*)	35.3% (±0.95)	**E**	37.27% (±0.9)	**C**	3.71%	3.83% (±0.1)	**E**
White Alone	41.4% (±.1)	41.64% (±0.74)	**E**	41.04% (±0.69)	**E**	4.49%	4.51% (±0.08)	**E**
Black Alone	1.6% (±.1)	1.49% (±0.26)	*E*	1.43% (±0.24)	*E*	0.17%	0.16% (±0.03)	*E*
All Other Race(s)	3.3% (±.1)	3.43% (±0.35)	*E*	3.3% (±0.32)	*D*	0.36%	0.37% (±0.04)	*E*
Totals	100%	100%		100%		10.8%	10.8%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

There were fifty alcohol retailers identified as Department Stores (i.e. Targets and K-Marts) in Orange County. Table 59 reinforced the previous observations that as the absence of retailers in the built environment increases, the absence distribution approaches a race neutral function.

Table 59 OC Summary Statistics of Cells with Zero Department Stores

Cells with Zero Dept Store Retailers: 2,122 / 96.3% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.46% (±0.31)	**N**	18.79%	18.74% (±0.2)	**E**
Hispanic (any race**)**	34.2% (*)	33.96% (±0.45)	**N**	32.93%	32.7% (±0.3)	**E**
White Alone	41.4% (±.1)	41.68% (±0.39)	**N**	39.87%	40.13% (±0.25)	**E**
Black Alone	1.6% (±.1)	1.57% (±0.14)	*D*	1.51%	1.51% (±0.09)	*E*
All Other Race(s)	3.3% (±.1)	3.33% (±0.17)	*C*	3.21%	3.21% (±0.11)	*E*
Totals	100%	100%		96.3%	96.3%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

However, unlike previous retailer categories, there are no instances where two or more Department Stores occur in one cell in Orange County. This is shown in Table 60 where the *Pop % Cells* and *(Pop x L) % Cells* columns have the same values. While this scenario exhibited overrepresentation of Hispanic populations and neutral representation in the presence of Department Stores, the census tract summary statistics indicated un underrepresentation of Hispanic populations and overrepresentation of Asian populations. As with the discrepancies between cell and census tracts Pharmacy statistics, these differences were likely due to MAUP-related census tract boundary issues. Overall, this scenario exceeded the disparate distribution threshold for Hispanics and Whites.

Table 60 OC Summary Statistics of Cells with Department Stores

Cells with Dept Store Retailers: 50 / 3.7% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	20.77% (±1.12)	**E**	20.77% (±1.12)	**E**	0.72%	0.77% (±0.04)	**E**
Hispanic (any race**)**	34.2% (*)	40.28% (±1.7)	**D**	40.28% (±1.7)	**D**	1.27%	1.49% (±0.06)	**D**
White Alone	41.4% (±.1)	34.1% (±1.25)	**D**	34.1% (±1.25)	**D**	1.53%	1.26% (±0.05)	**D**
Black Alone	1.6% (±.1)	1.63% (±0.44)	*D*	1.63% (±0.44)	*D*	0.06%	0.06% (±0.02)	*E*
All Other Race(s)	3.3% (±.1)	3.23% (±0.56)	*D*	3.23% (±0.56)	*D*	0.12%	0.12% (±0.02)	*E*
Totals	100%	100%		100%		3.7%	3.7%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Wholesale Clubs was the final category for analysis. As Figure 38 shows, there were only sixteen Wholesale Clubs with alcohol licenses in OC. As a result, the population sample size for the absence of Wholesale clubs was 2,156 cells with 99.3% of the county population (see Table 61), while the population size for the presence was only 0.7% (see Table 62). As expected with the sample size only 16 cells short of the county-wide cell count, the absence of Wholesale Clubs was effectively the county-wide populations dynamics within the margins of error and race-neutral. On the other hand, the summary statistics for the 16 retailers was swamped by the margins of error and was excluded as unreliable.

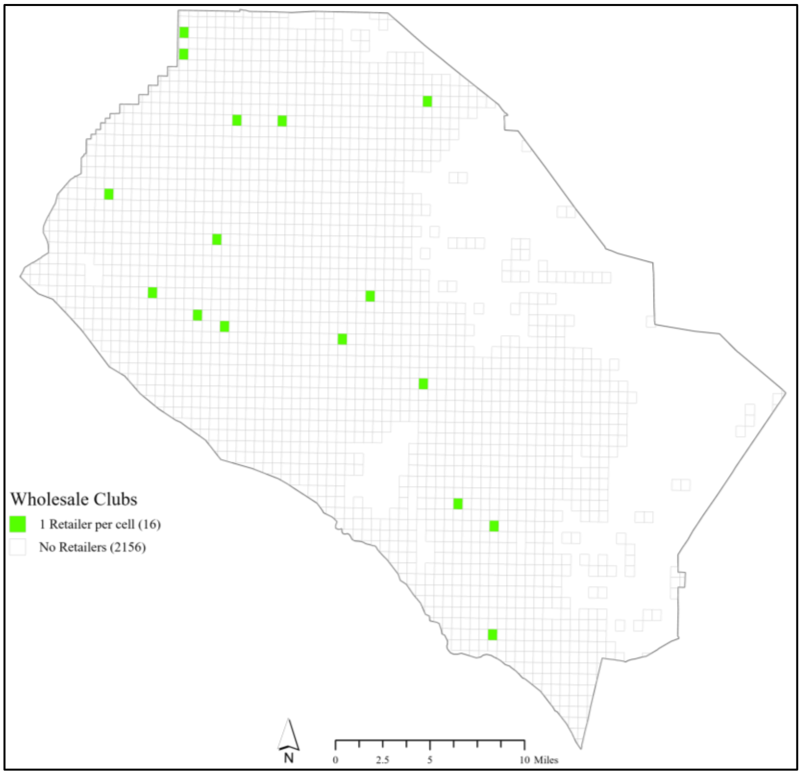

Figure 38 OC Cells with Wholesale Clubs

Table 61 OC Summary Statistics of Cells with Zero Wholesale Clubs

Cells with Zero Wholesale Club Retailers: 2,156 / 99.3% of OC Population						
	Pop % County	**Pop % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	19.46% (±0.31)	**N**	19.37%	19.32% (±0.21)	**E**
Hispanic (any race**)**	34.2% (*)	34.21% (±0.46)	**N**	33.95%	33.96% (±0.3)	**E**
White Alone	41.4% (±.1)	41.43% (±0.39)	**N**	41.1%	41.13% (±0.26)	**E**
Black Alone	1.6% (±.1)	1.57% (±0.14)	*D*	1.56%	1.56% (±0.09)	*E*
All Other Race(s)	3.3% (±.1)	3.33% (±0.17)	*C*	3.31%	3.31% (±0.11)	*E*
Totals	100%	100%		99.3%	99.3%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 62 OC Summary Statistics of Cells with Wholesale Clubs

Cells with Wholesale Club Retailers: 16 / 0.7% of OC Population								
	Pop % County	**Pop % Cells**	**Dist**	**(Pop x L) % Cells**	**Dist**	**% Expected**	**% Actual**	**Dist**
Asian Alone	19.5% (±.1)	25.56% (±3.11)	**E**	25.56% (±3.11)	**E**	0.14%	0.19% (±0.02)	**E**
Hispanic (any race**)**	34.2% (*)	32.54% (±4.13)	**E**	32.54% (±4.13)	**E**	0.25%	0.24% (±0.03)	**E**
White Alone	41.4% (±.1)	36.78% (±3.32)	**E**	36.78% (±3.32)	**E**	0.3%	0.27% (±0.02)	**E**
Black Alone	1.6% (±.1)	1.98% (±1.3)	*E*	1.98% (±1.3)	*E*	0.01%	0.01% (±0.01)	*E*
All Other Race(s)	3.3% (±.1)	3.14% (±1.1)	*E*	3.14% (±1.1)	*E*	0.02%	0.02% (±0.01)	*E*
Totals	100%	100%		100%		0.7%	0.7%	

*Estimate is controlled, margin of error treated as zero.

C: Race Correlated | D: Disparate Distribution | E: Margin of Error | N: Race Neutral | X: Exclude

Table 63 summarizes the *(Pop x L) % Cells* column values and overall distribution assessments of the license/retailers in scaled population grid cells scenarios. As the table indicates, the Hispanic population had the most overrepresentation scenarios. Likewise, the majority of scenarios exceeded the threshold for disparate distribution.

Table 63 OC Cells with Alcohol Licenses Population Summary

	Asian	Hispanic	White	Black	Other	Dist
Orange County	19.5% (±0.1)	34.2% *	41.4% (±0.1)	1.6% (±0.1)	3.3% (±0.1)	N/A
All Licenses	17.86% (±0.17)	**44.37% (±0.29)**	33.26% (±0.2)	1.62% (±0.07)	2.89% (±0.09)	**D**
Type 21	18.42% (±0.22)	**41.26% (±0.38)**	35.6% (±0.28)	1.64% (±0.1)	3.08% (±0.12)	**D**
Type 20	17.08% (±0.25)	**48.63% (±0.47)**	30.03% (±0.3)	1.58% (±0.11)	2.67% (±0.13)	**D**
Liquor Stores	17.97% (±0.33)	**43.64% (±0.59)**	33.78% (±0.41)	1.69% (±0.15)	2.92% (±0.17)	**D**
Grocery Stores	17.22% (±0.33)	**46.07% (±0.58)**	32.36% (±0.39)	1.52% (±0.14)	2.83% (±0.18)	**D**
Convenience Stores	17.11% (±0.34)	**50.08% (±0.65)**	28.6% (±0.41)	1.64% (±0.16)	2.58% (±0.18)	**D**
Gas Stations	19.7% (±0.48)	**39.69% (±0.78)**	35.69% (±0.56)	1.74% (±0.2)	3.17% (±0.25)	**D**
Pharmacies	16.96% (±0.54)	**37.27% (±0.9)**	41.04% (±0.69)	1.43% (±0.24)	3.3% (±0.32)	**C**
Department Stores	20.77% (±1.12)	**40.28% (±1.7)**	34.1% (±1.25)	1.63% (±0.44)	3.23% (±0.56)	**D**
Wholesale Clubs	**25.56% (±3.11)**	32.54% (±4.13)	36.78% (±3.32)	1.98% (±1.3)	3.14% (±1.1)	**X**

*Estimate is controlled, margin of error treated as zero

C: Race Correlated | D: Disparate Distribution | N/A: Not Applicable | X: Exclude

Table 64 summarizes the *Pop % Cells* values and overall distribution assessments of the zero license/retailers in scaled population grid scenarios. As the table indicates, the Hispanic population manifested reduced numbers in the census tracts without licenses, while the White population was overrepresented in most census tract without licenses. The distribution patterns of the absence of alcohol licenses at the cell level also provided two interesting patterns. First, somewhere between a sample size of 1,888 cells (Convenience Stores) and 1,945 cells (Gas Stations), the absence of license/retailer population dynamics started to closely track the county-wide dynamics. Second, sample sizes 1,888 and lower showed a consistent overrepresentation bias for White populations and underrepresentation of Hispanic populations. The Asian, Black, and Other populations across all samples tracked closely to their county-wide dynamics, with values either slightly under or over the margins of error.

Table 64 OC Cells with Zero Licenses Population Summary

	Asian	**Hispanic**	**White**	**Black**	**Other**	**Dist**
Orange County	19.5% (±0.1)	34.2% *	41.4% (±0.1)	1.6% (±0.1)	3.3% (±0.1)	N/A
All Licenses	20.47% (±0.31)	25.81% (±0.39)	**48.49% (±0.4)**	1.52% (±0.14)	3.7% (±0.18)	**D**
Type 21	19.96% (±0.24)	29.39% (±0.33)	**45.6% (±0.31)**	1.52% (±0.11)	3.52% (±0.14)	**D**
Type 20	20.41% (±0.26)	28.44% (±0.35)	**46.01% (±0.33)**	1.53% (±0.11)	3.6% (±0.15)	**D**
Liquor Stores	19.7% (±0.27)	31.3% (±0.38)	**44.01% (±0.34)**	1.53% (±0.12)	3.46% (±0.15)	**C**
Grocery Stores	20.06% (±0.28)	31.46% (±0.39)	**43.46% (±0.35)**	1.57% (±0.12)	3.45% (±0.15)	**C**
Convenience Stores	20.04% (±0.28)	29.86% (±0.39)	**45.03% (±0.36)**	1.54% (±0.12)	3.53% (±0.16)	**D**
Gas Stations	19.52% (±0.29)	33.17% (±0.42)	**42.41% (±0.36)**	1.54% (±0.13)	3.37% (±0.16)	**N**
Pharmacies	19.68% (±0.3)	34.06% (±0.44)	41.37% (±0.37)	1.58% (±0.13)	3.32% (±0.16)	**N**
Department Stores	19.46% (±0.31)	33.96% (±0.45)	41.68% (±0.39)	1.57% (±0.14)	3.33% (±0.17)	**N**
Wholesale Clubs	19.46% (±0.31)	34.21% (±0.46)	41.43% (±0.39)	1.57% (±0.14)	3.33% (±0.17)	**X**

*Estimate is controlled, margin of error treated as zero

C: Race Correlated | D: Disparate Distribution | N: Race Neutral | N/A: Not Applicable | X: Exclude

Overall, these results suggested a compelling argument for two race/ethnicity and alcohol licenses correlations. First, the Hispanic population is overrepresented in areas within ~0.5 miles (the approximate length of a cell side) of most alcohol retailers. Second, as the number of licenses/retailers in the built environment increases, the licenses are less likely to occur in White dominant cells. Whether similar correlations exist with other race/ethnicities is not clear. While there were some observations inconsistent with the county-wide population dynamics, they occurred with small sample sizes or were within the margins of error to be more than anecdotal observations.

4.2.2. Scaled Population Grid Alcohol License Density

The next step in analyzing the distribution of alcohol licenses at the cell level was to determine the density of alcohol licenses per cell. Figure 39 shows the license density per cell for all licenses in Orange County as a single group, the Type 21 licenses, the Type 20 licenses, and for licenses by each category of retailer (except Wholesale Clubs). First, scatter plots were generated for each race/ethnicity cell percentage versus each cell's licenses and retailers counts. Next, linear regressions were performed with the licenses/retailers per cell as the dependent variable for each scatter plot and the resulting trend lines were coded red if the race/ethnicity indicated a positive correlation with increasing population percentage and green if the race/ethnicity indicated a negative correlation with increasing population percentage. Finally, the results were rejected if the p-value was above 0.05. Because each cell has a whole number of licenses with a very small range of potential values, the individual regressions become less meaningful as their slope approaches zero.

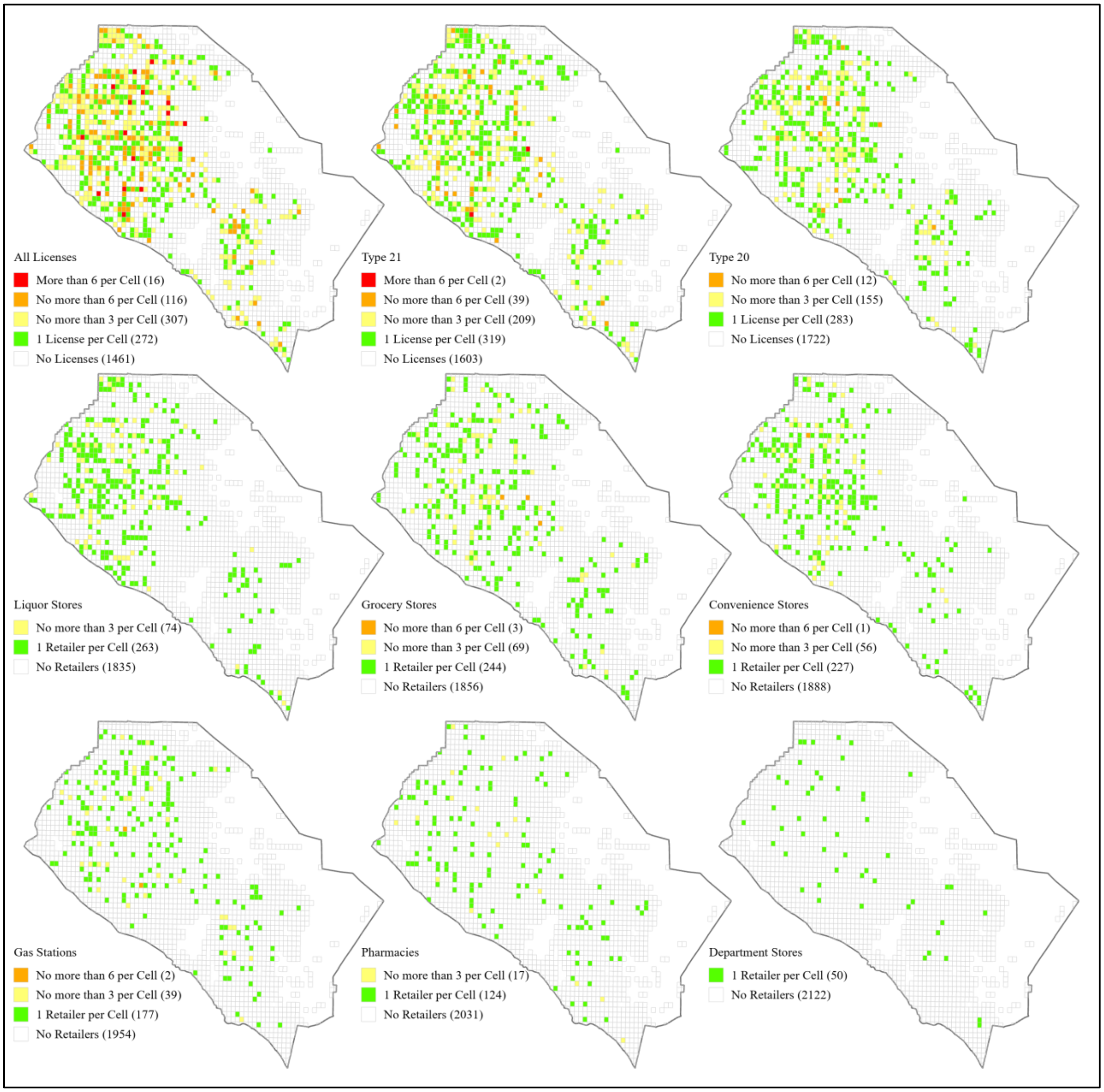

Figure 39 OC Alcohol Licenses per Cell

For the regressions with p-values less than 0.05, if the slope polarities between two or more populations were inconsistent, then the likelihood of a race-neutral distribution function was rejected and assumed to be a disparate distribution. To be clear, only the differences in the slope polarities between the populations were assessed. This methodology allowed for a quick visual inspection to determine the potential existence of race-neutral versus race-correlated distributions in the distributions per cell of the licenses/retailers. Out of ten regression scenarios, two (Department Stores and Wholesale Clubs) produced slopes with a value of zero (effectively a null condition since the slopes did not have a polarity) and two (Type 21 licenses and Gas Stations) were completely rejected because two or more results had p-values greater than 0.05.

Figure 40 shows that the trend line polarities between the White and Hispanic populations for All Licenses were reversed and their associated p-values were less than 0.05, while the Asian regression was rejected because the p-value was greater than 0.05. Notwithstanding the rejected Asian regression, the White and Hispanic results met this study's criteria for a race-correlated distribution.

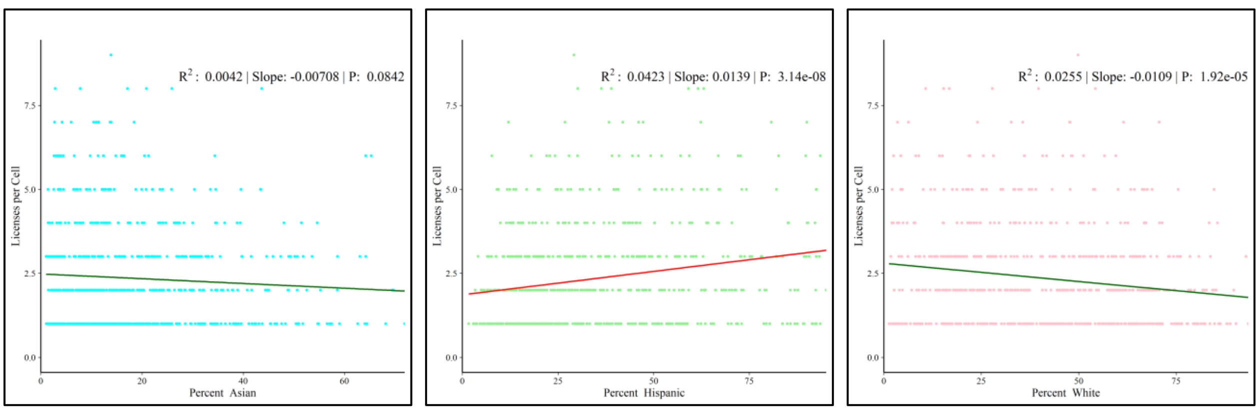

Figure 40 OC Linear Regressions on All Licenses per Cell

Figure 41 shows the regression results for the Type 21 licenses per cell scenario. Here, the high p-values for White and Asian regressions rendered the results inconclusive for comparisons and the entire scenario was rejected. Figure 42 depicts the Type 20 regressions which had two valid results with opposite slopes. Therefore, that scenario met the criteria for race-correlated distribution.

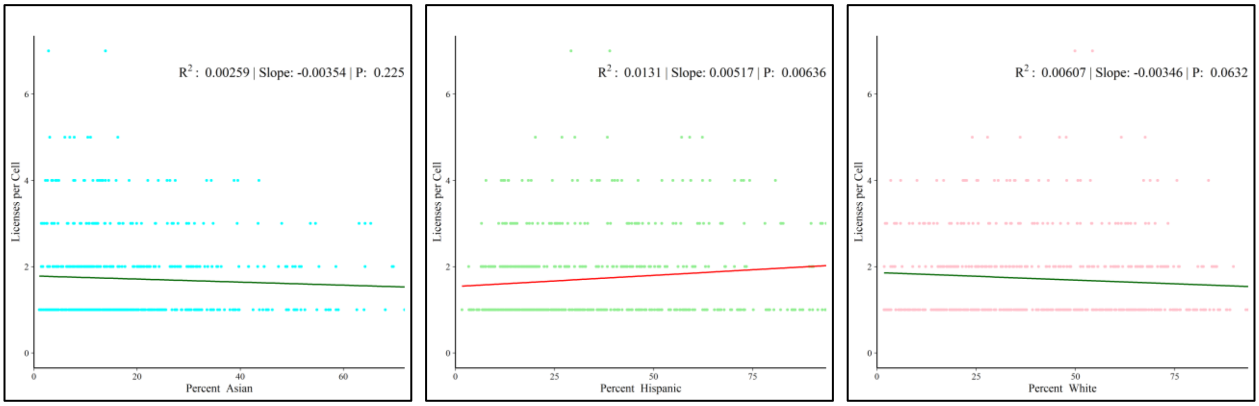

Figure 41 OC Linear Regressions on Type 21 Licenses per Cell

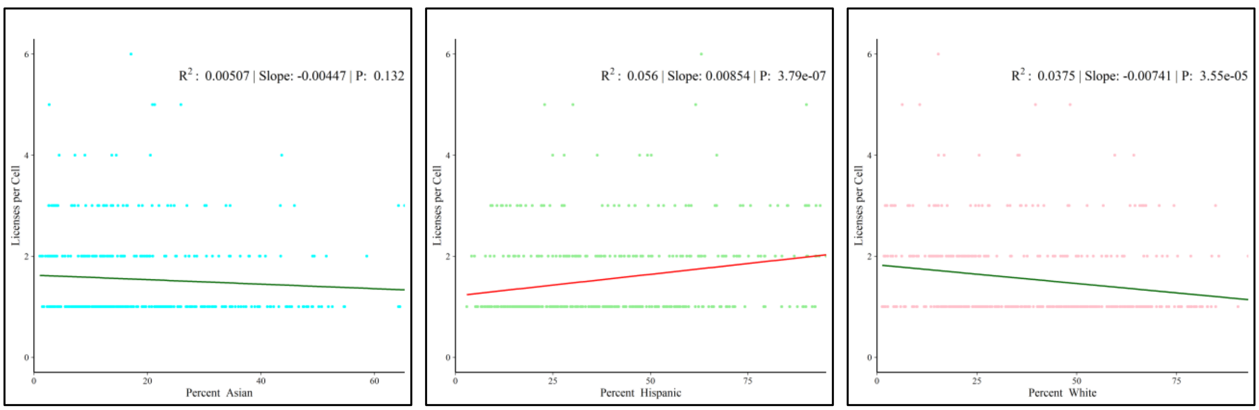

Figure 42 OC Linear Regressions on Type 20 Licenses per Cell

While the expectation was to compare the minority regression slope polarities to the White slope polarity, the Liquor Store regressions presented a scenario where the White regression was rejected (see Figure 43). Moreover, the Liquor Store category was composed entirely of Type 21 licenses, where the White and Asian regressions were rejected. This result supported the merit of analyzing both license type and retailer type and that race-correlated distributions can occur between minority populations as well as the majority population.

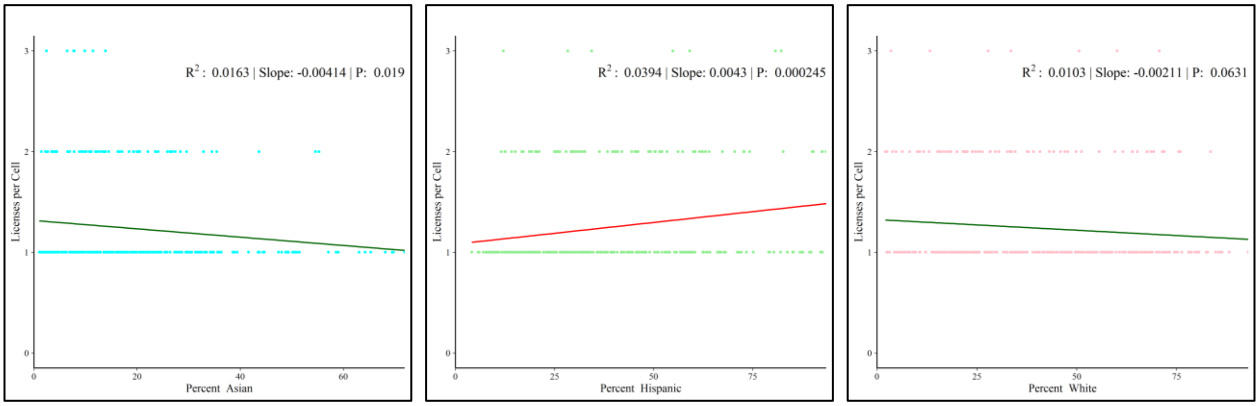

Figure 43 OC Linear Regressions on Liquor Stores per Cell

For the remaining regression scenarios—Grocery Stores (see Figure 44), Convenience Stores (see Figure 45), and Pharmacies (see Figure 46)—the Hispanic regressions produced results with a p-values below 0.05. While the Asian regression was rejected for Grocery Stores and the White regressions were rejected for Convenience Stores and Pharmacies the non-rejected slopes had opposite polarities to the Hispanic slopes. Thus, these three categories met the criteria for race-correlated distribution.

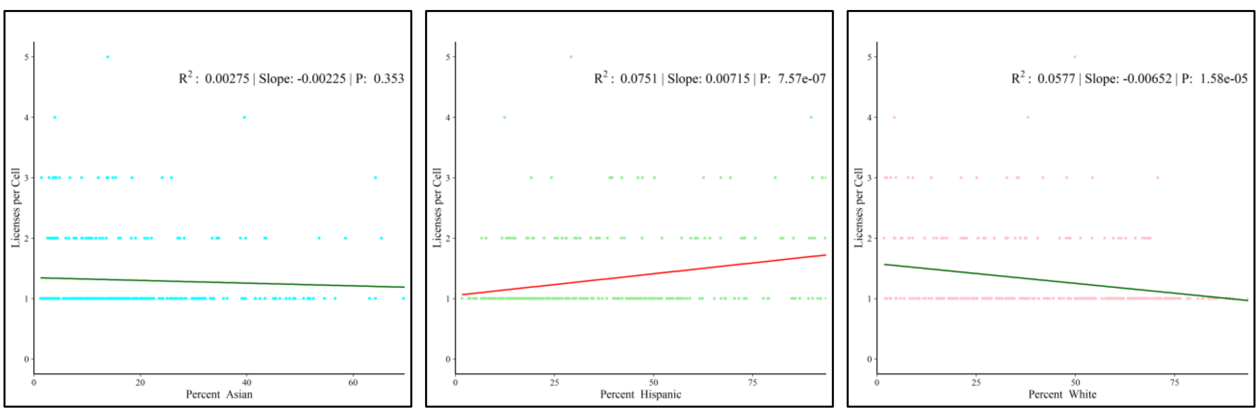

Figure 44 OC Linear Regressions on Grocery Stores per Cell

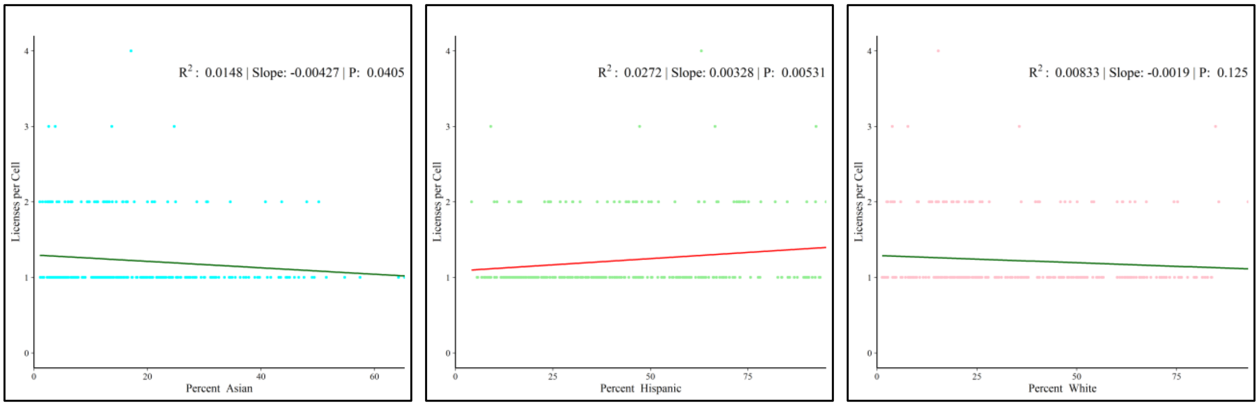

Figure 45 OC Linear Regressions on Convenience Stores per Cell

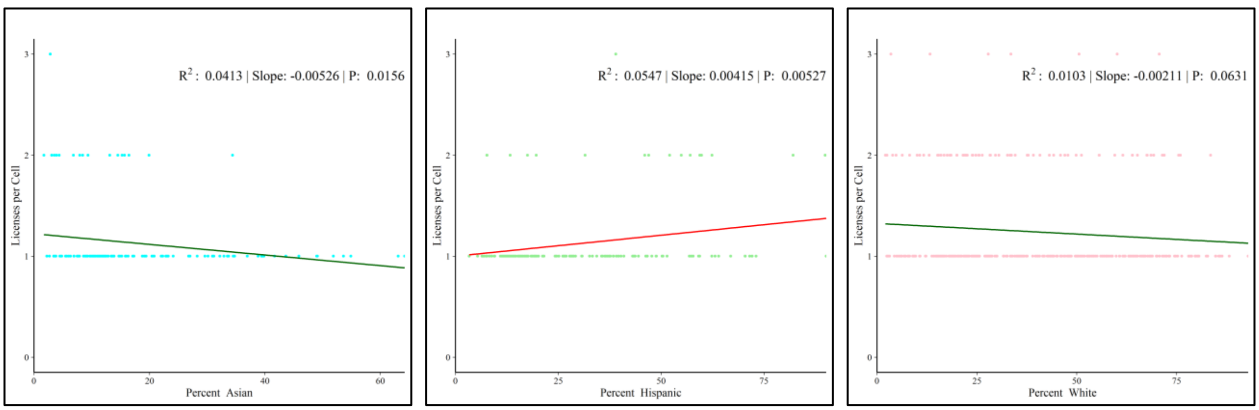

Figure 46 OC Linear Regressions on Pharmacies per Cell

Table 65 summarizes the results for the percent population versus licenses per cell regressions. For all the non-rejected results, the trend line slope polarities for the Hispanic population were always opposite to the White and Asian populations. These results met the study’s threshold for the presence of race-correlated distribution.

Table 65 Licenses per Cell Linear Regressions Trend Line Polarity Summary

	Asian	Hispanic	White	Black	Other	Dist
All	X	+	—	X	—	C
Type 21	X	+	X	X	X	X
Type 20	X	+	—	X	—	C
Liquor Stores	—	+	X	X	X	C
Grocery Stores	X	+	—	X	—	C
Convenience Stores	—	+	X	X	X	C
Gas Stations	X	X	X	X	X	X
Pharmacies	—	+	X	X	—	C
Department Stores	X	X	X	X	X	X
Wholesale Clubs	X	X	X	X	X	X

— Negative Slope + Positive Slope X: Excluded C: Race Correlated

Another useful metric is the distribution of alcohol licenses based on their density per 1,000 population. Figure 47 provides distribution maps of the metric for All Licenses, Type 21, Type 20, and all the retailers except Wholesale Clubs. However, there were 100 cells with a total population of less than 1,000 that also contained one or more licenses; as a result, some of those cells appeared in a higher license band than the number of licenses in the cell. This was particularly evident for Department Stores which only had one retailer per cell, but the cells with populations under 1,000 appeared to have more (see Figure 47 bottom right).

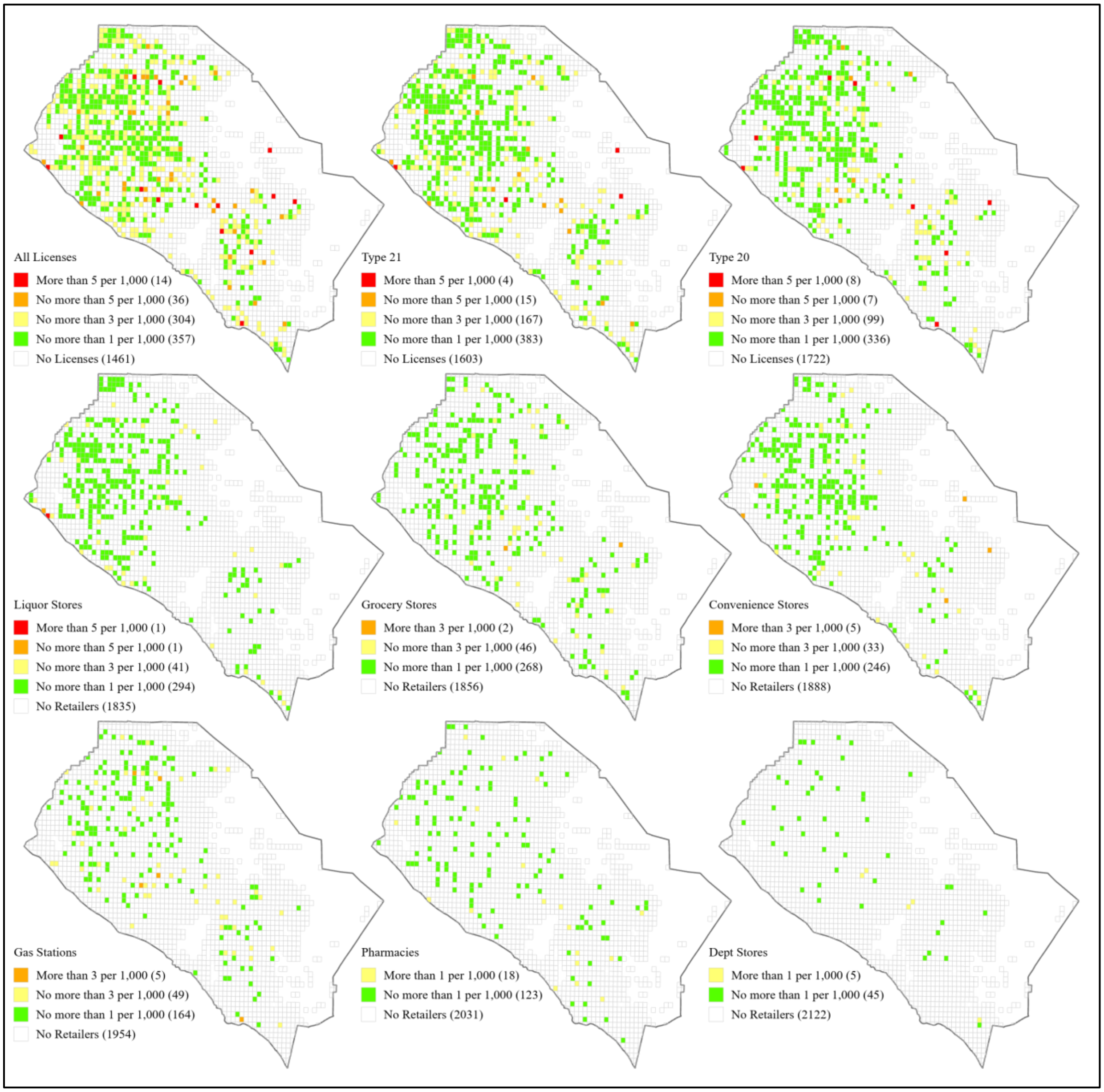

Figure 47 OC Alcohol Licenses per 1,000 Population per Cell

Scatter plots were generated for each race/ethnicity cell percentage versus each license type and for each retailer category per 1,000 population in each cell. Linear regressions were performed with the licenses/retailers per 1,000 population as the dependent variable and race/ethnicity percent as the independent variable for each scatter plot. The resulting trend lines were coded red if the race/ethnicity indicated a positive correlation with increasing population percentage and green if the race/ethnicity indicated a negative correlation with increasing population percentage. Finally, the results were rejected if the p-value was greater than 0.05. For example, the results for Department Stores and Wholesale Clubs were rejected as all race/ethnicities had p-values greater than 0.05. For the regressions with p-values less than 0.05, if the slope polarities between two or more populations were inconsistent, then the likelihood of a race-neutral distribution function was rejected and assumed to be a race-correlated distribution.

Starting with All Licenses, all the regressions had p-values below 0.05 (see Figure 48). Moreover, the White trend line had the opposite slope polarity to both the Asian and Hispanic trend lines. Likewise, the Type 21 regression p-values were all below 0.05 and the White trend line had the opposite slope polarity to the Asian and Hispanic lines (see Figure 49) Finally, for the Type 20 regressions the Asian result was rejected, but the White and Hispanic trend lines had opposite polarities. All the scenarios satisfied the criteria for race-correlated distributions since they all had one or more races with opposite slope polarities.

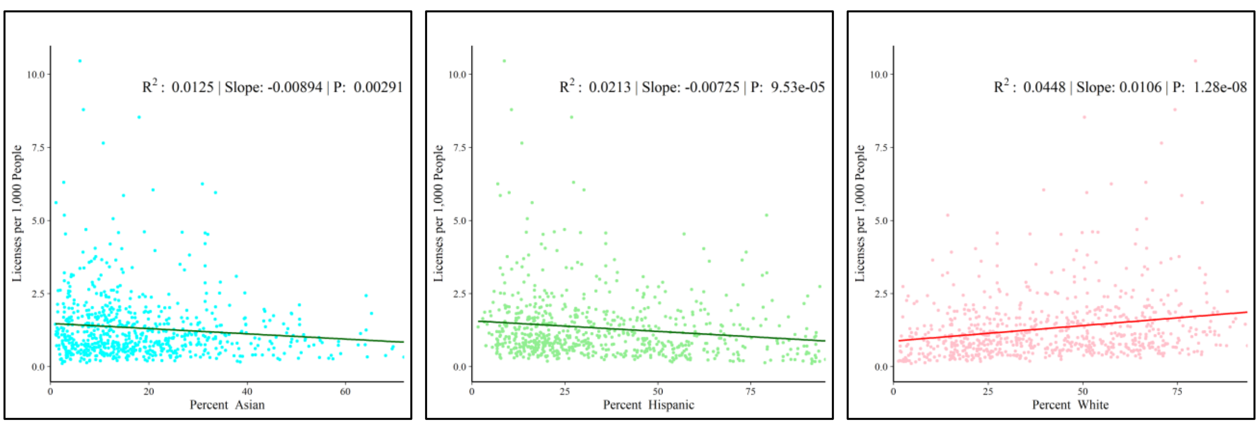

Figure 48 OC Linear Regressions on All Licenses per 1,000 People per Cell

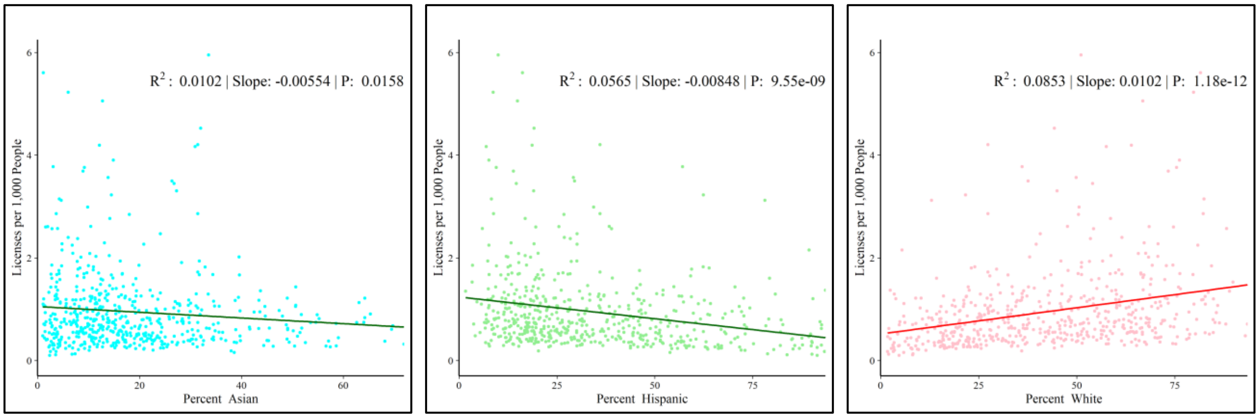

Figure 49 OC Linear Regressions on Type 21 Licenses per 1,000 People per Cell

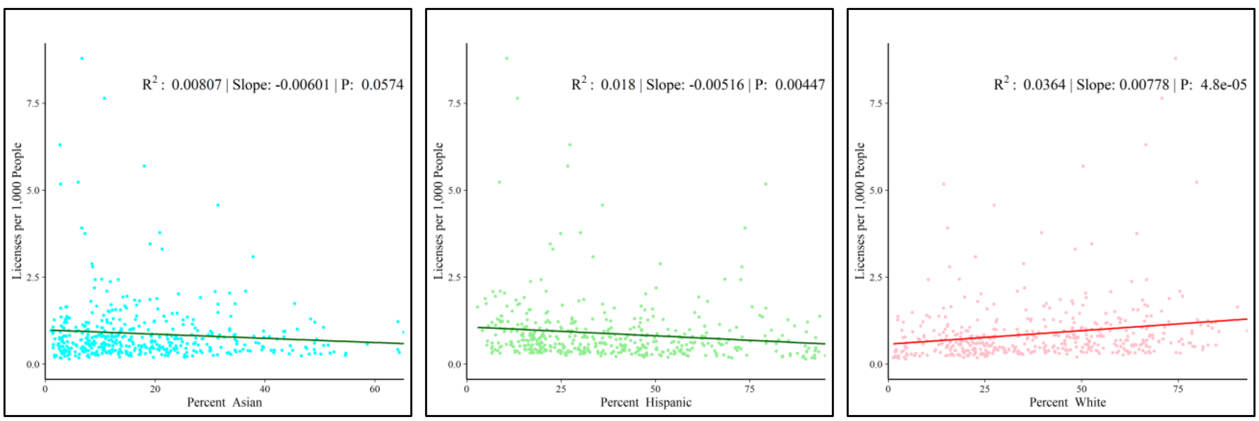

Figure 50 OC Linear Regressions on Type 20 Licenses per 1,000 People per Cell

The regressions for the retailer categories followed similar patterns, with all satisfying the criteria for race-correlated distributions. For Liquor Stores, both Asian and Hispanic trend lines were the opposite polarity of White (see Figure 51). The Asian regression result was rejected for Grocery Stores, but the Hispanic and White trend lines had opposite polarities (see Figure 52). The same polarity occurred for Asian and Hispanic regressions with Convenience Stores, but both were opposite to White (Figure 53). The Asian results were rejected for both Gas Stations and Pharmacies, but Hispanic and White regressions had opposite polarities for both (see Figure 54 and Figure 55).

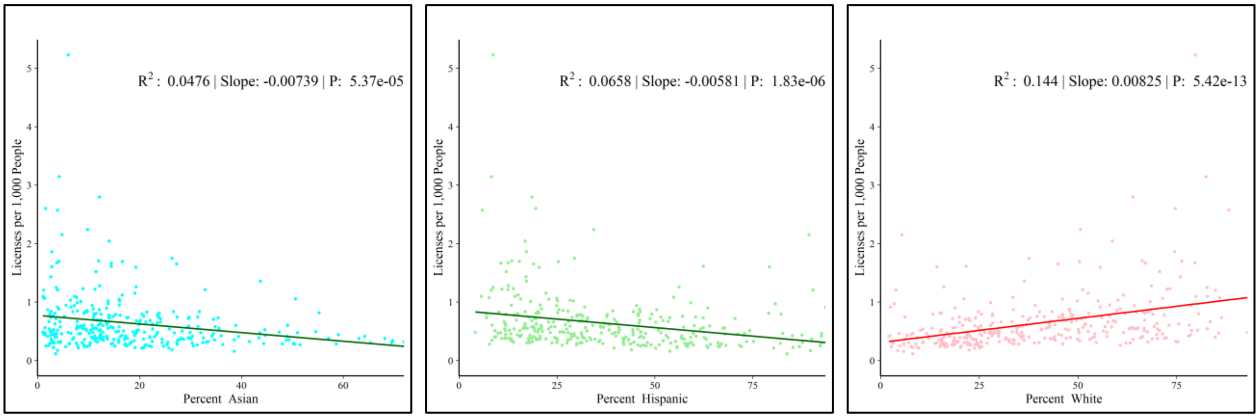

Figure 51 OC Linear Regressions on Liquor Stores per 1,000 People per Cell

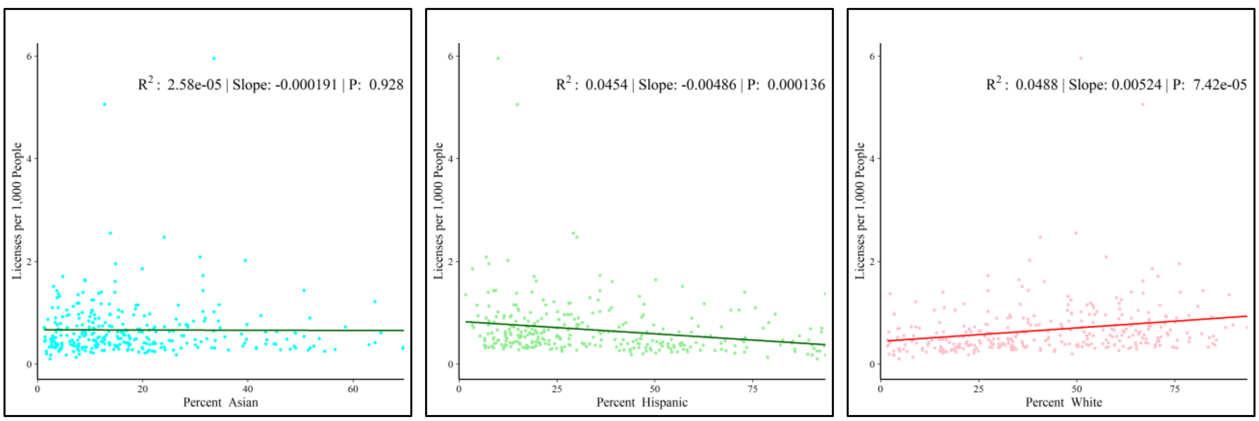

Figure 52 OC Linear Regressions on Grocery Stores per 1,000 People per Cell

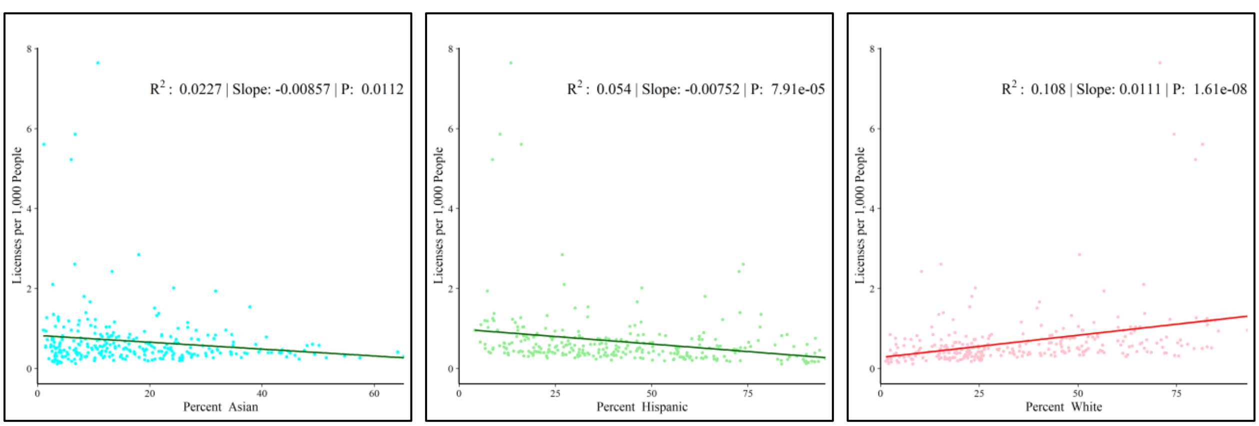

Figure 53 OC Linear Regressions on Convenience Stores per 1,000 People per Cell

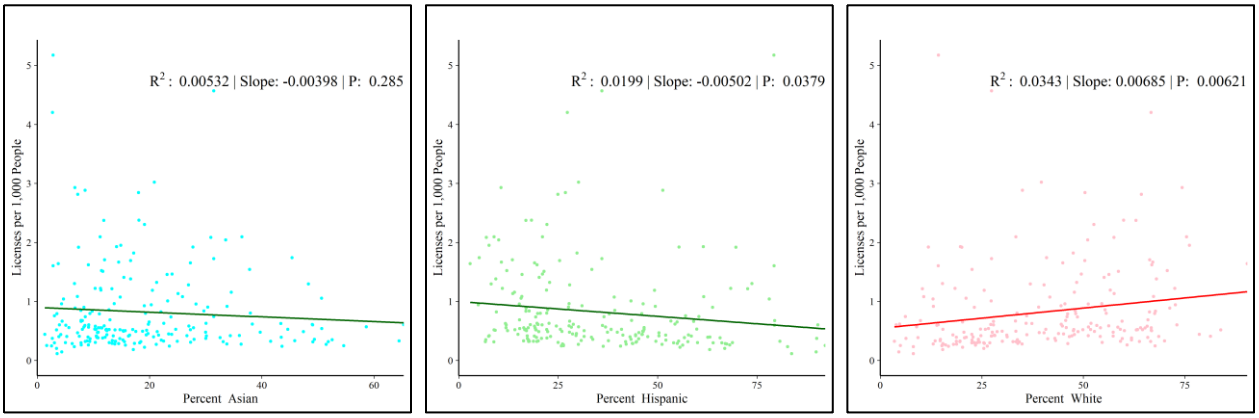

Figure 54 OC Linear Regressions on Gas Stations per 1,000 People per Cell

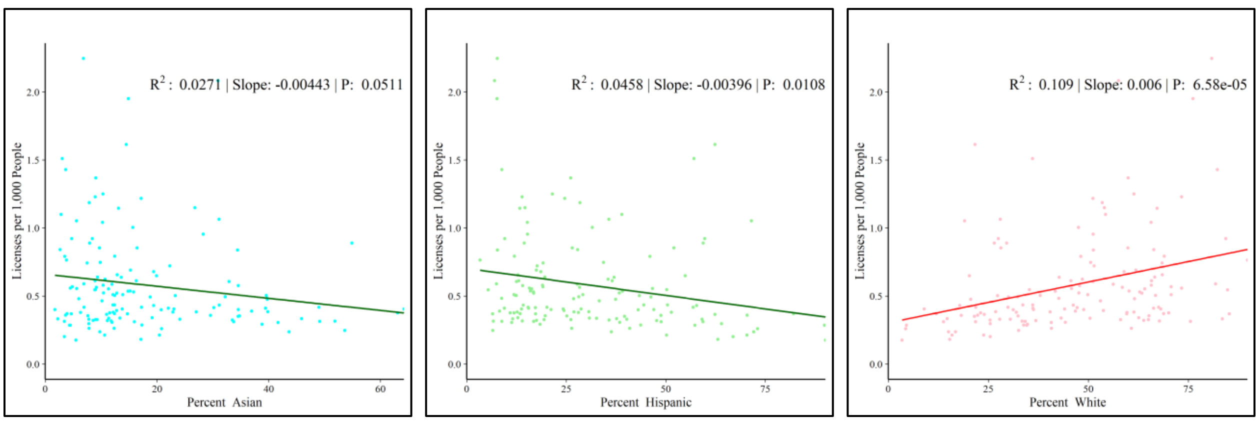

Figure 55 OC Linear Regressions on Pharmacies per 1,000 People per Cell

Table 66 summarizes the results for the percent population versus licenses per 1,000 people regressions. Overall, there were only two scenarios where the results were rejected: Department Stores and Wholesale Clubs. The non-rejected results for the other scenarios, on the other hand, satisfied the criteria for race-correlated distributions.

Table 66 Cell Linear Regressions per 1,000 People Trend Line Summary

	Asian	Hispanic	White	Black	Other	Dist
All	—	—	+	X	+	**C**
Type 21	—	—	+	X	+	**C**
Type 20	X	—	+	X	X	**C**
Liquor Stores	—	—	+	X	+	**C**
Grocery Stores	X	—	+	X	X	**C**
Convenience Stores	—	—	+	X	X	**C**
Gas Stations	X	—	+	X	X	**C**
Pharmacies	X	—	+	X	X	**C**
Department Stores	X	X	X	X	X	**X**
Wholesale Clubs	X	X	X	X	X	**X**

— Negative Slope +Positive Slope X: Excluded C: Race Correlated

4.2.3. Scaled Population Alcohol License Hot Spots: Getis-Ord Gi Statistic*

A Getis-Ord Gi* statistic—specifically the ArcGIS Pro Optimized Hot Spot tool—was run for All Licenses to determine the presence of statistically significant clustering at the cell level. The tool output was reviewed to identify the neighborhood distance (~1.8 miles), and then the tool was run again for the Type 21 licenses, Type 20 license, and for each retailer category (see Figure 56). The distance band was set to ~1.8 mile for each run.

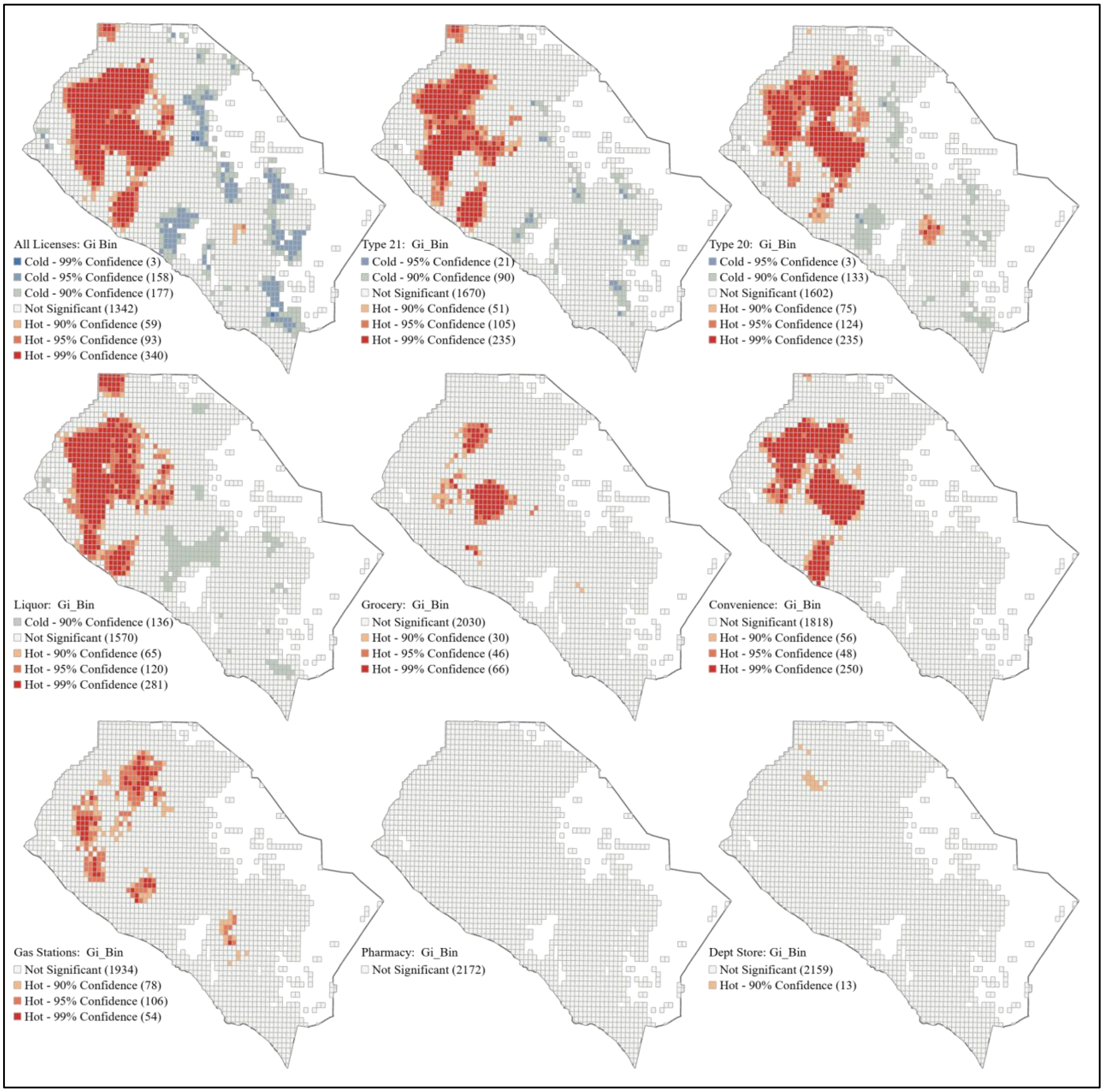

Figure 56 OC Optimized Alcohol License Hot Spots Based Upon Cell Boundaries

As depicted in Figure 56, the Optimized Hot Spot analysis detected areas of hot spot clustering in the northern portion of the county and some cold spot clustering in the southern portion for most license and retailer combinations. However, the Pharmacy category showed no clustering, while the Department Store category showed negligible hot spot clustering.

The next step was to perform race/ethnicity summary statistics on the confidence level bins for All Licenses, Type21, Type 20, Liquor Stores, Grocery Stores, Convenience Stores, and Gas Stations. The remaining retailer categories were not evaluated due to insufficient sample sizes. Table 67 has the summary statistics for All Licenses. The Hispanic Population was consistently overrepresented in the Hot Spot bins and underrepresented in the Cold Spot bins while the converse was true for the White population. The Asian population, however, was overrepresented only in the 95% bin of the Hot Spots and underrepresented in all other bins. While the results in the Cold 99% bin were unreliable due to the sample size (N=3), the other bins had sufficient samples to evaluate the difference between observed and county-wide values. Overall, the majority of values exceeded the disparate distribution threshold of 10% difference from the county-wide proportions.

Table 67 OC Cell Based All Licenses Optimized Hot Spot Summary Statistics

	Cells	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	2172	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	340	20.91% (±0.11)	**C**	55.0% (±0.2)	**D**	20.45% (±0.11)	**D**	1.43% (±0.04)	**C**	2.22% (±0.05)	**D**
Hot 95% Confidence	93	16.0% (±0.05)	**D**	42.64% (±0.09)	**D**	37.11% (±0.06)	**D**	1.47% (±0.02)	**E**	2.77% (±0.02)	**D**
Hot 90% Confidence	59	17.13% (±0.04)	**D**	36.76% (±0.06)	**C**	40.96% (±0.04)	**N**	1.81% (±0.02)	**D**	3.35% (±0.02)	**E**
Cold 90% Confidence	177	18.45% (±0.04)	**C**	12.82% (±0.03)	**D**	63.11% (±0.05)	**D**	1.35% (±0.01)	**D**	4.27% (±0.02)	**D**
Cold 95% Confidence	158	16.35% (±0.03)	**D**	10.8% (±0.03)	**D**	67.52% (±0.06)	**D**	0.82% (±0.01)	**D**	4.51% (±0.02)	**D**
Cold 99% Confidence	3	14.44% (±0.0)	**X**	13.37% (±0.0)	**X**	67.77% (±0.01)	**X**	0.31% (±0.0)	**X**	4.11% (±0.0)	**X**

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

The summary statistics of the Type 21 licenses, while varying in degree, followed the same pattern as All Licenses (see Table 68). Moreover, the Type 20 summary statistics indicated that the population living in the 235 Hot 99% Confidence cells was almost 65% Hispanic, nearly twice their representation across OC (Table 69). This was a significant degree of overrepresentation considering that there were only 711 cells with alcohol licenses. Overall, the majority of values for the Type 21 and Type 20 licenses surpassed the disparate distribution threshold of 10% difference from the county-wide proportions.

Table 68 OC Cell Based Type 21 Licenses Optimized Hot Spot Summary Statistics

	Cells	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	2172	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	235	23.94% (±0.1)	**D**	47.79% (±0.16)	**D**	24.15% (±0.1)	**D**	1.53% (±0.04)	**E**	2.59% (±0.04)	**D**
Hot 95% Confidence	105	15.86% (±0.05)	**D**	54.38% (±0.1)	**D**	26.26% (±0.06)	**D**	1.19% (±0.02)	**D**	2.31% (±0.03)	**D**
Hot 90% Confidence	51	16.41% (±0.03)	**D**	46.79% (±0.05)	**D**	32.98% (±0.04)	**D**	1.34% (±0.01)	**D**	2.48% (±0.01)	**D**
Cold 90% Confidence	90	16.49% (±0.02)	**D**	9.95% (±0.02)	**D**	68.36% (±0.04)	**D**	0.88% (±0.01)	**D**	4.32% (±0.01)	**D**
Cold 95% Confidence	21	15.8% (±0.01)	**D**	11.63% (±0.01)	**D**	67.39% (±0.02)	**D**	0.78% (±0.0)	**D**	4.4% (±0.01)	**D**

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Table 69 OC Cell Based Type 20 Licenses Optimized Hot Spot Summary Statistics

	Cells	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	2172	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	235	18.04% (±0.09)	**C**	63.59% (±0.18)	**D**	15.12% (±0.08)	**D**	1.47% (±0.04)	**E**	1.78% (±0.04)	**D**
Hot 95% Confidence	124	21.44% (±0.07)	**C**	39.71% (±0.11)	**D**	34.06% (±0.07)	**D**	1.82% (±0.03)	**D**	2.97% (±0.03)	**D**
Hot 90% Confidence	75	17.53% (±0.04)	**D**	37.06% (±0.07)	**C**	40.39% (±0.05)	**N**	1.57% (±0.02)	**E**	3.45% (±0.02)	**E**
Cold 90% Confidence	133	20.2% (±0.04)	**N**	11.23% (±0.03)	**D**	62.92% (±0.06)	**D**	0.89% (±0.01)	**D**	4.76% (±0.03)	**D**
Cold 95% Confidence	3	26.0% (±0.01)	**X**	14.66% (±0.01)	**X**	55.02% (±0.01)	**X**	0.84% (±0.0)	**X**	3.48% (±0.0)	**X**

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Turning to the retailer categories, the Liquor Store category had the greatest number of retailers (N=418), all of which had Type 21 licenses. Table 70 shows that the Liquor Store summary statistics generally followed the results of the Type 21 licenses, although there was only a single cold bin. These statistics indicated that the heaviest clustering of Liquor Stores occurred in Hispanic dominant cells.

Table 70 OC Cell Based Liquor Stores Optimized Hot Spot Summary Statistics

	Cells	**Asian**	**Dist**	**Hispanic**	**Dist**	**White**	**Dist**	**Black**	**Dist**	**Other**	**Dist**
County Statistics	2172	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	281	24.2% (±0.1)	**D**	46.39% (±0.17)	**D**	25.35% (±0.1)	**D**	1.47% (±0.04)	**E**	2.58% (±0.05)	**D**
Hot 95% Confidence	120	15.47% (±0.05)	**D**	50.14% (±0.11)	**D**	30.16% (±0.06)	**D**	1.56% (±0.02)	**E**	2.66% (±0.03)	**D**
Hot 90% Confidence	65	14.15% (±0.03)	**D**	57.27% (±0.08)	**D**	25.34% (±0.04)	**D**	1.07% (±0.01)	**D**	2.18% (±0.02)	**D**
Cold 90% Confidence	136	27.39% (±0.06)	**D**	11.16% (±0.05)	**D**	55.54% (±0.07)	**D**	1.53% (±0.03)	**E**	4.37% (±0.03)	**D**

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Grocery Stores, Table 71, had second highest retailer count (N=412), and those retailers held either a Type 20 (N=112) or a Type 21 (N=300) license. The Optimized Hot Spot analysis also indicated less clustering overall for Grocery Stores compared to Liquor Stores. But like Liquor Stores, the summary statistics showed the greatest clustering in Hispanic dominant cells.

Table 71 OC Cell Based Grocery Stores Optimized Hot Spot Summary Statistics

	Cells	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	2172	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	66	9.14% (±0.04)	**D**	81.42% (±0.11)	**D**	7.51% (±0.03)	**D**	0.9% (±0.02)	**D**	1.02% (±0.02)	**D**
Hot 95% Confidence	46	21.39% (±0.04)	**C**	59.54% (±0.07)	**D**	15.63% (±0.03)	**D**	1.38% (±0.01)	**D**	2.07% (±0.02)	**D**
Hot 90% Confidence	30	34.61% (±0.04)	**D**	37.22% (±0.06)	**C**	24.42% (±0.03)	**D**	1.25% (±0.01)	**D**	2.5% (±0.01)	**D**

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Moving to the two remaining two categories, Convenience Stores (N=347) had 296 Type 20 licenses, while Gas Stations (N=270) had 255. Table 72 has the summary statistics for Convenience Stores and Table 73 the statistics for Gas Stations. Both these categories also showed that Hispanic population was overrepresented in all bins while the White population was underrepresented.

Table 72 OC Cell Based Convenience Stores Optimized Hot Spot Summary Statistics

	Cells	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	2172	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	250	17.49% (±0.09)	**D**	61.23% (±0.19)	**D**	17.91% (±0.09)	**D**	1.4% (±0.04)	**D**	1.97% (±0.04)	**D**
Hot 95% Confidence	48	23.32% (±0.03)	**D**	44.34% (±0.06)	**D**	27.61% (±0.03)	**D**	1.68% (±0.01)	**E**	3.05% (±0.02)	**C**
Hot 90% Confidence	56	25.69% (±0.04)	**D**	39.59% (±0.07)	**D**	30.21% (±0.04)	**D**	1.69% (±0.02)	**C**	2.81% (±0.02)	**D**

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Table 73 OC Cell Based Gas Stations Optimized Hot Spot Summary Statistics

	Cells	Asian	Dist	Hispanic	Dist	White	Dist	Black	Dist	Other	Dist
County Statistics	2172	19.5% (±0.1)	N/A	34.2% *	N/A	41.4% (±0.1)	N/A	1.6% (±0.1)	N/A	3.3% (±0.1)	N/A
Hot 99% Confidence	54	20.5% (±0.04)	**C**	48.63% (±0.06)	**D**	26.89% (±0.04)	**D**	1.65% (±0.01)	**E**	2.33% (±0.01)	**D**
Hot 95% Confidence	106	20.42% (±0.06)	**N**	45.17% (±0.1)	**D**	29.96% (±0.06)	**D**	1.85% (±0.02)	**D**	2.6% (±0.03)	**D**
Hot 90% Confidence	78	27.93% (±0.05)	**D**	37.42% (±0.07)	**A**	30.78% (±0.05)	**D**	1.4% (±0.02)	**D**	2.47% (±0.02)	**D**

*Estimate is controlled, margin of error treated as zero

C: Correlated | D: Disparate | E: Margin of Error | N: Race Neutral | N/A: Not Applicable | X: Exclude

Overall, the Cell Based Optimized Hot Spot scenarios indicated high clustering in Hispanic dominant cells and White population underrepresentation. The majority of *Dist* column values also surpassed the disparate distribution threshold.

In order to observe the potential occurrence of more macro-scale clustering, the Hot Spot Analysis was performed using a 3-mile distance band as a proxy for a reasonable distance an OC resident would drive to a convenient retailer (see Figure 57). Although this was less than double the optimized distance band value used above, and the same distance band value used to create the census tract optimized hot spot analyses, the observational results were rejected as too hyper-clustered for useful analysis. Moreover, the Pharmacy and Department Store categories still indicated insignificant clustering at this distance band value.

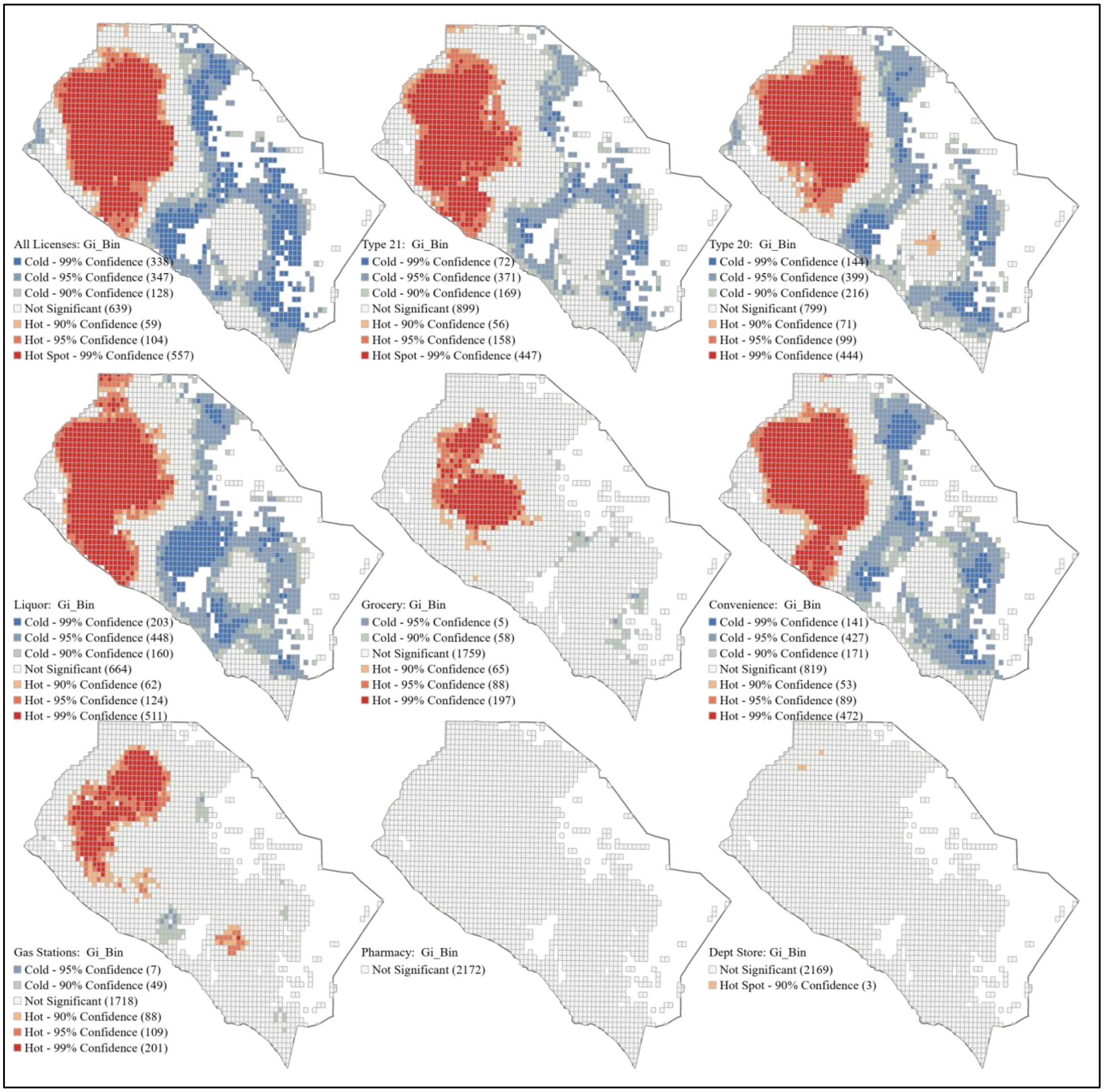

Figure 57 OC Alcohol License Observational Hot Spots Based Upon Cell Boundaries

While setting the distance band value to arbitrarily longer distances did produce evidence of macro-clustering with the Pharmacy category, it further increased the hyper-clustering of the other scenarios. For example, setting the distance band value to 6.4 miles (the value used to create the optimized hot spot results with the census tracts) resulted in the northern part of the county becoming a solid hot spot while the southern part of the county was a solid cold spot.

Ultimately, the attempt to generate a Cell-based Observational Hot Spot Analysis was abandoned as the results did not appear to provide any meaningful insight.

4.3 Quantification of Race Neutral and Disparate Distributions

This study utilized six different analytical methods applied to census tracts and five different methods applied to scaled population grid cells—110 different evaluation points—in an attempt to quantify race-based distribution patterns of alcohol licenses (see Table 74). Out of the 110 evaluation points, 29 results were excluded from analysis because they had less than 20 census tracts or cells represented in the results or their linear regression p-values were greater than 0.05. The remaining 81 points were suitable for race-neutral versus disparate distribution analysis. Of those 81 results, 74 deviated from what would be expected if race-neutral functions were operating. Finally, 34 results manifested a race-correlated distribution, while the remaining 40 results exceeded thresholds defined to identify occurrence of disparate distributions.

Looking specifically at the licenses results, All Licenses and Type 20 Licenses manifested 7 disparate distribution and 3 race-correlated results out 11 tests. Type 21 Licenses, on the other hand, had 5 disparate distribution results and 4 race-correlated results. These outcomes suggest that California's race-neutral licensing regulations alone cannot address the various factors that together result in some communities of color having higher distributions of alcohol retailers than their county-wide presence would predict, while majority white communities have fewer alcohol retailers then their county-wide presence would predict.

As for the retailer results; first, Wholesale Clubs was effectively excluded from analysis because of the small sample size (N=16). Next, Department Stores, Pharmacies, and Gas Stations exhibited some race-neutral distributions and had the least disparate distribution results. Liquor and Convenience Stores, on the other hand, exhibited disparate distribution in the majority of their results. Grocery Stores appeared to be race-correlated with some disparate distribution.

Table 74 Summary of Distribution Evaluation Points

		All Licenses	Type 21	Type 20	Liquor Stores	Grocery Stores	Convenience Stores	Gas Stations	Pharmacies	Dept Stores	Wholesale Clubs
Census Tracts	**Presence**	D	C	D	D	D	D	C	C	D	X
	Absence	D	D	D	D	C	D	C	N	N	N
	Density per Square Mile	C	C	C	C	C	C	C	C	X	X
	Density per 1,000 People	X	C	X	C	C	X	X	C	X	X
	Optimized Hot Spots	D	D	D	D	X	D	X	X	X	X
	Observational Hot Spots	D	X	D	D	X	D	D	X	X	X
Scaled Cells	**Presence**	D	D	D	D	D	D	D	C	D	X
	Absence	D	D	D	C	C	D	N	N	N	N
	Density per Cell	C	X	C	C	C	C	X	C	X	X
	Density per 1,000 People	C	C	C	C	C	C	C	C	X	X
	Optimized Hot Spots	D	D	D	D	D	D	D	X	X	X

Definitions:
C: Race-Correlated Distribution
D: Disparate Distribution
N: Race Neutral
X: Excluded from analysis

4.4 Census Tracts Versus Scaled Population Grid: Outcome Variations

As a general observation, there are significant variations between census tracts and scaled population grid cells at the atomic level—individual cells, tracts, and results of computations. This should come as no surprise as the two approaches are based on significantly different spatial units. Take for example Type 20 licenses (see Table 75). First, the total area covered by census tracts with Type 20 licenses is 446.8 square miles compared to 123.8 square miles covered by the cells; census tracts cover more than triple the cell area. Second, the tract-based population (N=2,050,182) is nearly double the cell-based population (N=1,085,899). However, these variations at the atomic level between scale provide further insight as to populations and licenses distribution patterns.

Table 75 Comparison of Type 20 Licenses between Tracts and Cells

	Tracts: 364 / 65.0% of OC Population 446.8 mi^2 / N=2,050,182 pop				Cells: 450 / 34.4% of OC Population 123.8 mi^2 / N=1,085,899 pop			
	% Expected	**% Actual**	**Pop % Tracts**	**(Pop x L) % Tracts**	**% Expected**	**% Actual**	**Pop % Cells**	**(Pop x L) % Cells**
Asian Alone	12.67%	12.78% (±0.17)	19.67% (±0.26)	18.99% (±0.19)	6.71%	6.12% (±0.11)	17.79% (±0.33)	17.08% (±0.25)
Hispanic (any race**)**	22.22%	25.9% (±0.26)	39.87% (±0.41)	43.04% (±0.31)	11.77%	15.54% (±0.2)	45.16% (±0.58)	48.63% (±0.47)
White Alone	26.9%	23.25% (±0.2)	35.79% (±0.31)	33.38% (±0.22)	14.25%	11.22% (±0.14)	32.6% (±0.39)	30.03% (±0.3)
Black Alone	1.02%	1.04% (±0.07)	1.61% (±0.11)	1.66% (±0.08)	0.54%	0.57% (±0.05)	1.65% (±0.15)	1.58% (±0.11)
All Other Race(s)	2.16%	1.99% (±0.09)	3.06% (±0.14)	2.93% (±0.1)	1.15%	0.97% (±0.06)	2.81% (±0.17)	2.67% (±0.13)

For instance, while the Asian, Hispanic, and White values in the tract-based *(Pop x L) % Tract* column and the cell-based *(Pop x L) % Cells* column both show that the Hispanic population has more exposure to Type 20 licenses, the tract-based values have less variance than the cell-based values. This indicates that in the aggregate more of the Hispanic population lives within ~0.5 miles of a Type 20 retailer than the other two races. Thus, the variations between the methods provides an insight that would not be apparent from either method alone. Overall, the two methods are complimentary and when compared together provide insight into patterns and distributions that operate at different scales.

Chapter 5 Conclusion

Systemic racism in the built environment is present when minority groups experience greater detriments or fewer benefits than nearby majority populations. Some detriments are easily identified: pollution, crime, dumps, and toxic water. Benefits, on the other hand, are not always as easily identified, while their absence from the built environment is just as impactful. Take for example access to clean water—a benefit often taken for granted—which promotes healthy communities, while its absence—a benefit denied in Flint, MI—precipitates a public health crisis. Or the unexpected benefit of open green spaces, which decreases environmental heat retention, while the lack of open green spaces, in the form of continuous concrete and asphalt surfaces, results in increased urban temperatures. These forms of systemic racism are often referred to as disparate impacts, which is a way of describing the effects of these detriments on the community. This study introduced the more nuanced term disparate distribution to describe the uneven distribution of a benefit or burden across the built environment.

5.1 Finding Disparate Distributions of Alcohol Licenses in Orange County

This study focused on whether race and ethnicity correlated with the distribution of alcohol licenses in the Orange County built environment because one of the major factors in the distribution of those licenses is a race-neutral licensing regulation. Alcohol licenses were chosen because the density of alcohol retailers and the sale of alcohol has been correlated with negative impacts on the communities where alcohol retailers are concentrated and the population lives within close proximity. While there has been less research on the impacts to the community based on type of retailer, it is reasonable to assume that the dissociative impact of easy access to alcohol in a community is not completely diminished simply because the access is through a pharmacy, grocery store, or some other type of retailer with associative qualities. Therefore, the type of retailer became another variable of interest in analyzing distribution patterns of alcohol licenses with reference to the racial/ethnic composition of the local population.

To analyze whether there were disparate distributions of Type 20 and Type 21 alcohol licenses, this study leveraged multiple straightforward statistical methods, commonly available datasets, and two forms of areal sampling to address and mitigate issues related to MAUP, aggregation, and spillover effects that can exaggerate or attenuate distribution analysis. Moreover, multiple reliable observations increased the objective quality of the results. Overall, this study found that both Type 20 and Type 21 licenses exceeded thresholds for disparate distributions across almost all evaluation points. For example, the Hispanic population was consistently overrepresented—exceeding their county-wide population representation proportion by more than 10%—in the licensing Hot Spot analyses. Likewise, the Liquor Stores, Convenience Stores, and Grocery Stores, also exceeded the thresholds for disparate distributions across the majority of evaluation points. On the other hand, Gas Stations, Pharmacies, and Department Stores also exhibited disparate distributions, but with significantly less evaluation points in agreement. In other words, these categories produced mixed summary statistics results of disparate distributions and no or few hot spot hots with statistical significance.

This study also identified four principal forms of disparate distribution. The first is overrepresentation of a minority race/ethnicity in the presence of licenses/retailers (presence). The second is underrepresentation of a minority race/ethnicity in the locations where licenses/retailers are not distributed (absence). The third is underrepresentation of the majority race in the presence of licenses/retailers. The fourth is overrepresentation of the majority race in the locations where licenses/retailers are not distributed.

These patterns were often found together, but there were instances where some of the evaluation points were race neutral and only one or two of the disparate distribution forms manifested in the other evaluation points. For example, the Hispanic population was almost always overrepresented in the presence of licenses/retailers, but the Asian population was frequently neutral or underrepresented. While this study focused on the Asian, Hispanic, and White populations to access disparate distributions, the Black and Other populations results manifested unique representation profiles different than the Asian, Hispanic, and White populations. For example, the Black population was more frequently overrepresented in the presence of licenses/retailers than the Asian population, but not as often as the Hispanic population, whereas the Other population was frequently underrepresented in the scenarios.

Thus, as to the forms of disparate distributions, this study found that the Hispanic population was consistently overrepresented in the presence of licenses/retailers and underrepresented in locations where licenses/retailers did not occur. Likewise, the White population was consistently underrepresented in the presence of licenses/retailers and overrepresented in locations without licenses/retailers. In other words, all four principal types of disparate distribution were found in Orange County. Moreover, Orange County is not unique or exotic in a way that would explain the disparate distributions.

These results indicate that requiring laws and regulations to avoid recognition of race is likely insufficient to ensure race-neutral distributions of benefits and detriments in the built environment. As a matter of public policy, laws and regulations should focus on race-neutral distributions of benefits and detriments across society, which can only occur by recognition that race matters. At least since the late 20th century, America has undertaken, as a matter of public policy, the project of addressing and correcting racism in all forms. This study, with its development of the concept of disparate distributions, extends that initiative with a framework of methodologies and datasets that can be replicated, tailored, and deployed to identify systemic racism in the built environment.

5.2 Limitations of the Study

One of the main limitations of the study is the accuracy of the race/ethnicity estimates at both the census tract and scaled population grid cell levels. Specifically, the scaled population grid data was created by areally weighted spatial interpolation of census tracts and LandScan 2018 data; any errors in the census tract estimates or LandScan 2018 population data would be multiplied as a part of the grid creation process.

Another limitation is this study relied on a single snapshot of the active licenses on the date of license data acquisition. While the entire dataset of licenses is likely fairly stable over time, there are constant minor changes as businesses move, licenses are transferred, new businesses start, and other businesses fold.

Also, the study only examined retailers with alcohol licenses, however, grocery stores, convenience stores, gas stations, etc. may exist in the built environment that do not have alcohol licenses. Examining the distribution of the alcohol-licensed and non-licensed retailers would provide greater insight as to how race correlates with retailer type distributions.

5.3 Areas for Future Study

This study provided a proof of concept framework for a multiscale disparate distribution analysis in a single California county. However, the datasets exist to analyze all counties in California as the licensing regulations operate at the state level. Moreover, this study could be used as a template for a temporal analysis of the changing license distributions over time.

Furthermore, while this study aggregated licenses to census tracts and scaled population grid cells, the spatial interpolation could be carried one step further to create zones around each license point to aggregate the local population to the license points at other scales for analysis. This study would also benefit from inclusion of additional socio-economic factors such as income, education level, and housing statistics. Finally, examining retailers with and without alcohol licenses would provide greater insight into race-correlated retailer distribution patterns.

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Appendix A: ABC License Types

Type	Description
01	Beer Manufacturer
02	Winegrower
03	Brandy Manufacturer
04	Distilled Spirits Manufacturer
05	Distilled Spirits Manufacturer's Agent
06	Still
07	Rectifier
08	Wine Rectifier
09	Beer and Wine Importer
10	Beer and Wine Importer's General
11	Brandy Importer
12	Distilled Spirits Importer
13	Distilled Spirits Importer's General
14	Public Warehouse
15	Customs Broker
16	Wine Broker
17	Beer and Wine Wholesaler
18	Distilled Spirits Wholesaler
19	Industrial Alcohol Dealer
20	**Off-Sale Beer & Wine**
21	**Off-Sale General**
22	Wine Blender
23	Small Beer Manufacturer
24	Distilled Spirits Rectifier's General
26	Out-of-State Beer Manufacturer's Certificate
27	California Winegrower's Agent
28	Out-of-State Distilled Spirits Shipper's Certificate
29	Wine Grape Grower's Storage

Type	Description
40	On Sale Beer
41	On Sale Beer & Wine – Eating Place
42	On Sale Beer & Wine – Public Premises
47	On Sale General – Eating Place
48	On Sale General – Public Premises
49	On Sale General – Seasonal
51	Club
52	Veteran's Club
57	Special On Sale General
59	On Sale Beer And Wine – Seasonal
60	On Sale Beer – Seasonal
61	On Sale Beer – Public Premises
62	On-Sale General Bona Fide Public Eating Place Intermittent Dockside Vessel
64	Special On-Sale General Theater
67	Bed and Breakfast Inn
70	On Sale General – Restrictive Service
71	Special On-Sale General License
72	Special On-Sale General For-Profit Theater, Napa
75	On Sale General – Brewpub
78	On Sale General Wine, Food and Art Cultural Museum
80	Bed and Breakfast Inn – General
82	Direct Shippers Permit
83	On-Sale General Caterer's License
86	Instructional Tasting License
87	Neighborhood-Restricted Special On-Sale General License
88	Special On Sale General for Historic Cemetery

Source: ABC (2019)