THE LEGACY OF REDLINING

AN INVESTIGATION OF LEAD EXPOSURE IN DRINKING WATER SAMPLES FROM CALIFORNIA PUBLIC SCHOOLS

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June 3, 2022

TABLE OF CONTENTS

ABSTRACT

De jure and De facto segregation have systematically affected the lives of people of color throughout the United States. Nearly 90 years ago, the Home Owners' Loan Corporation (HOLC) enacted discriminatory housing policies by refusing loan and rental applications to African American families that resided in neighborhoods designated a "risk" or "hazardous" to investment. Present-day redlined neighborhoods continue to experience higher rates of pollution and environmental hazards than their counterparts. Environmental hazards like lead have disproportionately affected neighborhoods and cities composed of minority populations, as our nation witnessed several years ago in Flint, Michigan. Lead levels in schools' water has become an increasing concern across California as outdated infrastructure releases lead into drinking water. California public schools were mandated under AB 746 to test water lead levels in schools built prior to 2010. This paper examines whether higher levels of lead exist in schools that reside in historically redlined neighborhoods compared to non-redlined neighborhoods. Through geospatial and statistical analysis, HOLC maps were digitized and analyzed with school lead level data to examine the legacy of redlining throughout eight California cities**.** We found no statistically significant relationship between lead levels and any of the historic HOLC grades in our regression estimates. Nevertheless, all four HOLC grades were significantly associated with testing frequency compared to schools in non-HOLC graded regions. Beyond econometric analysis our work also confirms prevalence of hotspots for both outcomes in some regions of the historically redlined cities of California.

GLOSSARY OF TERMS

Action level: An action level indicates that the amount of lead in the water exceeds an established level.

Action level Exceedance: According to California State Law, lead levels have to be greater than 15 ppb for remedial action to take place. Remedial action takes place once the Action Level Exceedance threshold is met.

AB 746: Assembly Bill 746 mandated water testing throughout every California school built before 2010.

De Jure Segregation: Discriminatory practices that were intentionally written into government-enacted law.

De Facto Segregation: Discriminatory practices that were not overtly written into law but took place nonetheless.

HOLC: Home Owners' Loan Corporation

HOLC Grades: The HOLC used grades A, B, C, and D to determine the level of risk associated with individuals residing in particular neighborhoods.

ppb: parts per billion

Redlining: A discriminatory lending practice that denied loans to individuals based on the racial composition of the applicant's neighborhoods. Redlining was established in the 1930's but its legacy continues to affect people of color throughout the United States.

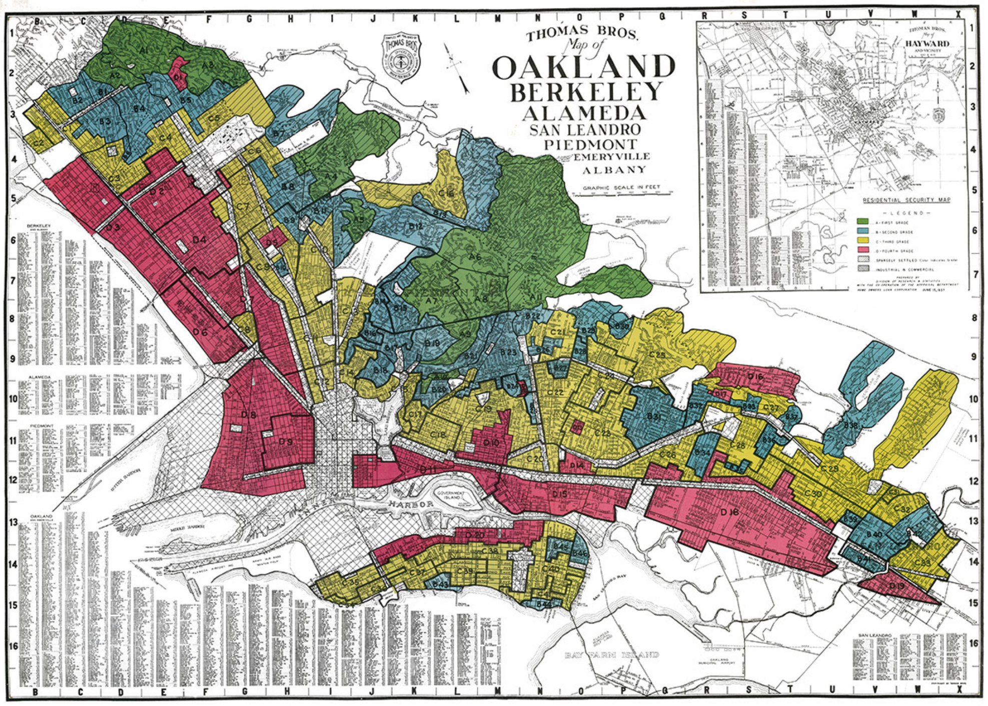
SWRCB: State Water Resource Control Board.

1. INTRODUCTION

The environmental justice movement has gained considerable momentum in recent years. Backed by decades of research, it has been demonstrated time and time again that communities of color disproportionately bear the brunt of environmental harms. These communities are exposed to toxins in the air they breathe and the water they drink at a far higher rate than predominantly white neighborhoods. While the study of environmental injustice dates back to the 1970s, a concerted effort to address these disparities is more recent (Borunda, 2021). On January 27th, 2021, in one of his first days in office, President Biden issued an executive order formalizing the commitment of his administration to ensure that the federal government develops "...programs, policies, and activities to address the disproportionately high and adverse health, environmental, economic, climate, and other cumulative impacts on communities that are marginalized, underserved, and overburdened by pollution"(The White House, 2022). While these efforts are welcome and necessary, they are also long overdue.

America's history is filled with explicitly racist policies whose effects persist to this day. Of these, historical redlining and its continued impact upon urban populations of color are among the better known. In the 1930s and in the midst of the Great Depression, America's Home Owners' Loan Corporation (HOLC) drafted a series of maps grading the risk of investment in metropolitan areas across the country. "Hazardous" neighborhoods, colored red on these maps, later inspired the term "redlining." (see Figure 1). This led to decades of systemic disinvestment in redlined communities composed primarily of people of color. Lenders diverted funds away from redlined communities into whiter, suburban neighborhoods outside of the urban cores in cities across the United States. For decades, researchers have studied the lingering impacts of redlining. Just weeks prior to this writing, a new study emerged demonstrating how historical redlining helped shape present-day disparities in air pollution (Lane et al., 2022). Historical redlining has also recently been associated with increased COVID-19 risk factors (Li et al., 2021). We want to advance existing research into the legacy of redlining by better understanding the complex relationship that HOLC maps from the 1930s have on present-day inequality.

Figure 1: 1930's Home Owner Loan Corporation Security Map for Oakland



Note: This figure shows a 1937 map for "Residential Security Grades"in Oakland, California.
Source: University of Richmond Mapping Inequality

The water crisis in Flint, Michigan made national headlines when it was reported that lead levels in the public water supply far exceeded the federal standard of 15 parts per billion (ppb). This was the result of the local government switching its water supply from Detroit's water system to the polluted Flint River in an effort to save costs (Denchak, 2018). The result was that the predominantly African American population of Flint was exposed to unsafe levels of lead in the public water supply, including children and pregnant women. Lead exposure is correlated with a host of health and developmental risks. The Environmental Protection Agency and Center For Disease Control agree that there is no safe level of lead in a child's blood, as it can cause learning and behavioral problems, lower IQ, hyperactivity, and slowed growth among other issues (Environmental Protection Agency, n.d.). These effects can compound disadvantages for those exposed to lead early in life.

For our capstone project, we conducted a cross-sectional study to explore the legacy of historical redlining as it relates to lead levels in drinking water in California public schools. In

2017, the California State Assembly passed AB 746, which required that all California K-12 schools constructed prior to 2010 be tested for unsafe levels of lead (California Water Boards, n.d.). We obtained the testing data from the California State Water Board, which consisted of over 40,000 observations across over 7,000 California schools. California has 8 historically redlined cities: San Francisco, Oakland, Sacramento, San Jose, Stockton, Fresno, Los Angeles, and San Diego. We compared lead levels from schools in redlined neighborhoods in these cities with those that were not in redlined neighborhoods. We utilized U.S. Census data, as well, which allowed us to incorporate racial and median household income metrics into our analysis.

We believe that the results of our analysis would reflect findings in recent studies establishing the correlation between historically redlined neighborhoods and present-day disparities. While a number of studies have explored the social determinants of health in redlined neighborhoods, to our knowledge no scholarly work has tested the link between redlining and lead contamination in public school water supplies. We hypothesized that public schools residing in historically redlined neighborhoods might demonstrate higher levels of lead than those not in redlined neighborhoods. Additionally, we believed that historically redlined neighborhoods were presently composed predominantly of people of color with lower than average household incomes.

Our report is structured into several main parts. The background section explores the origins of redlining, its educational and economic impacts, and discusses existing research on health disparities in redlined neighborhoods. We then go into detail on our methodological process, covering both the theoretical and statistical methods that drove our research and yielded our results. The discussion section goes into greater detail regarding the implications of our findings. We describe the limitations we encountered when conducting our analysis, offer insight into how future environmental justice research may be conducted, and propose policy recommendations based on our results before concluding our report.

2. BACKGROUND

2.1 Redlining and The Great Migration

The history and legacy of redlining in the United States is prevalent throughout every geographical region, even in parts of the West where de jure segregation was not as common compared to the Jim Crow South. Major metropolitan areas particularly in California, such as

San Diego, Los Angeles, Fresno, Sacramento, Oakland, Stockton, and San Francisco experienced prevalent Redlining in rental properties and mortgage lending. The term redlining is primarily used to describe areas or neighborhoods of metropolitan areas where banks would refuse to lend to. These neighborhoods tended to be occupied by minorities, particularly African-Americans. The spatial dispersion of people of color throughout California cities is due to two factors. 1) Waves of immigrants settling into 'ethnic enclaves' in California cities. 2) The migration of African American families from the Jim Crow South (Pearcy 2020). The arrival of African-American families into California is what is known as 'The Great Migration'.

The Great Migration started at the height of WWII when the need for civilian workers was in high demand and economic opportunity in the South was still bleak. Especially along the West Coast, cities such as Richmond, California became the destination for many African-Americans. During this time, the African-American population went from 270 to 14,000 (Rothstein 2017). By the 1950's more than 2.5 million southern-born African-Americans now resided outside of the South and made their home throughout the United States (Tolnay 2003). While this demographic change affected the cultural and economic mobility of cities throughout the United States. It also had an impact on the housing market. As African Americans started moving into the California Bay Area and occupying jobs that had previously only been offered to white workers, their economic opportunities may have increased but their living conditions did not. Housing discrimination had been legal in the United States since 1866. It wasn't until 1968 that it became unlawful (Rothstein 2017). While African American workers may have been working alongside white workers in Ford Factories, Kaiser Yards, etc, they were not allowed to live next to them. Housing could not keep up with rapid population growth, the federal government instilled public housing but ensured that they were segregated in what was supposed to be temporary structures. These temporary poorly built structures were specifically built for the African American population, while white workers who needed housing were put up away from the polluted overcrowded areas of the city and into the hillside suburbia (Fortson 2017). The actions taken by Banks, Realtors, Cities, etc. in response to The Great Migration have impacted the generational wealth, health, income, and education of African Americans. Historical disinvestment in neighborhoods still presents little opportunity for residents to purchase property or leave.

2.2 Education and Residential Segregation

The most well-known institution that established Redlining was HOLC or Housing Owner's Loaning Corporation. Residential Security maps were created with the intention to guide loan officers, appraisers, and Real Estate agents on areas that were considered risky to lend to (Frank & Mitchell 2018). Not only has this housing policy affected neighborhoods and generational wealth, redlining has had a profound impact on the education system. The absence of de jure segregation does not undermine the overwhelming presence of de facto segregation in modern American neighborhoods. The Supreme Court decision of Brown v. Board which integrated the American public school system did not put a stop to educational and residential segregation in the United States, it merely made it more difficult for it to be codified. Brown v Board is viewed as a symbolic gesture rather than a substantive one (Mcneal 2009). While the Supreme Court decision may have symbolized a progressing era. For many students today, their schools are becoming increasingly more segregated. The Supreme Court case Community Schools v. Seattle School District No. 1 (2007) highlights the lack of integration in American schools nearly fifty years after the passing of Brown v Board (1954). Segregation fifty years later is still a problem in many American schools. To combat persisting educational segregation, the Seattle School District allowed for race to be a deciding factor for school placements for students, which resulted in pushback from the community. Schools residing in segregated neighborhoods, either through the means of redlining or other racially charged policies, tend to perform lower and are allocated fewer resources both monetary and tangible. Resource-rich schools are often found in the affluent white neighborhoods where Black, Latino, and Asian students are less likely to reside (Jargowsky 2014). The relationship between public schools and housing only contributes to the continued legacy of Redlining and its present-day impact on children and their education. Schools in major American cities are not equal across zip codes. Schools residing in formerly redlined neighborhoods continue to deal with lower quality infrastructure and resources[1]. Non-white school districts on average receive $2,226 less than a white school district, this problem only worsens on an individual student basis where students of color receive about $1,600 less than the average student in the United States[2]. The lack of

[1] Source: https://nlihc.org/resource/new-research-impact-redlining-educational-outcomes
[2] Source:https://www.npr.org/2019/02/26/696794821/why-white-school-districts-have-so-much-more-money

resources provided to school districts and students of color contributes to old and deteriorating school infrastructure.

2.3 Redlining and Disinvestment

Extensive literature exists evaluating the role that disinvestment, a product of redlining, has played in the deterioration of urban neighborhoods. Disinvestment, simply put, is the diversion of funds from one neighborhood to another. An example of this would be taking money from deposits in inner cities and investing it in nearby suburbs, divesting urban neighborhoods of their economic power (Wisniewski, 1977). One study on the Washington, D.C. area indicated that nearly 90% of the mortgage loans made by local savings and loans associations were diverted to Maryland and Virginia suburbs (Werner, et al., 1976). The behavior of lending institutions plays an important role in the availability of mortgage credit to interested parties by encouraging or discouraging investment and improvements. Choosing not to extend credit to homeowners and potential homeowners in redlined neighborhoods compounds and accelerates decay, thereby setting in motion a downward spiral of worsening conditions in under-resourced neighborhoods.

While historical redlining refers to the process by which the Home Owners' Loan Corporation (HOLC) in the 1930s drew up maps grading certain neighborhoods composed of minorities as "hazardous" to investment, it now broadly describes the presumption by lending institutions that an area is no longer stable due to various characteristics, such as age and racial composition (Larkin, 1976). While the process was formally banned in 1968 with the Fair Housing Act, lending practices that create obstacles to obtaining mortgage credit keep de facto redlining and systemic disinvestment in minority neighborhoods alive and well. Some of these practices include requiring greater down payments, higher fixed interest rates, the refusal to issue loans beneath a certain threshold, and applying a more rigid appraisal process than would be required on a similar home in a different neighborhood (Werner, et al., 1976). The result is that money for new investment and restoration is kept out as housing conditions decline.

There is limited access to data that may assist our understanding of the impact that harmful lending practices had on historically redlined neighborhoods. No federal records on lending exist, so researchers have turned to local sources, such as city governments and title companies (Hillier, 2003). Despite this limitation, spatial analyses have been undertaken with available data in historically redlined areas, such as New York, Philadelphia, and Michigan, producing mixed results.

Despite informal redlining practices continuing to be exploited, albeit in subtler form, the legacy of historical redlining may be observed when considering current levels of racial segregation and economic disadvantage in HOLC-designated “hazardous” neighborhoods. Comparing the original redlining maps with current neighborhood demographics demonstrate the persistence of exclusionary practices from decades earlier. For example, among historically redlined neighborhoods, most remain low-to-moderate income (74%) and minority-majority areas (64%) (Mitchell et al., 2020). Other comparisons indicate that historically redlined neighborhoods are actually more segregated and economically disadvantaged, with a greater share of minority populations, older housing stock, and lower home values (Perry et al., 2019). Despite redlining being banned over 50 years ago, residents of these neighborhoods continue to suffer the consequences of government-sanctioned disinvestment.

2.4 Health in Redlined Neighborhoods

Residents of redlined neighborhoods face significant health inequalities. A number of contemporary studies have examined the link between redlining and its influence on predicting present-day health outcomes and social determinants of health. Most of the literature on health in redlining communities explores different dimensions of health outcomes thereby providing extensive evidence of the injustices the residents of disadvantaged redlined neighborhoods face to date. For example, past research examining the relationship between HOLC maps and preterm birth found that the odds of giving premature birth increase significantly for pregnant women in redlined neighborhoods compared to non-redlined areas (Lee et al. 2021, Hollenbach et al., 2021; Krieger, Van Wye, et al., 2020; Nardone, Casey, et al., 2020). Moreover, a positive relationship has also been observed between redlined neighborhoods and the poor mental, physical, and self-reported health of their residents (Lee et al. 2021; Lynch et al., 2021; McClure et al., 2019). A recent ecological study analyzing a broad range of fourteen indicators of health in nine historically redlined metropolitans across the U.S. found similar disparities in health outcomes, unhealthy behaviors, and preventive health measures (Nardone, Chiang, et al., 2020).

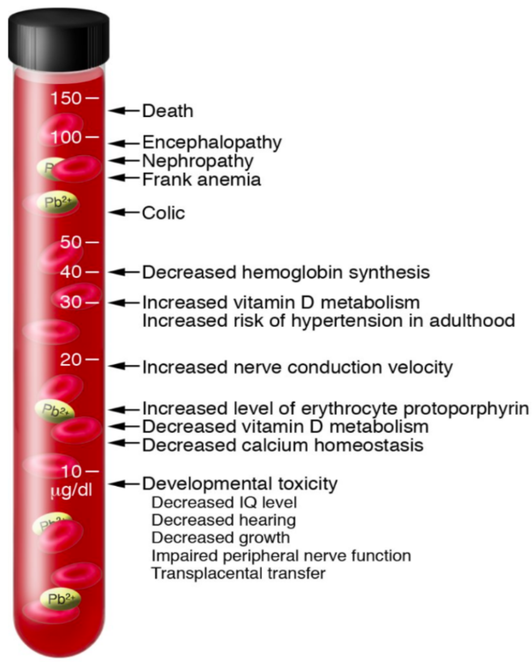
A number of studies have explored the association of health outcomes such as asthma, cancer, and tuberculosis on HOLC grades (Lee et al. 2021; Zhou et al, 2017; Nardone, Casey, et al, 2020; Nardone, Chiang, et al., 2020; Krieger, Wright, et al, 2020; Huggins, 2017). A recent study by Nardone, Casey, et al,(2020) assessed the role of redlining in asthma-related emergency visits in eight formally redlined cities of California from 2011 to 2013. They found that age-adjusted asthma rates were 39 percent higher in residents of D-graded census tracts compared to C-graded census tracts. Even after adjusting for the present-day poverty rate, diesel particle emissions, and other factors these asthma health inequalities persisted (Nardone, Casey, et al, 2020). Similarly, spatial analysis in Austin, Texas unveiled the prevalence of higher cases of tuberculosis in redlined neighborhoods in the southeast area of the city during the 1950s (Huggins, 2017). On the contrary, the association between cancer and redlining revealed mixed results (Lee et al. 2021).

Investigation into neighborhood determinants of health illustrates similar patterns of place-based disparities (Lee et al. 2021; Lynch, et al., 2021; Benns et al., 2020; Jacoby et al., 2018; Li, et al, 2021). Compared to non-redlined neighborhoods, the risk of injuries and emergency department visits from gun-related violence is significantly higher in redlined neighborhoods. In Philadelphia, Pennsylvania the rate of emergency department visits was estimated to be 13 times higher amongst residents of redlined than non-redlined neighborhoods (Lee et al. 2021; Jacoby et al., 2018). Additionally, in the context of neighborhoods and their built environment, a recent study in Texas documents significant differences in land surface temperature between zip codes in redlined versus non-redlined areas. Areas with disproportionately higher land surface temperatures also experienced higher rates of heat-related emergency visits (Li, et al, 2021; Lee et al. 2021).

Built environments along with a mix of social-economic factors serve as pathways through which present-day health disparities manifest in HOLC-graded cities of the past. Place-based disparities are further exacerbated by reduced access to quality food, transportation, education, health care, and preventative services in these disadvantaged neighborhoods(Lynch et al., 2021). Residents of redlined neighborhoods are more likely to be people of color with limited income. Most redlined neighborhoods also exhibit a disproportionately higher burden of pollution due to their proximity to highways and other sources of emissions such as industries, landfills, and fracking sites (Lee at el., 2021). A decline in living conditions in redlined neighborhoods is attributed to limited green spaces, fewer trees, and a lack of basic neighborhood amenities. A recent study by Namin et al. (2020) found a gradient in tree canopy by HOLC grade in 115 historically redlined cities across the U.S. Their results show that tree canopy coverage was significantly higher in better neighborhood grades (A and B) compared to redlined neighborhoods (graded as D on the HOLC mortgage risk assessment maps).

Researchers also argue that the risk of exposure to toxins such as lead is substantially high in redlined neighborhoods (Lee et al. 2021). Lead is a known neurotoxin and high concentration of lead in the blood is associated with serious adverse mental and physical health outcomes (See [Figure 2](#)). Lead can enter the body through ingestion and inhalation through multiple sources and pathways such as air, soil, and water. Young children are particularly vulnerable to the detrimental effects of lead since they absorb four times as much ingested lead as adults from a given source (World Health Organization[3]).

Figure 2 : Adverse Health Effects of Lead in Children



Note: The harmful health effects can be observed at lowest level of lead concentration. *Source: Bellinger, D. C., & Bellinger, A. M. (2006). Childhood lead poisoning: the torturous path from science to policy. The Journal of clinical investigation, 116(4), 853-857.*

According to the Centers for Disease Control and Prevention, low levels of lead exposure in children have been linked to damage to the central and peripheral nervous system, learning disabilities, shorter stature, impaired hearing, and impaired formation and function of blood cells[4]. These health outcomes are directly associated with behavioral problems and reduced cognitive abilities amongst children that persist into adulthood (Muller, Sampson, and Winter, 2018). An increase in childhood blood lead levels from 2.4 to 10 µg/dL reduced IQ score by 3.9 points (Lanphear et al., 2005). Hence, the ramification of prolonged lead exposure presents a serious threat not only in the form of adverse health effects but also learning disabilities, especially amongst young children. To the point that the long-term adverse health outcomes and

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[3] Source: https://www.who.int/news-room/fact-sheets/detail/lead-poisoning-and-health
[4] Source:https://www.cdc.gov/nceh/lead/prevention/health-effects.htm

disabilities from lead exposure are irreversible and perpetuate over a lifetime, it becomes imperative to prevent lead poisoning from occurring in the first place.

3. METHODOLOGY

3.1 Research Approach

The legacy of historical redlining is still prevalent in California communities today. Environmental justice advocates have long investigated the connection between historical segregationist policies and their connection to present-day health consequences within communities of color. Redlining, as a practice, is a form of geographic inequity. This refers to the socio-spatial patterns in which nonwhites are continuously exposed to toxins at a higher rate than their counterparts (Pulido 1996). The study of environmental racism as a discipline focuses on garnering research to make more informed policy decisions on the effects and impacts political and corporate powers have on the environment in relation to the health of people of color. A critical question of environmental racism research is understanding whether the environmental hazard occurred before non-white populations settled or after (Pulido 1996). Some researchers have criticized this point, arguing that discrimination occurs regardless of which variable occurred first. In terms of redlining, this key question can help us better understand whether there is a relationship between policies such as redlining and high levels of lead in schools' drinking water supplies.

We conducted a cross-sectional study to understand differences in lead concentration and testing frequency for water samples collected at schools residing in redlined and non-redlined neighborhoods. We obtained secondary data from three different publicly available sources[5]. To test our hypothesis, we implemented multivariate regression estimation using open source spatial and statistical packages[6] in Python version 3.7 (see References). The HOLC designated grades are the main predictor variables in our estimation. Subsequently, we incorporated census tract data on median household income, and ethnic composition alongside HOLC city status as covariates. These covariates capture some of the differences in neighborhood characteristics explaining in part some of the resulting variations in lead outcomes. Beyond the primary objective of this study, we also checked for discrepancies in the frequency of lead sampling at

[5] Note: Details provided in the Data and Methods section.

[6] Open source main packages including *Geosnap, Geopandas, Pandas, and Matplotlib* among other

schools in redlined versus non-redlined neighborhoods. To investigate these discrepancies, we estimated a Negative Binomial regression model using testing frequency as our second outcome. In total, we estimated four different specifications of the regression models based on sample size and covariates for both of the outcomes. We extend the scope of our analysis by examining the statistical and spatial distribution of both outcomes along with the income and ethnic makeup of the HOLC-graded areas in the eight cities. We aim to reaffirm patterns of socioeconomic disparities vis-à-vis the legacy effects of redlining as established in the existing literature. Besides statistical modeling, we also examine global and local indicators of spatial autocorrelation. Estimates of spatial randomness and clustering enable us to advance scholarship on the efficacy of AB 746, pointing to the presence of hotspots and coldspots within the study area.

3.2 Data and Methods

3.2.1 Study Outcomes

In order to test our hypothesis, we assembled quantitative data from the Division of Drinking Water at the California State Water Resource Control Board (SWRCB). This dataset in particular was state-mandated under Assembly Bil (AB) 746. The bill was signed into law by Governor Jerry Brown in 2017. AB 746 mandates that all K-12 schools in California test their drinking water for lead. This mandate went into effect on January 1, 2018, and was to be carried out by schools through local community water systems. Only schools that were constructed prior to January 1, 2010, were required to be tested. All lead reporting was required to be sampled by July 1, 2019. Schools were still fully operating at normal capacity during this time, ensuring each sample was not affected by school closures due to the Covid-19 pandemic.

This is the only comprehensive statewide dataset publicly available to gauge lead exposure in drinking water supplies at the school level. Nearly 8,000 unique schools with a total of 43,978 observations were part of the original spreadsheet obtained from the SWRCB website[7]. These observations represent samples collected at multiple points of use outlets per school site. The data includes information on school-specific unique identification code, water system public identification number, school testing status, testing date, the location where each drinking water sample was obtained (eg, classroom, bathroom), the type of water source that was tested (eg, fountain, sink), the lead level for each sample, and whether the level exceeded the state action

[7] Source: https://www.waterboards.ca.gov/drinking_water/certlic/drinkingwater/leadsamplinginschools.html

level (15 ppb) along with the reported sample results (Umunna et al., 2020). It is important to note that observations for both private and public schools are included in the original SWRCB dataset. Our sample set, however, consists only of lead data from public schools in California. This decision was made due to the different funding metrics of private schools and the lack of public resources utilized by private schools, particularly towards their infrastructure.

For the purpose of our research, we requested the relevant shapefile for schools directly from the Division of Drinking Water personnel. This shapefile contains the geographic location of schools that were sampled under AB 746[8]. To conduct our research, the pertinent public school coordinates in shapefile were first merged with the original lead sample dataset and later spatially joined with HOLC grades and census tract data (see description in section 3.2.2). The process resulted in a total of 7,555 observations for public schools across California.

3.2.1.a Highest Lead Concentration

It is essential to highlight that the sample results of lead in water are measured in parts per billion. Results above 15 ppb violate the state standard and represent action level exceedance (ALE). The original dataset reported precise figures for lead concentration above 5 ppb, however, the exact values of lead concentration below 5 ppb are not documented. To overcome this challenge we subset our data for values set above 5 ppb (the standard set for bottled water by the Food and Drug Administration). This approach helps us focus our attention on the main issue of the high level of lead toxicity as asserted by the public health advocates[9]. Hence, a total of 1,320 observations from at-risk public schools in California were retained in our subsample.

Moreover, we addressed issues of multiple observations (the result of sampling done at different locations inside each school) by selecting only the highest value of lead concentration reported per school site. Some schools recorded staggering high levels of lead in their original samples between 640-2,000 ppb[10]. These out-of-compliance schools cited fixtures that had been shut down or unused for months and even years as plausible explanations behind these unwarranted results. The accumulation of lead in stagnant water is a constant reminder of how much toxic exposure older infrastructure can render. From here onwards, the highest level of lead

[8] Source:https://www.arcgis.com/apps/MapJournal/index.html?appid=9d17731cae2c4452957fadc5d8ee2d75 For more check the ArcGIS story map at the "Lead Sampling of Drinking Water in California Schools website
[9] Source:https://edsource.org/2018/gaps-in-california-law-requiring-schools-to-test-for-lead-could-leave-children-at-risk/602756
[10] Source:https://edsource.org/2018/gaps-in-california-law-requiring-schools-to-test-for-lead-could-leave-children-at-risk/602756

concentration in parts per billion reported at each public school is indicative of our first outcome variable.

3.2.1.b Testing Frequency

Based on the current state policy, wide variability exists in the number of samples collected at each school location. The SWRCB dataset does not provide a record for testing frequency. However, to assemble evidence of sampling inconsistencies, we computed the frequency of testing at each school. In the SWRCB dataset, each school sample is assigned an eleven-digit unique alphanumeric identification code. The first seven digits represent the water system number followed by the school ID and outlet location from where the sample was collected (example: 1510001-AAB-E). Schools with high lead levels are resampled to detect potential sampling errors or problems of contamination. Hence, if an outlet is resampled the alphanumeric identification code appears more than once. To avoid the possibility of double-counting stemming from resampling, we dropped the duplicate values of the unique identification code.

Afterward, we proceed to calculate the testing frequency using the number of times a school address appeared in the cleaned data as a proxy. This number helps us deduce how many observations were recorded at each address. Intuitively, the observations match the number of unique samples collected and tested at each school. Testing frequency (a count measure) is the second outcome of choice in our analysis. We followed the same procedures as before to append the frequency outcome with the relevant school shapefile.

3.2.2 Covariates

In our investigation, we explored data from eight historically redlined cities of California including Los Angeles, San Diego, Sacramento, San Francisco, San Jose, Oakland, Fresno, and Stockton. The digitized spatial boundaries for HOLC grades can be accessed through the University of Richmond the "Mapping Inequality" website[11,12]. The historic 1930s HOLC mortgage risk assessment maps had four grades A, B, C, and D. Each of the grades was assigned a color code in the appraisal maps and documents. The most "desirable" grade (A) was depicted in green color whereas the "hazardous" grade (D) was color-coded in red. With the passage of

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[11] R.K. Nelson, L. Winling, R. Marciano, N. Connolly, and E.L. Ayers. Mapping Inequality. American Panorama. https://dsl.richmond.edu/panorama/redlining

[12] **Acknowledgment**: The digitized HOLC data shapefiles and the code to combine the maps with 2010 census tracts data were provided courtesy of Dr. Sergio Rey (*sergio.rey@ucr.edu)*

time, the historic HOLC boundaries differ geographically from modern census tracts. Moreover, post-1930 the HOLC designated areas represent a smaller fraction of the urban footprint in most major metropolitan areas across the country (Lane et al. 2022). To reconcile these differences we followed the spatial interpolation techniques applied in Rey and Knaap (2022) where they "form the union of intersections between the HOLC boundaries and modern census tracts, and then interpolate socioeconomic attributes from the Census to these intersection polygons". Figure 3 portrays the intersecting polygons that result from spatial interpolation for all of the eight redlined cities. The polygons are color-coded to match the relevant HOLC grades they received decades ago. We impute each school residing in HOLC polygons to their corresponding grade. The remaining school locations are given a value of "N" signifying they belong to tracts not graded during the 1930's federal housing policy.

The 2010 decennial census tract data for *median household income* (MHI) in dollars and racial composition indicators were retrieved directly from the "The Geospatial Neighborhood Analysis Package" or *geosnap*[13]. The package comes preloaded with 30 years of US census data and is a powerful tool to explore, model, analyze, and visualize the social and spatial dynamics of neighborhoods. In our analysis, we seek to identify the social and environmental injustices ethnic minorities face to this date as a repercussion of past systemic racist policies. Assessment of the ethnic makeup of a community serves as a guide to discern who bears the burden of environmental hazards. To measure the ethnic makeup of a census tract we applied the following formula:

$$POC_{i,c} = 1 - \frac{\omega_{i,c}}{T_{i,c}} \tag{1}$$

where $POC_{i,c}$ i.e. *people of color,* represent the share of tract population that is people of color, $\omega_{i,c}$ is the white population, and $T_{i,c}$ is the total population in tract *i* of city *c* (Rey and Knaap, 2022).

Additionally, we compared lead outcomes amongst the historic redlined cities to other counties that never received the treatment of HOLC. We created a binary variable called *HOLC city status,* which equals one for the eight redlined cities and zero for the remaining counties.

[13] *Geosnap* is open source package available at: https://github.com/spatialucr/geosnap

Figure 3: HOLC Maps for Historically Redlined Cities in California

[View Full-Size Image]

Note: Eight cities in California were appraised for the 1930s HOLC mortgage risk assessment maps. This figure shows all cities with matching color codes based on the designated grades. Top panels show 1: Fresno, 2: Stockton, 3: Sacramento, 4: San Jose. The bottom panel shows 5: Los Angeles, 6: Oakland, 7: San Fransico, 8: San Deigo. On each map “A grade” is green, “B grade” is blue, “C grade” is yellow, and “D grade” is colored red.

4. RESULTS

4.1 Data Distribution

4.1.1 Summary Statistics[14]

Overall, 3.8% of schools out of the 7,555 have lead concentrations above 15 ppb from samples collected between 2017- and 2019 (See Figure 4 below). The number of at-risk schools increases by roughly 4 times when the remedial standards are set above 5 ppb.

Figure 4: Lead Results in Schools Drinking Water Supplies

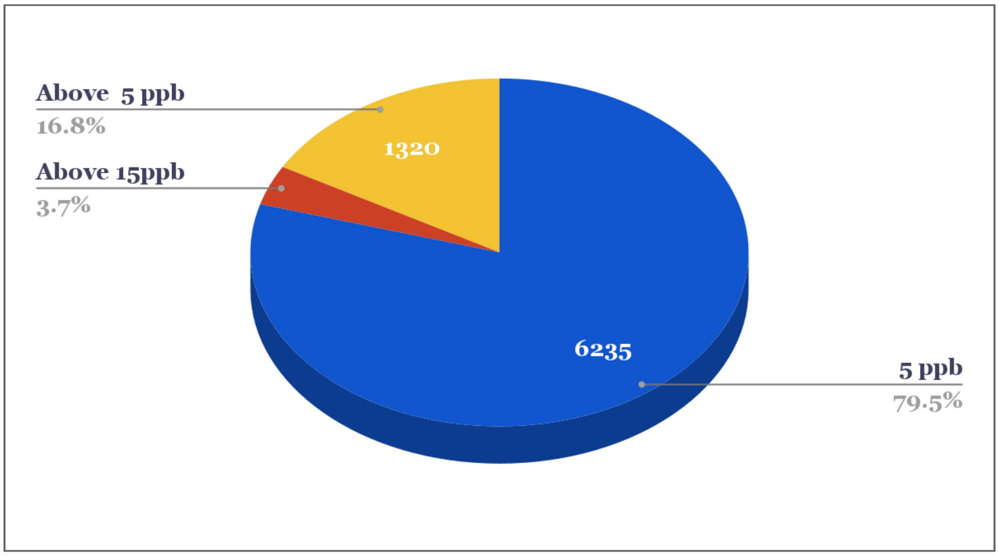


Table 1 provides information on the count of public schools in our data by HOLC grades. The observations for all four HOLC grades represent 10 to 11 percent of our school data while a vast majority of schools fall under the non-graded parts of the state.

Table 1: No. of Observation By HOLC Grade

HOLC Grades	Public Schools	At-Risk Public Schools
A	41	10
B	117	30
C	357	70
D	261	38
N	6,776	1,172
Total	**7,555**	**1,320**

[14] For additional reference see Table 2 in Appendix

Figure 5: Number of Schools in each Category of Lead Concentration based on HOLC Grades[15]

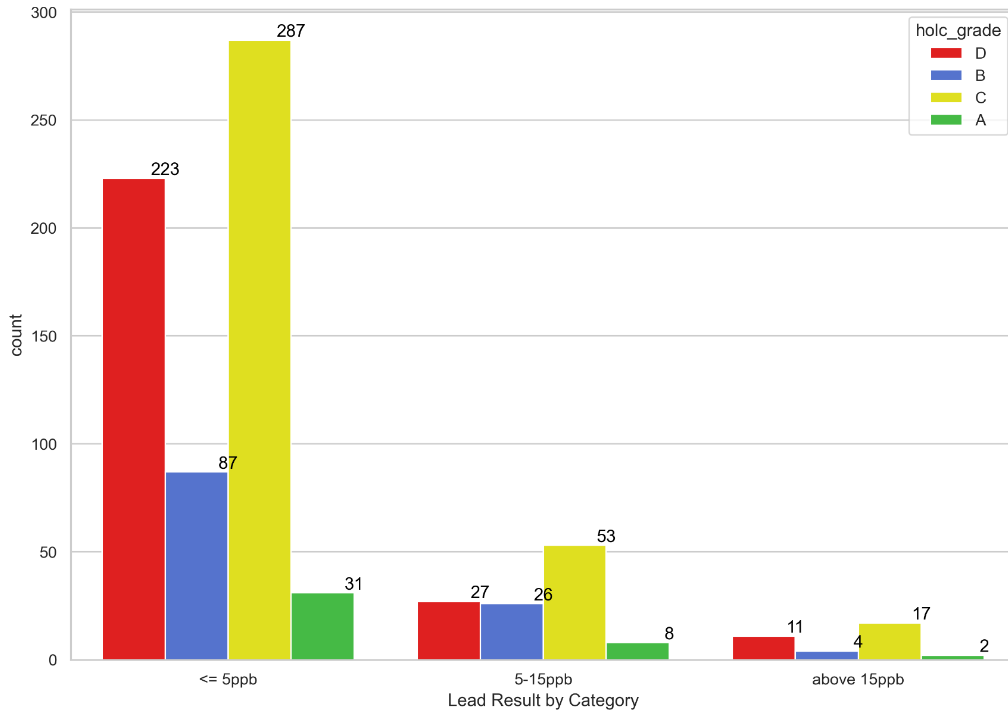
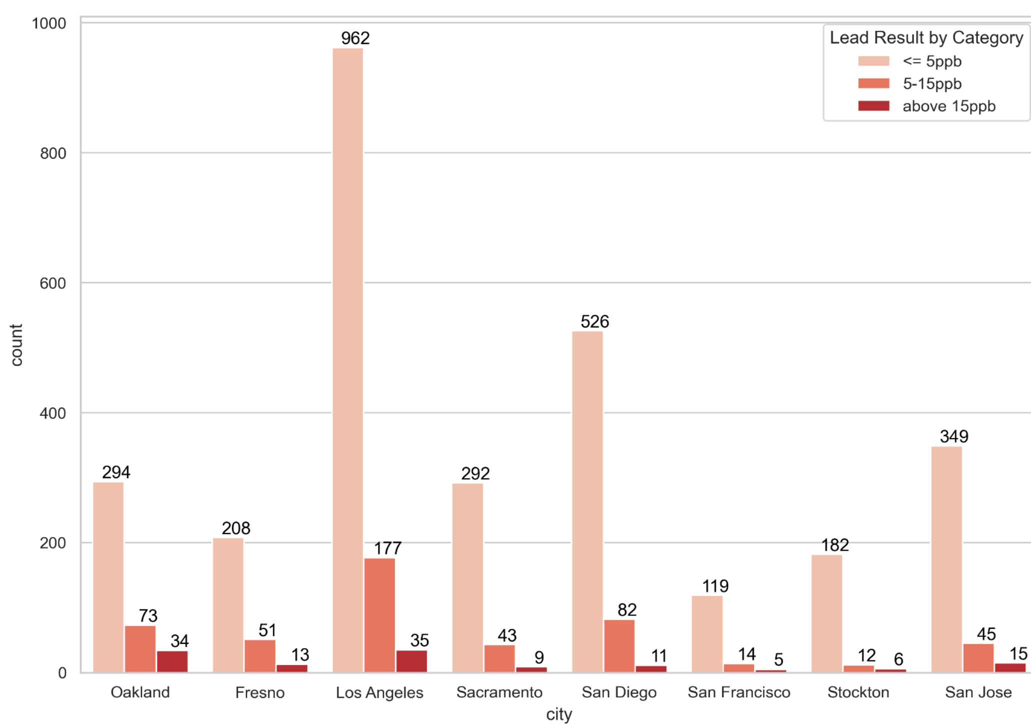


Figure 6: Number of Schools in each Category of Lead Concentration by Redlined Cities[16]



[15] For simplification we excluded the nongraded areas (N) to generate the plot

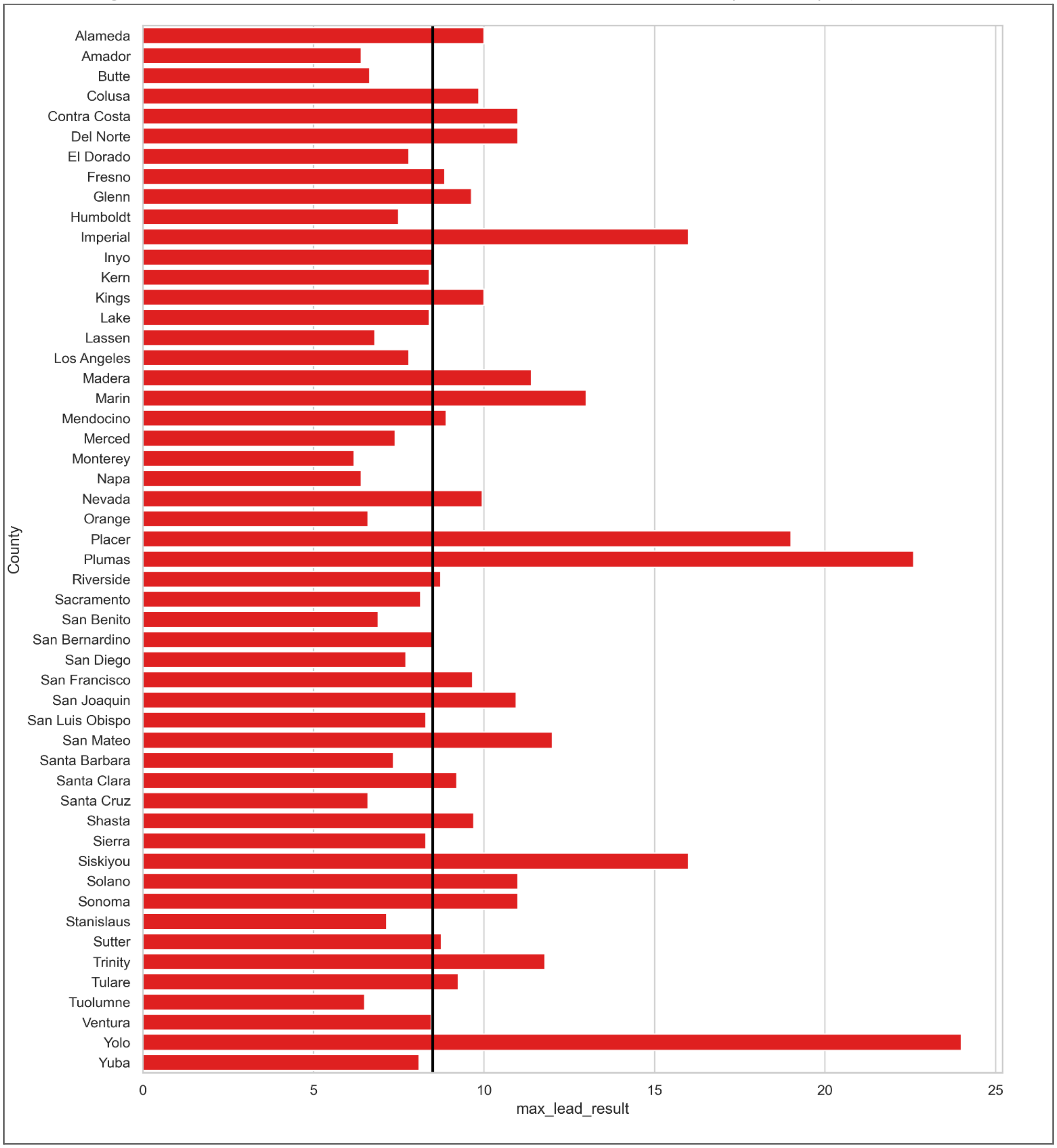
[16] This figure shows the entire county level data that is not constrained by HOLC graded regions only

Figure 5 gives the number of schools in each HOLC grade based on their lead results. The sample lead results are classified into three categories, below 5 ppb, between 5 to 15 ppb, and above 15 ppb. Each category has roughly the same sample of schools by HOLC grades. We also visualized the number of schools in each category according to the city. The results are provided in Figure 6.

The distribution of lead results according to the county is given in Figure 7a. The figure looks at the level of lead in at-risk schools. The median level for lead concentration in counties including San Mateo, Placer, Yolo, Merced, and Imperial far exceeds the median lead concentration (8.5 ppb) observed in our subsample. These results suggest that disadvantaged suburban communities are at much higher risk of lead contamination in their school drinking water supplies. Despite high concentrations of lead, we see visible disparities in testing frequencies across disadvantaged communities compared to other regions in the state (Figure 8a). In particular, median frequency is highest in Alameda and Contra Costa counties.

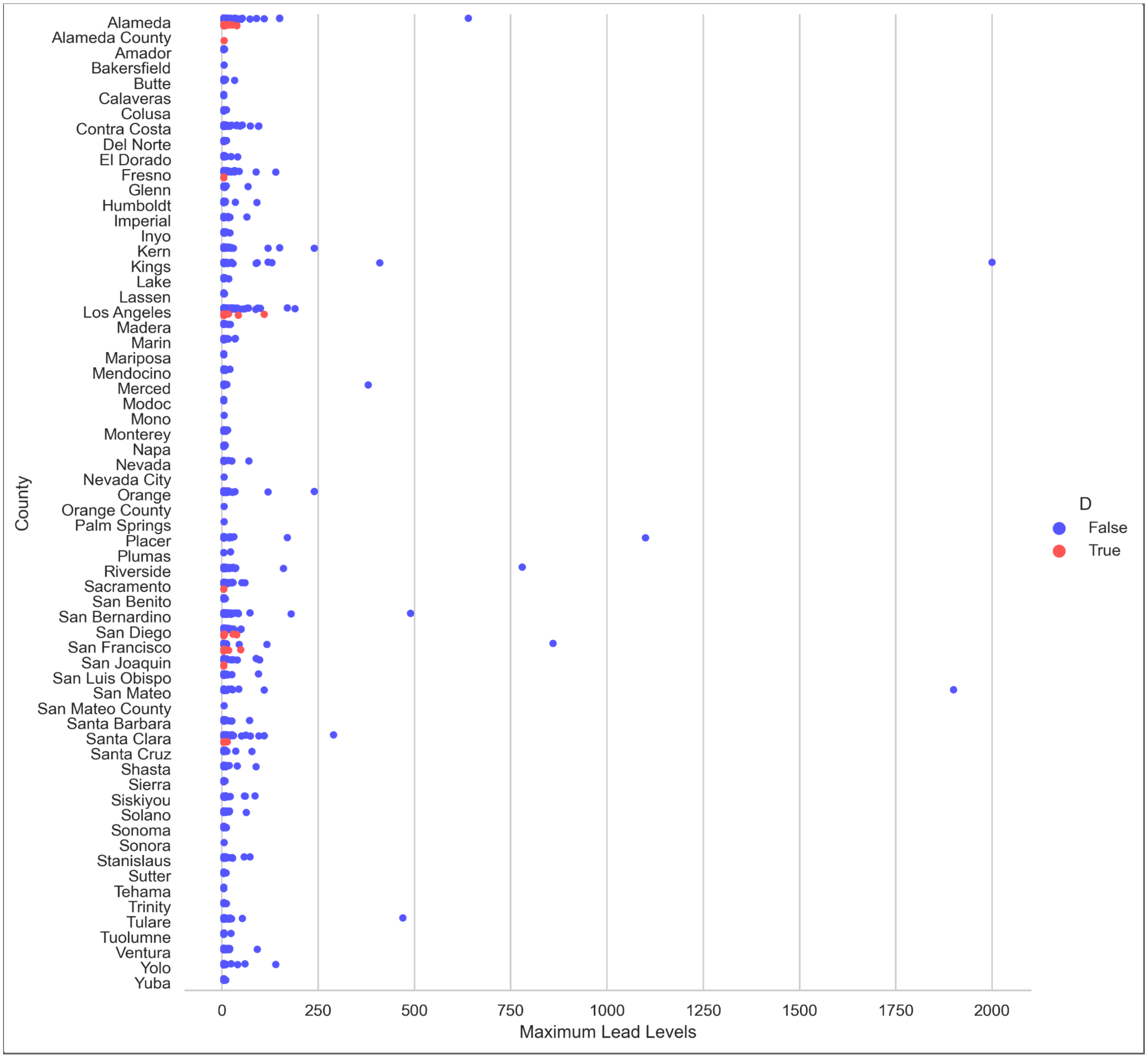
Figure 7b demonstrates the distribution for the entire sample of 7,555 schools. The data distribution shows which counties have outliers. On average the lead levels are below 5 ppb, however school in Kings county recorded lead concentrations as high as 2000 ppb. We also split the distribution by Grade D within the HOLC cities for better representation of the data. Similarly, for a thorough examination of the testing frequency, data for schools in each county is provided in Figure 8b. It is evident that the spread of testing frequency fluctuates anywhere between one to twenty-six tests per school site. Predominantly, the highest testing frequency counts are tied to Alameda and Contra Costa counties.

Figure 7a: Median Lead Concentration in At-Risk Schools by County (N=1,320)



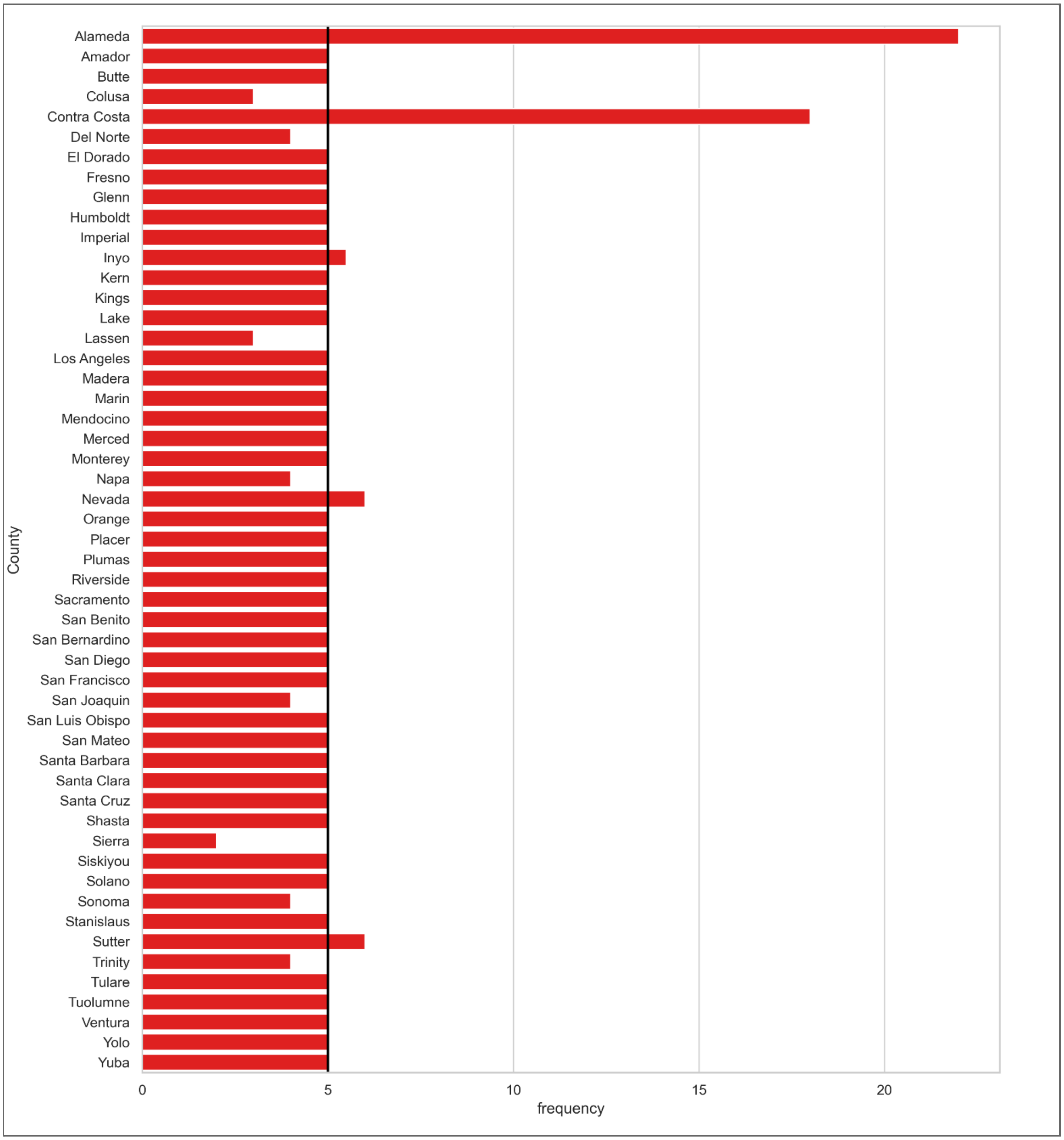
Note: The black line is drawn at 8.5. This represents the median value of lead results for at-risk schools

Figure 7b: Lead Concentration by County (N=7,555)
Split by Grade D



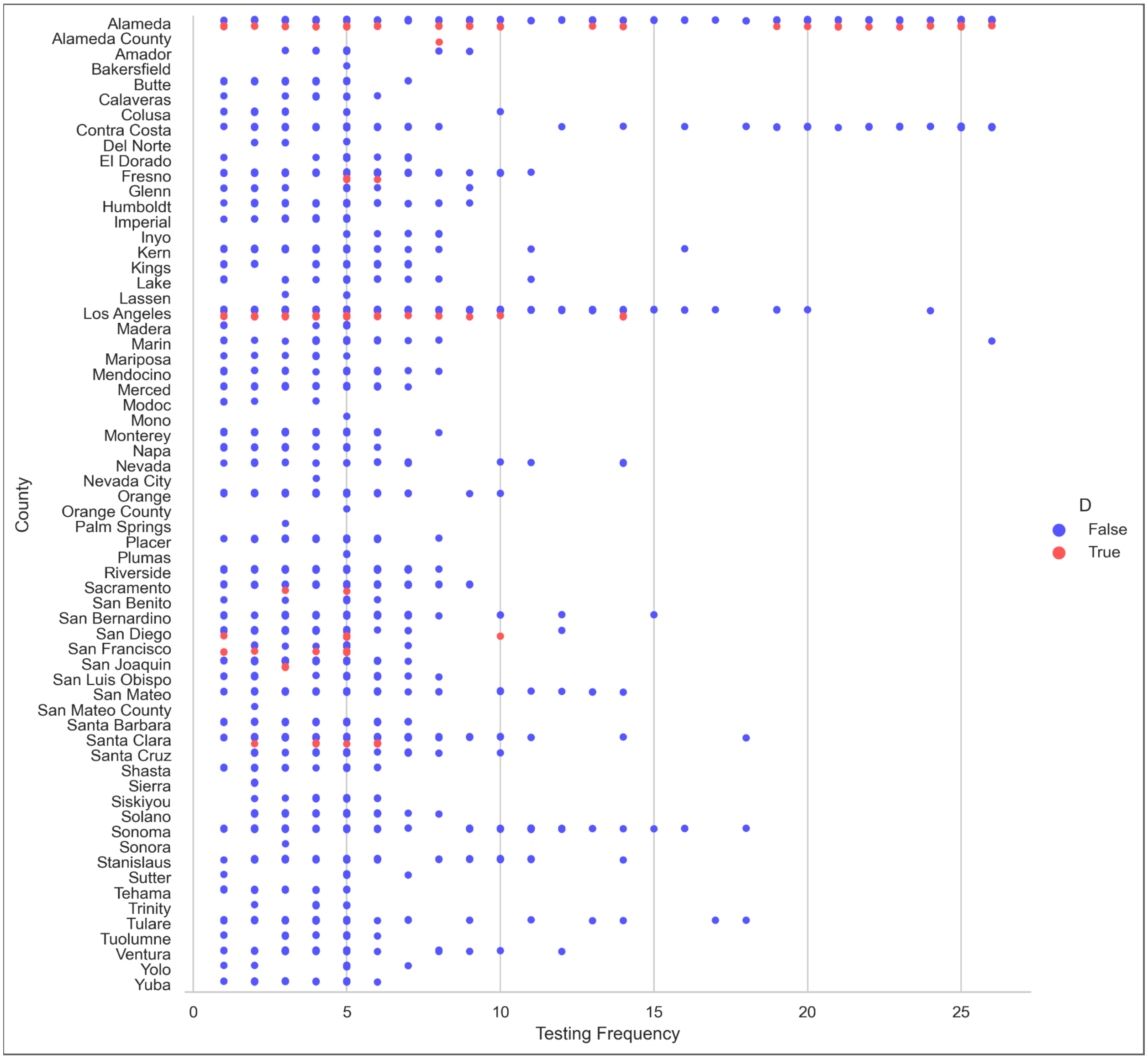
Note: This figure illustrates the distribution of lead levels in drinking water supplies at schools. The red dots represent the results of testing frequency in HOLC grade "D"

Figure 8a: Median Frequency in at-risk schools by County (N=1,320)



Note: On this figure, the black line is drawn at 5. This line represents the median value of testing frequency for at-risk schools

Figure 8b: Frequency by County (N=7,555)
Split by Grade D



Note: This figure illustrates the distribution of testing frequency. The red dots represent the results of Testing Frequency in HOLC grade "D"

Furthermore, Table 2 shows the mean values of median household income, percentage of people of color, lead sample results, and testing frequency for the 7,555 public schools in California. It lists the mean values for a subset of at-risk schools (lead above 5 ppb). Grade A has the highest value of median household income of $151,518 (N= 1,320). From Table 2 it becomes apparent that the mean of lead sample results (in ppb) is also higher in grade A compared to D . Summary statistics for the variables are reported in Table 8 (See Appendix).

Table 2: Mean Values for Indicators by HOLC Grade

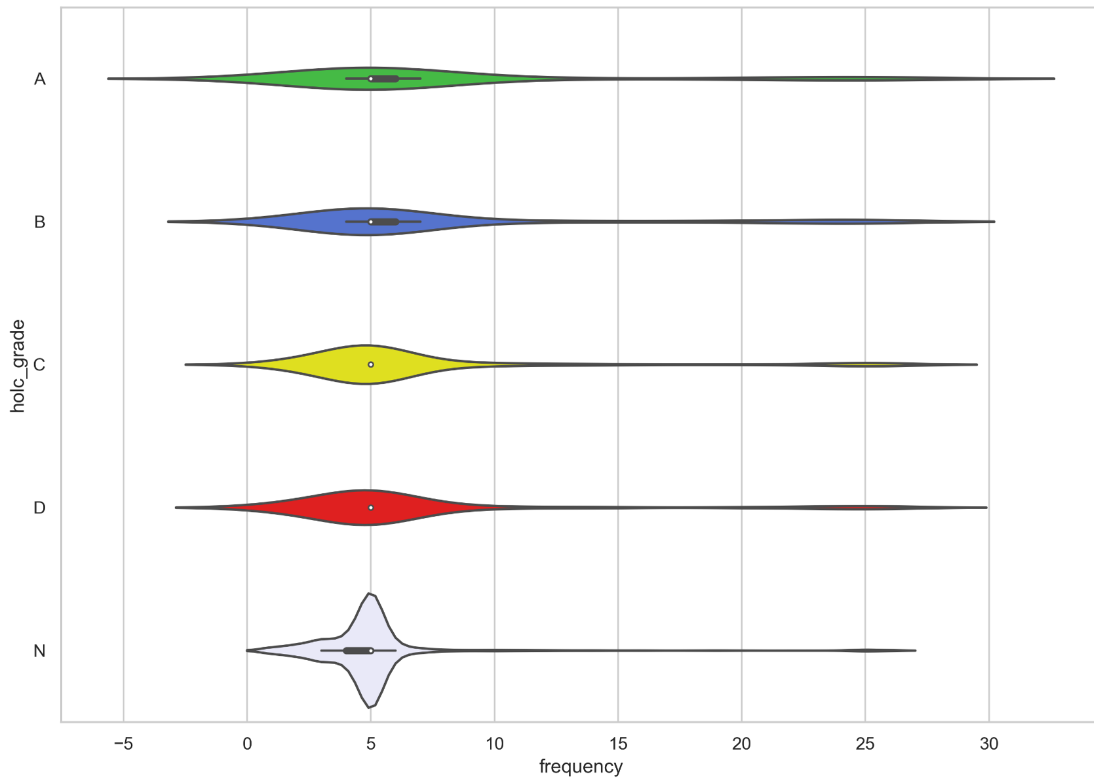
Sample N= 7,555 Schools				
Mean values by HOLC Grade	Median Household Income (USD)	%People of Color	Lead Sample Results (in ppb)	Testing Frequency (Count)
A	163,041	36%	8.89	8
B	88,688	60%	6.54	8
C	65,276	72%	8.13	7
D	58,592	80%	6.55	7
N	79,115	55%	8.11	5
Subsample N= 1,320 Schools				
Mean values by HOLC Grade	Median Household Income (USD)	% People of Color	Lead Sample Results (in ppb)	Testing Frequency (Count)
A	151,518	39%	20.96	12
B	83,442	60%	11.02	9
C	61,913	73%	20.97	11
D	53,757	83%	15.65	10
N	74,573	56%	22.98	6

Additionally, the distribution of frequency of testing by HOLC grades is explored using violin plots in Figure 9. The violin plot is a unique way to convey the distribution of a variable. "In the middle of each density curve is a small box plot, with the rectangle showing the ends of the first and third quartiles and central dot the median"[17]. We see a difference in frequency distribution in the HOLC grades. While the median value of testing frequency is situated near 5 as seen by the white dot inside all the separate plots, Grades A and B tend to have a larger spread for lead testing frequency compared to C and D. This is intriguing given the total number of schools in A grade are far less than C and D grades (See Table 1). Furthermore, the distribution

[17] Source:https://chartio.com/learn/charts/violin-plot-complete-guide/

for the non-graded regions representing roughly 90 percent of our data (N= 7,555) exhibits a leftward skewed distribution.

Figure 9: Testing Frequency by HOLC Grades



Note: In this figure, the vertical axis illustrates all four HOLC grades (A, B, C, and D) along with the non-graded census tracts (N), whereas the horizontal axis shows the values of testing frequency at schools

Next, Figure 10 shows violin plots for census tract median household income for each HOLC grade in California[18]. Grade A, has an elongated shape and the highest median value for median household income compared to the rest. The redlined neighborhoods (D grade) have significantly lower median household income (close to $ 58,000) in 2010 (see Table 1).

Likewise, the distribution for people of color in California can be seen in Figure 11. The distribution of ethnic makeup shows distinctive patterns arising from HOLC grade. In grade A, there is a significantly lower percentage of people of color compared to grade D. Grade B and the non-graded areas represented by N, show a similar bimodal distribution for the people of color.

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[18] Note: We used the full data set N = 7,555 for these results.

Figure 10: Distribution of Median Household Income by HOLC Grades

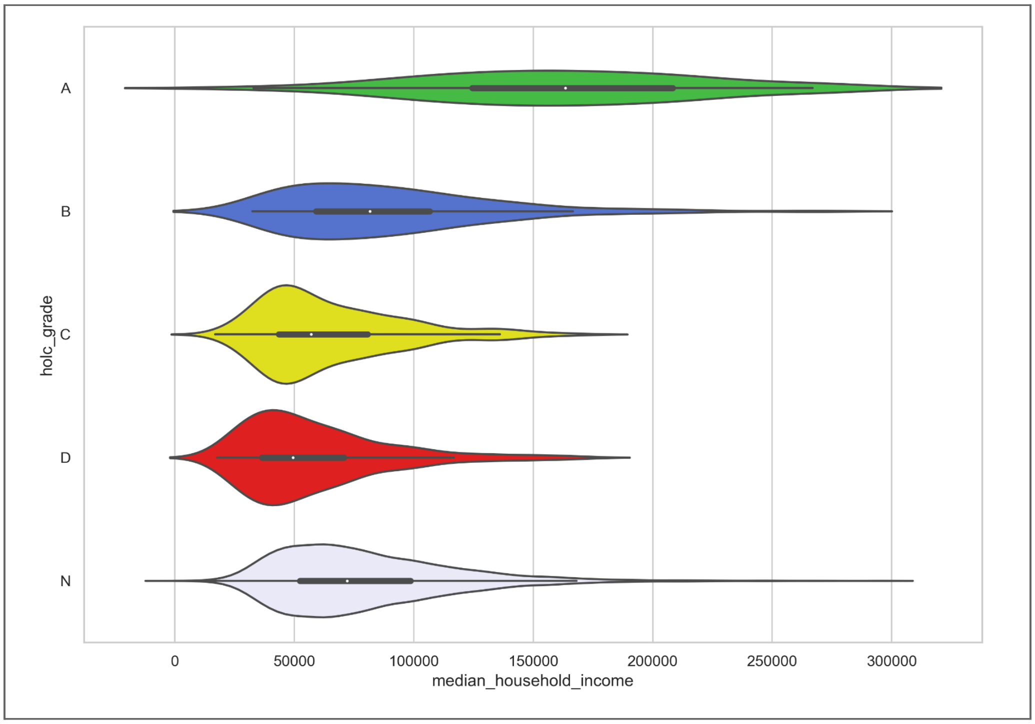
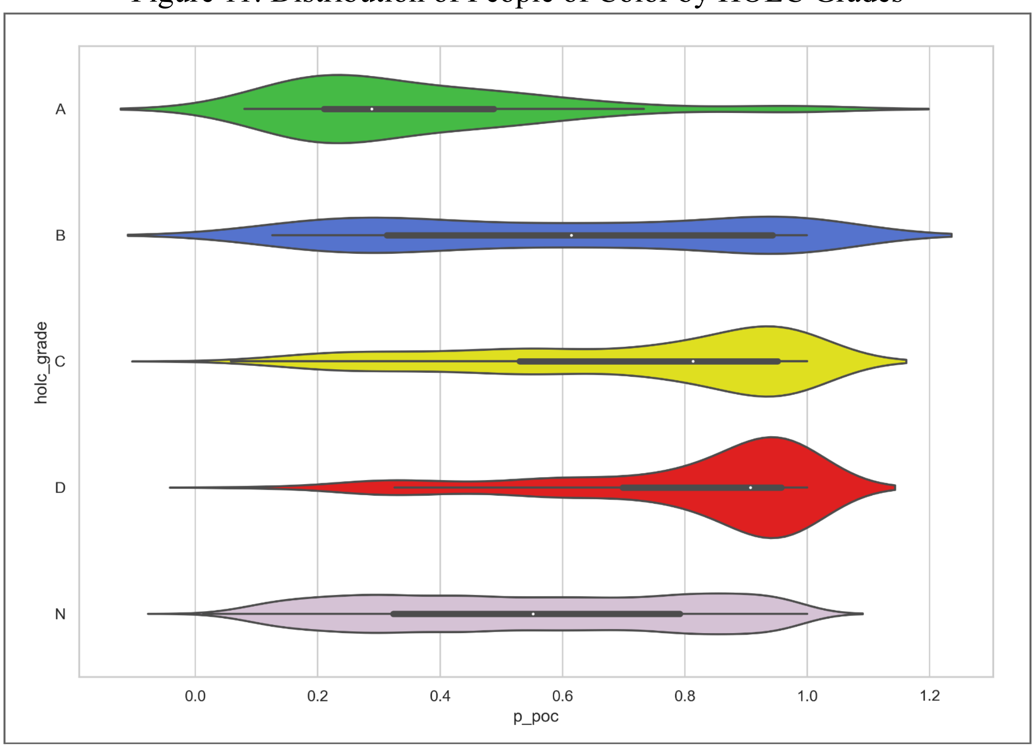
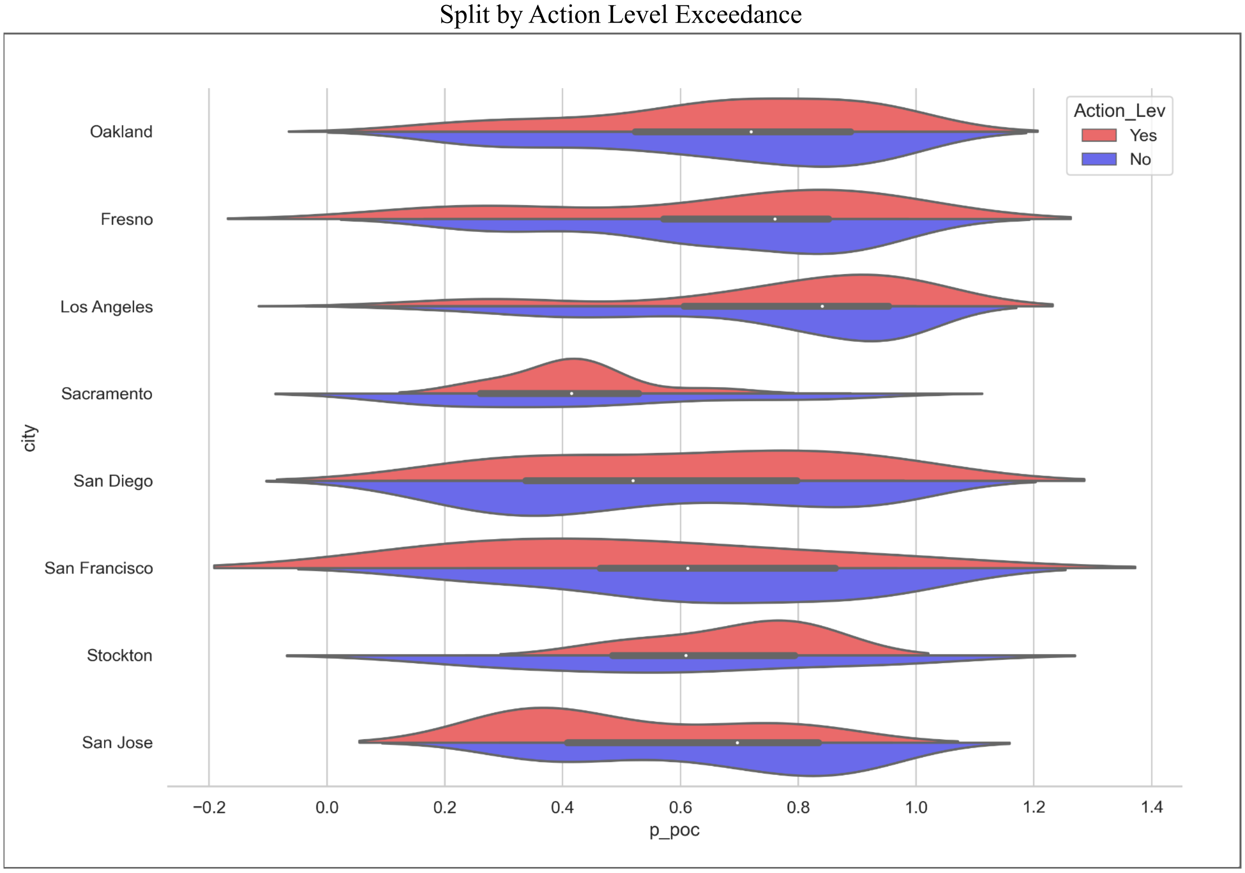


Figure 11: Distribution of People of Color by HOLC Grades



In order to understand how communities of color are affected by out of compliance (above 15 ppb) schools in the redlined cities, we evaluated the distribution of action level exceedance. It is necessary to recall that only 287 out of the total sample of 1,320 schools had lead levels that required remedial actions under AB 746. Remedial actions include resampling, removing and replacing contaminated faucets, notifying parents, and providing alternative sources of water. Figure 12 shows the violin plots for the overall ethnic makeup of each redlined city split by the action level exceedance in schools. Seemingly, cities like Oakland, Fresno, San Jose, and Los Angeles have higher percentages of people of color as shown by the white dot on Figure 12. The dispersion of people of color by action level exceedance markedly differ between all of the redlined cities. For example, cities like Stockton divulge polarized distribution by action level exceedance while the violin plot for San Diego has a more uniform distribution of ethnic makeup.

Figure 12: Distribution of People of Color in HOLC Cities
Split by Action Level Exceedance



Note: The red color shows the distribution of people of color by action level exceedance (above 15 ppb). In comparison, the blue color reflects the original distribution of people of color in each of the redlined cities.

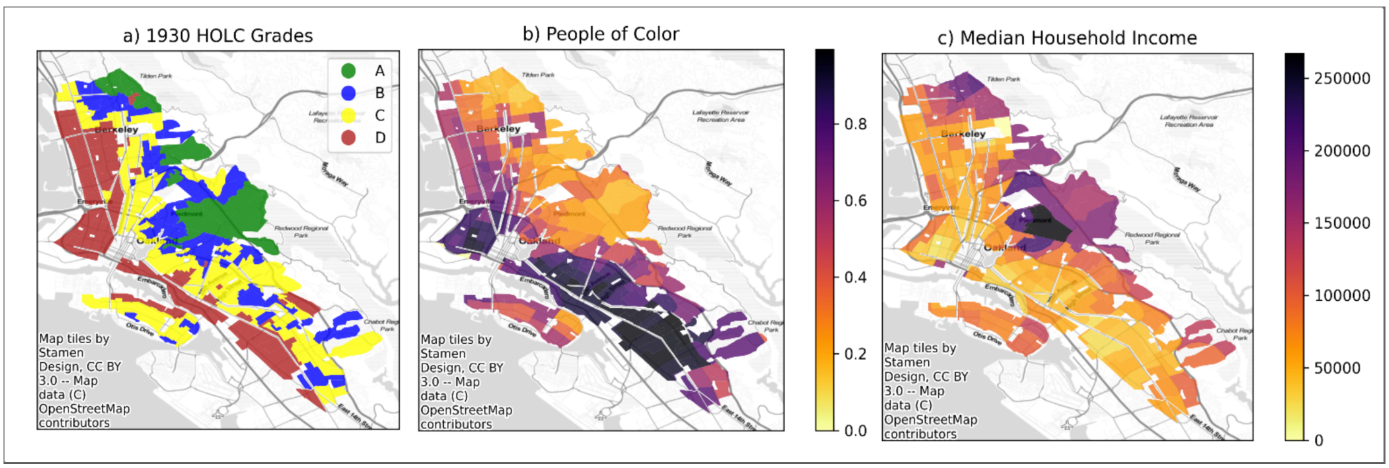
4.1.2 Spatial Distribution

4.1.2. a Choropleth Maps

Geographic analysis of median household income and racial composition are reported on choropleth maps for the eight redlined cities in California (also see Appendix). For example, Figure 13 map (a) shows the color scheme according to the HOLC designation in Oakland California, while maps (b) and (c) indicate the distribution of people of color and median household income respectively.

Figure 13: Choropleth Map: Oakland, California

View Full-Size Image



Note:. Map (a) shows the reconciled 1930's HOLC grades with modern 2010 census tracts. Census tracts belonging to 1930s HOLC grade A are shaded in green whereas grade D are colored red. Maps (b) show the percent of people of color and map (c) represent median household income in 2010. On the choropleth maps (b) and (c) the highest values of the people of color and median household income are represented in deep purple whereas the lowest values are shown in yellow. Additional maps for the remaining redlined cities are provided in the appendix.

Choropleth maps are types of thematic maps that highlight the distribution of a given variable within the predefined geographic boundary or spatial enumeration units. The enumeration units used in our analysis are census tracts. For uniformity, we implement the same sequential color scheme[19] across each city. The colors on the choropleth maps vary from yellow to deep purple. The darkest shades of purple denote the highest value of the indicators while the lowest values are shaded in yellow. Due to differences in income and ethnic makeup across the

[19] Color map= inferno_r from matplotlib

HOLC cities, we are leaving the data unclassified (Refer to the scale on maps (b) and (c) to review the distribution).

Close inspection of the maps in Figure 13 (see Appendix) reveals consistent patterns of disparities across all eight cities. Similar to the violin plots, in most instances, grade C and D geographically corresponds to high proportions of people of color and low median household income compared to grades A and B. Profound intra-city disparities are monitored across the major metropolitan cities like Los Angeles, San Diego, Oakland, and San Francisco. These patterns point towards intergenerational disadvantages explained in part by the systemic racial policies of the past.

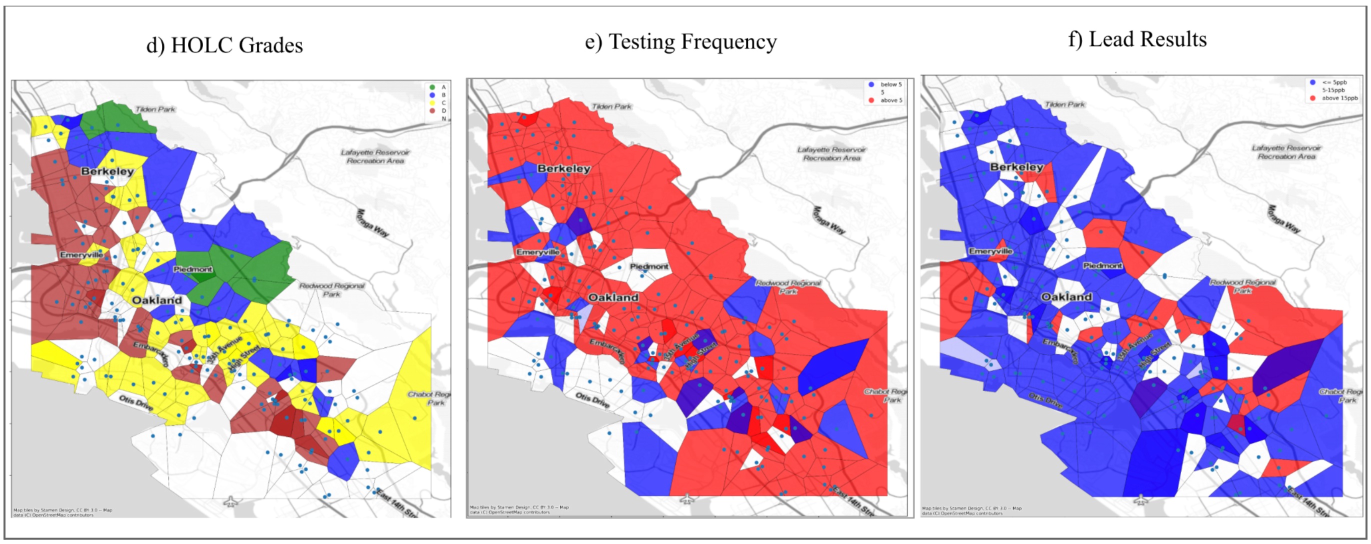
4.1.2.b Voronoi Diagrams

The distribution of lead concentration and frequency of testing at schools are outlined on maps (e) and (f) in Figure 14 (see also Appendix). We conceptualize the distribution using a novel technique known as the "Voronoi diagram". On the Voronoi diagram, each polygon contains exactly one initiation point (in this case the school) and every point in a given Voronoi polygon is closer to its generating points than others (Burrough et al. 2015). In most geospatial analyses, this technique is used to illustrate distance within a polygon to its centroid and accessibility to school locations. To maintain a consistent cartographic message, we generated a Voronoi polygon for each school point within the geographic bounds of the HOLC designated grades for all eight redlined cities similar to the choropleth maps.

A one-to-one relationship is applied to assign the outcomes of interest from school points to each of the accompanying Voronoi polygons. The merit of this approach is evident in the maps shown in Figure 14. Consequently, a vivid distribution of the data emerges that is harder to ascertain when projecting only point values for lead concentration and frequency of testing per school site. Furthermore, to facilitate a comparison of the outcomes with the HOLC grades, we allocated the color codes (green, blue, yellow, and red) to each voronoi polygon matching its corresponding HOLC grade. For example, a voronoi polygon around a school point situated in grade A is assigned a green color, and those in D grade are denoted in red (See map (d) in the panels on Figures 14 in Appendix). Overall this is an effective approach to simplify our illustration, however, there are a few caveats. Unlike the census tracts polygons, each voronoi polygon may intersect census tracts with different HOLC grades. In other words, one voronoi polygon might contain multiple HOLC grades, unlike a single school point that belongs to only one HOLC graded region. Thus a one-to-one join of the HOLC grades (based on school points) to voronoi polygons results in oversimplification and should be interpreted with caution. Fundamentally, a one-to-one spatial join fails to accurately capture the entirety of the HOLC-graded aerial units represented in Figure 3.

Figure 14: Voronoi Diagrams: Oakland, California

View Full-Size Image



Note:. Map (d) is based on a one-to-one join of voronoi polygons with HOLC grades. On maps (e) and (f) the highest values of the categorical variables are represented in red whereas the lowest values are colored blue. The blue dots represent school locations. Additional maps are available in appendix. To review the full-size images of each HOLC graded region in the redlined cities click on the following links:

Fresno, **Oakland**, **San Diego**, **San Francisco**,
San Jose, **Sacramento**, **Stockton**, **Los Angeles**

We used a diverging color scheme to accentuate the distribution of our study's outcome variables on maps (e) and (f) (Figure 14). The same blue, white, and red scheme for the frequency and lead concentration outcomes was applied across all cities. The higher values are presented in red and the lower values are colored blue inside all the panels (See maps (e) and (f) in Figure 14). For the sake of clarity and consistency, we reconfigured the lead levels and testing frequency as categorical variables. Largely, this data conversion helps generalize the outcomes for the eight cities. At the same time, the resulting voronoi polygons help facilitate a contrast between the two parameters.

We divided the lead concentration into three tiers, ranging from “at and below 5 ppb”, “above 5 to 15 pbb”, and “above 15 ppb”. Hence, the number of schools mandated to take remedial action is shown in red, while white color is assigned to at-risk schools, and the remaining polygons with values at and below 5 ppb are shaded in blue. Across all eight cities, the number of white polygons exceeds those in red. Stark contrasts appear in cities like Stockton, and San Jose that have no polygon with action level exceedance (in red) but a notable number of white polygons highlighting the at-risk schools. This is a salient theme, reflecting how the current legislative standards in California are insufficient when it comes to securing preventive measures at every at-risk school.

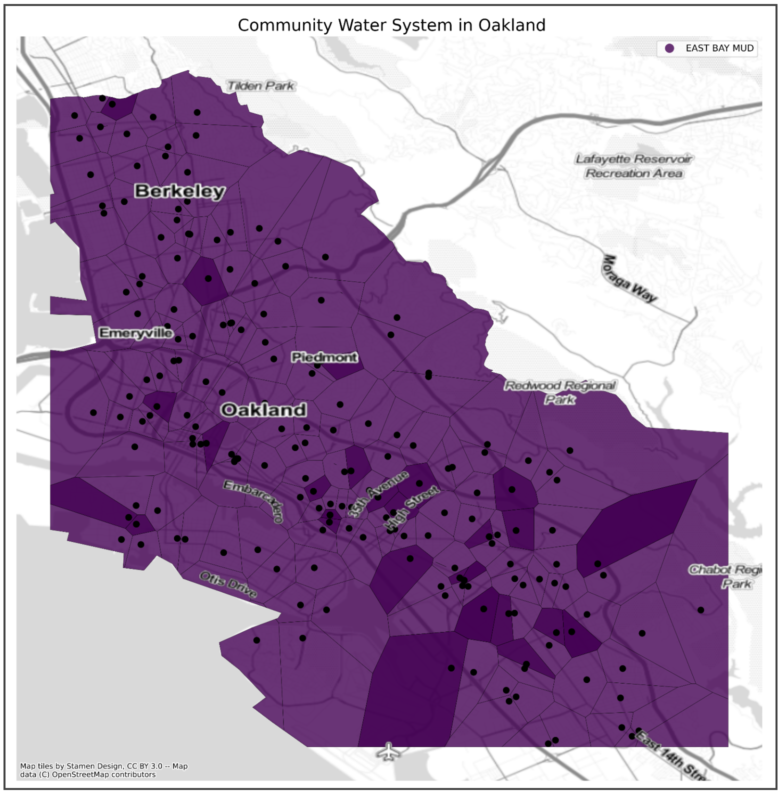
Similarly, for testing frequencies, we categorized the count into three bins, where any value between 1 to 4 counts of lead samples is rendered in blue. Testing frequencies that meet the recommendation put forth by SWRCB (5 tests per site) are represented in white. Lastly, voronoi polygons for schools with a testing frequency above 5 counts are depicted in red. Within the confines of our mapping area, the frequency of testing shows wide variations for all cities. In particular, results from Oakland are astounding, the city has a significantly large number of red polygons compared to other cities. Interestingly, Oakland, which is part of Alameda County, has the highest median testing frequency than elsewhere (Figure 8 a). In almost every HOLC city, we observe a chunk of school polygons that had fewer tests than the recommended number (shown by the blue areas).

To isolate and test if community water systems are responsible for inducing differences in testing frequency we ascribed a one-to-one spatial join of voronoi polygons to the school’s water provider. Anomalies were observed wherein in most HOLC graded areas we found the same community water system reported diverging number of tests across schools. (see Figure 14A). Constrained by the SWRCB data, we cannot provide a plausible explanation for these perplexing results. It's unclear what was the rationale behind uneven testing for schools throughout the state. To glean evidence researchers should ask what are the factors governing a community water system's choice in adopting an optimal number of testing at a school site?

Up to this point, the Voronoi Diagrams led us to summarize data distribution in a more meaningful manner, yet, we cannot say much about the correlation between the geographic location of schools (specified by voronoi polygon) and the value of the attributes such as lead levels in water and frequency of testing. In order to understand if these attributes for schools within geographic bounds of HOLC designated grades are spatially random or exhibit a degree of clustering, we have to rely on measures of spatial autocorrelation.

Figure 14A: Community Water Service Provider in Oakland, California

View Full-Size Image



Note: The black dots represent the school location in Oakland. Since there is only a single community water service provider in that region, East Bay MUD, the entire map is colored the same. To access the additional community water systems for each of the redlined cities click below or review appendix.

Fresno, Oakland, San Diego, San Francisco,
San Jose, Sacramento, Stockton, Los Angeles

4.2 Results

4.2.1 Spatial Autocorrelation

4.2.1. a Global Spatial Autocorrelation (Moran's I)

Spatial autocorrelation allows researchers to understand the functional relationship between a point and the space around it. Global Moran's I (GMI) gives us an advantage in helping to summarize statistical results in a map while also determining any randomness that occurs in our data. A positive value of GMI signifies that similar values are situated close to each other in other words they are clustered in space, whereas a negative value for GMI suggests that similar values of any variable tend to be located further away from each other. We can also empirically test the values of GMI for statistical inference using the p-values. A small p-value for a given GMI will lead us to reject the hypothesis that the map is random. For our estimation we used queen contiguity as spatial weights to estimate GMI for all eight redlined cities.

Table 3 states the results of GMI for lead levels and the accompanying p-value for each of the eight HOLC cities. It is important to recognize that our sample for GMI estimation comprises only the voronoi polygons used earlier on in our analysis. Based on results from the p-values (at a 5 percent significance level), the lead concentrations produce statistically significant clusters for two HOLC cities including Fresno and San Francisco. In the remaining cities, however, the spatial distribution of lead results in schools drinking water supplies is completely random.

Table 3: Global Moran's I for Lead Concentration in Drinking Water at Schools

HOLC City	**Global Moran' I**	**P-Value**
Fresno	0.06	0.021
Oakland	-0.0	0.306
Los Angeles	0.025	0.087
San Diego	0.05	0.061
San Jose	0.024	0.254
Stockton	0.055	0.165
Sacramento	-0.03	0.308
San Francisco	0.01	0.05

The results for GMI for testing frequency are listed in Table 4. Only four of the redlined cities such as Fresno, Oakland, Los Angeles, and San Diego, exhibit statistically significant clusters of voronoi polygons for testing frequencies at a 5 percent significance level.

Table 4: Global Moran's I for Testing Frequency in Drinking Water at Schools

HOLC City	Global Moran' I	P-Value
Fresno	0.19	0.008
Oakland	0.14	0.001
Los Angeles	0.505	0.001
San Diego	0.19	0.001
San Jose	-0.17	0.069
Stockton	0.014	0.313
Sacramento	0.05	0.192
San Francisco	0.006	0.31

4.2.1.b Local Indicators of Spatial Autocorrelation (Moran's I)

The Global Moran's I feature an overall trend of the data with regards to spatial autocorrelation. Contrary to that, a more focused indicator is Local Moran's I (LMI). It deviates from the global trend at a much more refined geographic scale thus yielding a sophisticated micro-level analysis[20]. The use of Local Indicators of Spatial Autocorrelation such as LMI, allows us to analyze the lead results of schools that neighbor each other to help us better understand the relationship, if any, that exists between each school's lead levels. LMI visualizes what is known as hot and cold spots. Each map breaks the school point results into HH (high-high), HL (high-low), LH (low-high), LL (low-high) and NS (not-significant). Using the voronoi maps discussed above, each color-coded indicator on the maps below provides a single summary for each polygon. HH indicates that the schools in the polygon reported high levels of lead and are surrounded by schools with high levels as well. HL indicates schools with high levels of lead are surrounded by schools with low levels of lead. This logic is then flipped for LH and LL. Utilizing this method of geospatial analysis allows summarization of each polygon's lead levels throughout all eight California Redlined cities. The same approach is applied to check for the geographic concentration of testing frequency for each locale. In order to compute LMI, we reprojected our data to spherical Mercator and used eight nearest neighbors as our spatial weights matrix.

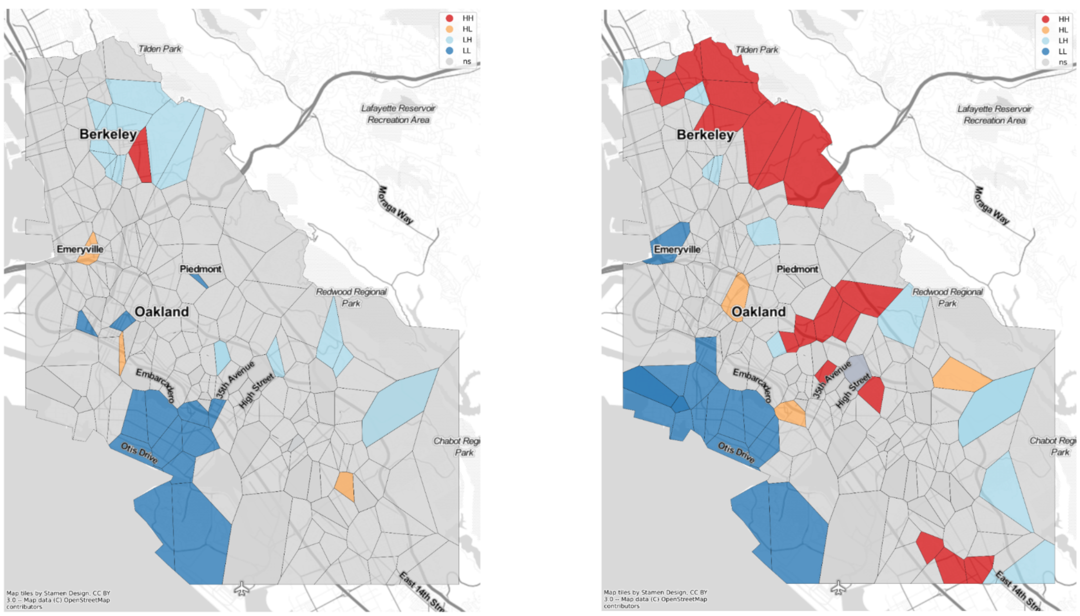
Figure 15 shows the location of statistically relevant hot and cold spots for both the indicators side-by-side at a threshold value of 5%. A closer inspection of the resulting LISA

[20] https://geographicdata.science/book/notebooks/06_spatial_autocorrelation.html

maps reveals that voronoi polygons with the highest lead concentrations are considerably lower in number across all cities. The absence of statistically significant hotspots (red color) for both lead concentrations and frequency of testing is found on maps of Sacramento and Stockton. Distinctly, in redlined cities like Oakland, Fresno, Los Angeles, and San Diego we found a higher likelihood of statistically significant clustering for testing frequency. Interestingly, in our study region Oakland has the same community water system, East Bay MUD, responsible for testing yet we see heterogeneity in the number of tests per school that fall under its jurisdiction.

Figure 15: Local Indicator of Spatial Autocorrelation (LISA) for Oakland, California

View Full-Size Image



Map A Local Moran Cluster for Lead Results

Map B Local Moran Cluster for Testing Frequency

Note: The red regions in the maps show statistically significant hotspots (HH), the yellow color shows HL, light blue depicts LH, the dark blue voronoi polygons are cold spots (LL). The remaining grey areas are not considered statistically significant at 5 percent confidence level. LISA maps for additional redlined cities in California are available in Appendix. To review the full-size images of each HOLC graded region in the redlined cities click on the link below:

Fresno, **Oakland**, **San Diego**, **San Francisco**
San Jose, **Sacramento**, **Stockton**, **Los Angeles**

4.2.2 Regression Results

For the reliability of our results, we used both the full data with N= 7,555 and a subsample of 1,320 at-risk schools to determine the association between lead and frequency of testing in school and HOLC grades. The results are presented in Tables 5 and 6.

Table 5: Multivariate OLS Regression Estimation Results

Outcome Variable: Lead Results				
	(1)	(2)	(3)	(4)
A	-2.018	0.783	-8.946	0.480
	(30.028)	(6.270)	(30.734)	(6.382)
B	-11.958	-1.566	-8.256	-0.846
	(17.483)	(3.732)	(17.791)	(3.778)
C	-2.005	0.022	4.462	1.016
	(11.634)	(2.173)	(12.155)	(2.264)
D	-7.324	-1.558	-0.229	-0.545
	(15.585)	(2.525)	(16.074)	(2.620)
HOLC City Status			-9.511	-1.595
			(5.870)	(1.024)
Intercept	22.977***	8.109***	8.428	6.748***
	(2.762)	(0.486)	(10.503)	(1.870)
Median Household Income			0.000**	0.000
			(0.000)	(0.000)
People of Color			8.611	1.140
			(11.042)	(1.965)
Observations	1,320	7,552	1,319	7,551
R^2	0.001	0.000	0.005	0.001
Adjusted R^2	-0.003	-0.000	0.000	-0.000
Note:		*p<0.1; **p<0.05; ***p<0.01		

4.2.2.a Lead Concentration as Outcome

In all four ordinary least squares (OLS) regression estimations with lead results as the outcome variable, none of the formally 1930's HOLC designated grades was found to be statistically significant (Table 5). For models 3 and 4 in our multivariate estimation, we added median household income, people of color, and HOLC city status as covariates. Median household income generated inconsistent results between the two specifications. For instance, in the subsample group of at-risk schools with lead levels above 5ppb, median household income was found to be significant and positively associated with lead results ($p < 0.05$). However, as we increased the sample size (N= 7,555) median household income became insignificant at a 95% confidence interval. The remaining two covariates, people of color and HOLC city status have no causal association with lead results.

4.2.2.b Frequency as Outcome

Compared to our first model, the Negative Binomial for testing frequency produced inexplicable results (Table 6). For the first two models with A, B, C, and D grades as the only predictors of testing, we found strong statistically positive association between all the HOLC grades and testing frequency[21]. After including the additional covariates only grades C and D remained statistically significant at a 90 percent confidence level for the subsample (N = 1,320) with N (nongraded areas) as the comparison group.

Consistent with the previous estimations, median household income remains significantly associated with the testing frequency ($p<0.01$). It seems plausible that a higher frequency of testing resulted in early detection of the lead contamination problems in well-resourced communities. Contrary to what we expected, the ethnic makeup of the neighborhoods is not associated with either of the outcome variables. Even after adjusting for sample size (models 3 and 4 in Table) the people of color and the dummy for HOLC city status did not induce statistically significant results.

[21] Note: We used nongraded regions represented by N as the base case.

Table 6: Multivariate Negative Binomial Regression Estimation Results

Outcome Variable: Frequency of Testing				
	(1)	(2)	(3)	(4)
A	0.667^{**}	0.455^{***}	0.421	0.325^{*}
	(0.331)	(0.166)	(0.339)	(0.169)
B	0.408^{**}	0.457^{***}	0.309	0.424^{***}
	(0.195)	(0.099)	(0.199)	(0.100)
C	0.570^{***}	0.291^{***}	0.538^{***}	0.299^{***}
	(0.129)	(0.058)	(0.135)	(0.061)
D	0.528^{***}	0.295^{***}	0.524^{***}	0.312^{***}
	(0.173)	(0.068)	(0.179)	(0.070)
HOLC City Status			0.101	0.011
			(0.067)	(0.028)
Intercept	1.792^{***}	1.606^{***}	1.501^{***}	1.426^{***}
	(0.032)	(0.013)	(0.120)	(0.051)
Median Household Income			0.000^{***}	0.000^{***}
			(0.000)	(0.000)
People of Color			0.075	0.073
			(0.126)	(0.054)
Observations	1,320	7,552	1,319	7,551
R^2				
Adjusted R^2				
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

5. DISCUSSION

There is a clear and consistent present socio-economic divide between each HOLC grade and environmental hazards. Redlining continues to impact the median household incomes and economic disparities within neighborhoods that were historically redlined. Former Grade A neighborhoods still represent a population with a higher median income compared to Grade D neighborhoods. The ethnic makeup of formerly redlined neighborhoods is still disproportionately the same. White people make up a high percentage of the population in Grade A neighborhoods and people of color make up a higher percentage in Grade D or redlined neighborhoods. These patterns are comparable to findings from previous studies.

Despite what we might expect in terms of the legacy of place-based discriminatory policy, our findings imply otherwise. Redlined neighborhoods in California do not have higher levels of lead unlike previously suspected. Lead levels were not found to be impacted by the legacy of redlining. Part of this can be explained by the recent actions to replace lead pipes throughout California's water systems. Under SB-1398, state water systems are required to identify lead water pipes and replace them as soon as possible (2017). By July 1st, 2020 public water systems were to have identified and supplied a timeline to the state on the replacement of pipes. Although, the prevalence of Covid-19 at this time could have halted this process. Updated infrastructure both in schools and water systems may have led to lower lead results within some California schools.

Disinvestment and low funding for schools residing in redlined neighborhoods may not have impacted the prevalence of lead and the lead testing processes. The frequency of testing was permitted and executed by community water systems and not the local school districts. While each community water system differs by resources and area of coverage, our findings indicate that the lead testing policy was consistently implemented properly with the minimum recommended number of testing by the State Water and Resource Control Board. The distribution of lead results according to the county is given in Figure 7. Notably, the median level for lead concentration in counties including San Mateo, Placer, Yolo, Merced, and Imperial far exceeds the median lead concentration (8.5 ppb) observed in our subsample. These results suggest that disadvantaged suburban communities are at much higher risk of lead contamination in their school drinking water supplies. Redlining only occurred within metropolitan areas, but it is not to say that other discriminatory policies de jure or de facto did not affect structural funding and neighborhood investment. Despite high concentrations of lead, we see visible disparities in testing frequencies across disadvantaged communities compared to other regions in the state (Figure 8). In particular, median frequency is highest in Alameda and Contra Costa counties. Further research is needed to understand the prevalence of high-frequency testing occurring in these counties.

All eight redlined cities showed no statistically or visually significant indicator that more schools with an Action Level Exceedance (ALE) resided in historically redlined neighborhoods. For the purpose of our study, schools that indicated ALE showed lead results over 5 ppb. Granted, a relatively insignificant statistical relationship was found between redlined neighborhoods and higher levels of lead. Our research indicates safeguards that can be put in place to mitigate lead exposure for children across California. 1) lowering the level for action exceedance from 15 ppb to 5 ppb. 2) policies to decrease lead at the point of service outlets.

6. POLICY RECOMMENDATIONS

After researching the impacts of lead on child development and analyzing water sample results from public schools across California, our group has developed three policy recommendations that we reckon would lessen lead exposure in school settings and improve upon lead testing procedures currently in place. For each policy recommendation, we will evaluate its feasibility based on support, opposition, cost, and/or obstacles to implementation.

6.1 Revise Remedial Lead Standards from 15 ppb to 5 ppb

As we stated previously in our report, the EPA and CDC acknowledge that there is no safe level of lead consumption (Environmental Protection Agency, n.d.). Despite this concession, both federal and state standards for lead in drinking water are 15 ppb, placing children at risk even when consuming water containing “acceptable” levels of lead. We propose that California lower the action level exceedance limits for lead in public schools from 15 ppb to 5 ppb. This policy is not without precedent; several school districts in California have already adopted lower lead standards, including Oakland, San Diego, and Berkeley (Savidge et al., 2018). This reduction would also bring lead allowances in line with the Food and Drug Administration standards for bottled water (U.S. Food and Drug Administration, 2019).

When applying these lower standards to our original dataset, the number of schools with lead violations increases considerably. Approximately 3.8% of public schools registered lead levels over 15 ppb; reducing acceptable levels to 5 ppb would increase the number of violators to over 20% of the 7,555 that made up our school sample. Abatement costs would likely cost tens to hundreds of millions of dollars (The Pew Center on the States, 2010). We anticipate opposition to this measure from those who, absent financial support from federal or state partners, will likely shoulder the burden to lower lead levels: school districts and public water systems. In support of this initiative would be public health groups, such as the American Academy of Pediatrics, and concerned parents, as well as some proactive school districts that have already demonstrated the reduction of lead levels as a priority (Savidge et al., 2018).

6.2 Consistent Sampling and Reporting

We noticed numerous inconsistencies when analyzing lead testing results across California public schools. Testing location, frequency, and reporting varied considerably across our dataset. For example, some schools submitted the results of 26 samples taken from different sites on campus, while others submitted only one. The average number of samples taken from each school was 5. In addition to variation in testing frequency, the location of water samples differed from school to school, as well. We deemed this problematic because not all points-of-use pose an equal risk of consumption. A water sample taken from a locker room shower, for example, doesn't pose the same risk as a classroom water fountain. Finally, reporting details varied across schools. Some schools identified the exact sample site by using unique descriptors, such as room name followed by the faucet, but others were far less detailed ("cafeteria," "bathroom") or lacked a sample location altogether. While some of these inconsistencies can be attributed to the lack of specificity in the AB 746 bill language or limits to the data that we were provided, we propose ongoing, uniform, consistent, and transparent testing requirements.

First, schools should be required to submit the same number of water samples. A greater number of samples increases the likelihood that contaminated points-of-use are identified, shut off, and eventually repaired. Second, sample sites should be prioritized based on the risk of lead intake. Sampling water fountains, for example, should take precedence over showers or sinks, where the risk of lead finding its way into student bloodstreams is relatively low. Third, reporting requirements should be detailed and transparent, so there is no question where lead violations are occurring. Finally, lead testing should be ongoing. AB 746 mandated a single round of school testing, which has since been fulfilled. For schools that produced samples with excessive lead contamination, surveillance testing should continue on an established schedule until the problem has been abated. For non-violating schools, lead testing should still be required, but on a much less frequent basis.

While these additional requirements may be perceived as onerous by some, the implementation of these measures will generate more accurate, useful results. Because AB 746 lacked specificity in its bill language (California Legislative Information, n.d.), we can safely assume there are disparities in the samples produced across schools. Establishing testing and reporting standards is extremely important so that we may understand the magnitude of lead contamination in public schools.

6.3 Point-of-use Filtration Units at Schools

For schools with lead contamination concerns (determined by repeated lead violations in water samples), filtered drinking water should be provided to students until the problem is resolved. For the 1320 at-risk schools identified in our analysis (lead levels above 5 ppb), stations with point-of-use water filters should be strategically placed throughout the school so that students can conveniently access safe drinking water. Drinking fountains and faucets should be decommissioned while the school pursues abatement efforts.

This mandate would likely generate opposition by school districts since they would likely incur the cost of point-of-use filters. Lead water filters can cost thousands of dollars and would need to be replaced after prolonged use, but this solution would be far less costly than replacing pipes, faucets, and other water infrastructure. When the risk has been mitigated, which would be determined by clean water samples, schools would no longer be required to provide water stations.

In conclusion, we realize there are significant obstacles to implementing our recommended policies. The cost will generate the greatest opposition to their implementation. The cost of inaction, however, bears great costs of its own. According to some studies, not addressing the threat of lead in drinking water costs millions down the road (The Pew Center on the States, 2010). For children, in particular, lead exposure can compound existing disadvantages and lead to a host of problems later in life. In our estimation, the benefits outweigh the costs. Coordinated funding mechanisms at the state and federal levels should be created to help offset the costs otherwise bore by school districts and public water systems.

7. LIMITATIONS & FUTURE RESEARCH

The scope of our research was limited to the legacy of redlining and its association with lead exposure in school's drinking water. We ascertain the causes of lead exposure using HOLC designation grades, census tract level income, and ethnic composition. This approach ignores any individual school-level characteristics that can potentially cause variability in the lead test results. For example, the water delivery infrastructure and outlet in schools can vary by the year of construction and the number of funds a school district receives. These elements can provide further insights as to why we observe differences in our outcomes across schools. In essence, most resource-rich school districts would be better equipped to identify and fix hazards, such as lead, compared to resource-constrained schools. Resource-rich schools exhibit higher funding per pupil and tend to serve a higher SES population. The "Fundamental Cause Theory" helps explain that better access to resources yields healthier outcomes, this is especially true for children (Link and Phelan, 1995). Furthermore, under AB 746, a community water system that served a school site of a local educational agency was responsible for lead testing. Since our research focuses on place-based disparities, we did not consider the possibility of differences in lead sampling frequency due to the size and type of community water system. Throughout the research process, we encountered various limitations within our data set that hindered the scope and extent of our research. The school lead data retrieved from the California Water Resource Control Board was not entirely uniform in its formatting. This dataset also did not include individual school codes issued by the California Department of Education. This made the use of other cross-sectional data sets difficult. Almost every school had multiple samples, although it became unclear whether this was due to high lead levels that required resampling or were just multiple samples conducted at a school site. The data dictionary describing the variables and their appropriate measurements was absent from the California Water Resource Control Board website. Although through continued communication with the board we were able to gain access to the data dictionary, this was not readily available and transparent to the public. Full transparency and organizational clarity are vital towards the present and future research regarding lead levels in California schools.

Our contribution to the literature on environmental justice and redlining has continued to test and expand current research. With no relationship uncovered between redlining and high levels of lead in schools, we suggest future research continue to better understand the characteristics of schools/and or water systems that have high levels of lead. These variables were not explored but would be beneficial to understand patterns across different water systems. Prior research has shown water systems out of compliance have primarily served schools with a higher diverse population than water systems within compliance (Umunna et al. 2020).

Understanding the placement of recent city and county actions to replace lead pipes may also allow us to understand patterns in neighborhoods that were affected by an infrastructure update. Whether it occurred in historically redlined neighborhoods or not. It is known knowledge that higher lead levels result in cognitive decline. Future cross-sectional research into health and education policy may find significance in the test scores and academic performance of schools that reported over 5 ppb in their lead samples.

8. CONCLUSION

In concluding our analysis, we have determined that there is both good news and bad news as it relates to lead exposure and historical redlining. The bad news is that significant socioeconomic and environmental disparities exist in California's redlined neighborhoods 80 years after the HOLC drew up their discriminatory neighborhood maps. In our literature review and throughout our analysis, we found significant inequalities inherent to living in historically redlined neighborhoods, including greater minority populations, lower incomes, increased exposure to air pollution, and increased risks associated with the COVID-19 pandemic. The good news, as it relates to our hypothesis that schools in redlined neighborhoods would have higher levels of lead in their drinking water, is that we were unable to find a relationship between these variables. While this is only one metric by which to gauge the prevalence of environmental disparities experienced by children growing up in redlined neighborhoods, it brings limited comfort knowing that over the last 8 decades, California has significantly reduced the risk of students being exposed to lead at public schools.

Despite our analysis not establishing the hypothesized relationship, we also believe that state lead standards are too high at 15 ppb. As we stated earlier, federal agencies acknowledge that there is no safe level of lead consumption. The effects of lead exposure on children are severe and irreversible and can contribute to a host of learning and behavioral problems later in life. While only 3.8% of schools produced lead samples greater than 15 ppb, lowering the standard to the recommended 5 ppb meant that 20% of schools had unacceptable levels of lead. For schools currently unable to meet the 15 ppb standard, mitigation efforts should include the provision of safe, filtered drinking water and stringent sampling mandates to reduce the risk of children consuming lead-contaminated water. Once again, our findings, while somewhat encouraging, belie the reality that children are still being exposed to lead while attending public schools. Based on our research, we feel that aggressive measures should be taken to further lessen the risk of lead consumption among children.

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Table 7: Summary Statistics by HOLC Grade

	Sample N= 7,555 Schools			
Mean Values per HOLC Grade	Median Household Income (USD)	%People of Color	Lead Sample Results (in ppb)	Testing Frequency (Count)
A	163,041	36%	8.89	8
B	88,688	60%	6.54	8
C	65,276	72%	8.13	7
D	58,592	80%	6.55	7
N	79,115	55%	8.11	5
	Sample N= 1,320 Schools			
Mean Values per HOLC Grade	Median Household Income (USD)	% People of Color	Lead Sample Results (in ppb)	Testing Frequency (Count)
A	15,1518	39%	20.96	12
B	83,442	60%	11.02	9
C	61,913	73%	20.97	11
D	53,757	83%	15.65	10
N	74,573	56%	22.98	6

Table 8 : Summary Statistics

	Sample N= 7,555 Schools				
	%People of Color	HOLC City Status	Median Household Income (USD)	Testing Frequency (Count)	Lead Sample Results (in ppb)
Mean	57%	0.47	$78,355	5	8.04
25%	33%	0.00	$51,016	4	5.00
75%	82%	1.00	$98,031	5	5.00
Max	100%	1.00	$296,455	26	2000
	Sample N= 1,320 Schools				
	%People of Color	HOLC City Status	Median Household Income (USD)	Testing Frequency (Count)	Lead Sample Results (in ppb)
Mean	58%	0.47	$74,086	6	22.37
Min	5%	0.00	$17,175	1	5.02
25%	33%	0.00	$48,824	5	6.20
75%	83%	1.00	$91,858	6	13.10
Max	100%	1.00	$296,455	26	2000