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Traffic and the Racialized Built Environment: Applying a New Lens on HOLC "Redlining" Maps to Understand Traffic Safety Outcomes

By

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Acknowledgments

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Abstract

Traffic fatalities are understood to be a pressing cause of fatality in the United States, but the fundamental causes of inequities in their distribution are poorly understood. In this study, we aimed to understand the influences of one such fundamental cause: the implementation of antiquated neighborhood lifecycle theories through racially discriminatory policies. Through a propensity matching design within five American cities, we found evidence that traffic health disparities are tied to the perceptions of race and space held by governmental entities such as the HOLC, but are not necessarily tied to redlining or other policies derived from neighborhood lifecycle theories. Our discovered relationships also vary by city, leading to potential implications for future studies using HOLC maps to understand modern health inequities.

Keywords: HOLC; Redlining; health disparities; Traffic crashes; physical disorder; systemic racism

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1 Introduction

In 2021, traffic fatalities accounted for 42,915 deaths in the United States, with 51.5% of these deaths being people aged 16 to 44 (National Center for Statistics and Analysis, 2022).

Traffic fatalities are racially inequitable, with Black and Hispanic Americans facing higher traffic mortality rates per distance traveled than White Americans (Raifman & Choma, 2022). The large number of deaths caused by traffic has been a driving impetus behind Vision Zero initiatives, which aim to build a future in which zero people die from road crashes. These programs utilize a framework known as the Safe Systems approach, which attempts to expand traffic safety policies from simply focusing on building better drivers to social and institutional systems which work to reduce the risk of traffic crashes and severity of the resultant events (International Transport Forum, 2016). The Safe Systems approach has motivated not only improvements to automobile safety technology, but also built environment changes that motivate safer decisions by drivers, such as increased implementation of speed bumps and automatic speed cameras.

The prominence of the Safe Systems approach has motivated traffic safety researchers to focus on the proximal causes of road crash risk. This research is timely and useful for the Safe Systems approach, as improved understanding of how built environment factors and road mixtures correspond to traffic behavior in-the-moment better enables policymakers to design safer built environments. However, even as this approach motivates thinking about traffic crash risk as constructed by environmental factors which determine driver behavior, it fails to account for broader, upstream social factors which have structured the built environment in which modern communities live.

2 Literature Review

Previous studies on traffic health have heavily focused on the impacts of built environment design as it is known to heavily influence driver behavior and hence traffic safety outcomes. When driving, drivers actively and subconsciously evaluate multiple factors to determine whether to engage in risky behavior, such as speeding (Peterson & Gaugler, 2021). These factors vary from one's own subjective perceptions of how normal it is to speed (Ding et al., 2023; Peterson & Gaugler, 2021) to evaluations of the risk of crashing on a given roadway (Ding et al., 2023; Dinh & Kubota, 2013; Peterson & Gaugler, 2021) to perceived driving experience (Dinh & Kubota, 2013; Ellison & Greaves, 2015) and perceived benefit from speeding (Ellison & Greaves, 2015). As these evaluations are frequently the cause behind risky behavior, they are also a commonly used tool for lowering speeds through "traffic calming measures," or predominately (but not exclusively) built environment manipulations that motivate less risky behavior by drivers in order to improve traffic health outcomes (Sołowczuk & Kacprzak, 2022).

The impact of built environment factors on crash outcomes is reflected in traffic data. Das et al. (2019, 2022) find connections between traffic crashes and factors such as lane direction and lighting while Azin et al. (2025) demonstrate connections between lane width and crash injury. Built environment design as a traffic safety determinant also operates at scales larger than individual streets and intersections. Elvik (2001) and Bunn et al. (2003) conduct meta-analyses to find that area-wide traffic calming schemes, in which multiple traffic calming measures are implemented over an entire region, seem to result in fewer traffic crashes and lower crash severity. Sarkar et al. (2018) additionally find that large scale street network typology, such as betweenness, divergence ratio, and hull radius partially explain traffic severity, while Ukkusuri et al. (2012) show that land use, road network characteristics, and travel characteristics explain road crash frequency. Taken altogether, there is strong evidence supporting the link between built environmental factors, driver behavior, and traffic outcomes.

While this wealth of literature linking built environment design to traffic health outcomes is a boon for civil engineers, it is not alone sufficient to tackle health disparities in traffic safety outcomes. Link and Phelan (1995) argue that solutions and research which fails to emphasize upstream, fundamental social causes of disease and health inequities—such as systemic racism or classism—are unlikely to successfully block future pathways for these fundamental social causes to (re)create or intensify ongoing and future health disparities. There is evidence that these fundamental causes are at play in traffic safety but have gone unaddressed. Among studies which focus on built environment behavior, multiple authors decline to account for race, age, and gender in their conceptual models, but include these factors as relevant and unexplained covariates in their statistical models (Le et al., 2018; Sarkar et al., 2018; Ukkusuri et al., 2012). Dumbaugh et al. (2022) have additionally found that the impact of built environment factors may vary by the class and racial makeup of communities, with urban arterials posing a three-times larger hazard to low-income communities than to high income communities. Thus, if the traffic safety literature is to support and guide the implementation of built environment implementations in a variety of communities, it is necessary to develop more robust theorization concerning the relationship between upstream factors and traffic safety outcomes.

2.1 Systemic Racism and the Limitations of HOLC

Within the context of the United States, a common fundamental cause of disease is systemic racism, defined by Bailey et al. (2017) as "the totality of ways in which societies foster racial discrimination through mutually reinforcing systems of housing, education, employment, earnings, benefits, credit, media, health care, and criminal justice." The effects of systemic racism are often inter-generational and lingering, leading many health researchers to look toward historical events and policies to better understand modern health outcomes. In particular, the past five years have seen a surge in research investigating the impact of racially discriminatory home loan lending on health outcomes, also known as "redlining," a shift motivated in part by the newfound easy access to Home Owner's Loan Corporation (HOLC) investment risk maps through Nelson and Winling (2023). Created in the late 1930s, HOLC maps have held a controversial status in the health and urban planning literature, with the operationalization and interpretation of the redlining maps often being called into question (Fishback et al., 2024; Markley, 2024).

On face, HOLC redlining maps are investment risk maps intended to classify neighborhoods by investment risk and racial makeup, with each neighborhood being divided into one of five classifications:

- Grade A: "Best"—areas with lowest investment risk, largely white neighborhoods; demarcated with blue lines
- Grade B: "still desirable"—areas with low investment risk, which are still largely white; demarcated with green lines
- Grade C: "definitely declining"—areas with worse built environment quality or "infiltration" but non-native or non-white populations, viewed as having higher investment risk; demarcated with yellow lines
- Grade D: "hazardous"—areas with large amounts of non-white populations, viewed as having the highest investment risk; demarcated with red lines.
- Commercial or Industrial: areas not considered as primarily residential by the HOLC, and hence not assigned a true loan risk rating.

Given the racially explicit nature of these grades and the labeling of the maps as "investment risk maps," modern public health researchers have used the HOLC redlining maps as tools for understanding the influence of historic home loan discrimination on modern health outcomes (Bassler et al., 2024; Diaz et al., 2021; Hollenbach et al., 2021; A. Nardone et al., 2021; A. L. Nardone et al., 2020; Schwartz et al., 2021). Numerous associations between the grades and health disparities have been identified. Areas which received lower HOLC grades tend to possess increased adverse birth outcomes (Hollenbach et al., 2021; A. L. Nardone et al., 2020), worse access to green spaces (A. Nardone et al., 2021), longer times to viral suppression of HIV (Bassler et al., 2024) and even increased tobacco retailer density (Schwartz et al., 2021). As the aforementioned studies tend to imply (Hollenbach et al., 2021; A. L. Nardone et al., 2020; Schwartz et al., 2021) or explicitly state (A. L. Nardone et al., 2020), this would seem to be strong evidence for the influence of redlining on modern health disparities. Vitally, however, direct connections between the HOLC maps and health outcomes have been criticized for not taking into account the production and usage—or lack thereof—the documents (Fishback et al., 2024; Markley, 2024; Michney, 2022).

Understanding this debate and the true potential of HOLC maps as tools for uncovering the lingering effects of historic systemic racism requires first discussing this often ignored historical context in which these maps were created.

During the late 1920s and early 1930s, the United States faced a national foreclosure crisis in which the annual number of non-farm residential and commercial mortgage foreclosures more than quadrupled over a period of six years (Fishback et al., 2013). This foreclosure crisis prompted the creation of the Home Owner's Loan Corporation, an agency which was tasked with refinancing at-risk home loans on more generous terms to allow mortgage holders additional grace in securing funds (Fishback et al., 2013). By 1936, the agency had already refinanced fully 97% of the loans it would ever refinance, and started to transition its focus from rescuing home loans to consolidating the home loans it now possessed (Michney, 2022). It was only at this transition period that HOLC began the creation of its eponymous redlining maps (Michney, 2022).

The HOLC maps thus had few if any pathways to directly influence home loan lending practices. As their creation only began in 1936, they were created too late to influence the refinancing decisions of the HOLC, and retrospective analysis of HOLC lending in three municipal areas–Baltimore City, Maryland; Peoria, Illinois; and Greensboro, North Carolina—has found that the HOLC was quite willing to refinance home loans in regions they would later assign C- or D- grades (Fishback et al., 2024; Michney, 2022). Not only were the maps not viable as internal decision making tools for HOLC, they were not shared with private real estate agencies or banks in any notable capacity, and even sharing with other federal agencies seems to have been incredibly limited (Fishback et al., 2024; Michney, 2022). Additionally, while the maps were created with a shared goal of capturing some form of loan risk, the methods through which field agents pursued this goal were far from uniform, limiting the extent to which any two maps can be viewed as easily and directly comparable (Fishback et al., 2024). Taken altogether, the HOLC maps had few if any avenues to influence home loan lending practices and cannot be taken to be simple and direct reflections of realized redlining practices.

2.2 HOLC Maps Proxy the White Spatial Imaginary

Although HOLC maps cannot be taken as direct reflections of agency decision making, they still have potential usage in the social sciences as tools to capture the white spatial imaginary. The white spatial imaginary, as described by Lipsitz (2007), "views space primarily as a locus for the generation of exchange value" in which "the effects of segregated housing give white homeowners advantages and amenities unavailable to most minority home seekers." HOLC maps proxy this white spatial imaginary. The documents were themselves created by a team of 13 white, native-born field agents as composite documents intended to reflect the exchange value of property in American cities—an exchange value which was considered to plummet if the property contained non-white families—as seen by local real estate agents, home loan brokers, and other experts (Michney, 2022). They were grounded in a theory of the neighborhood life cycle which asserted that neighborhoods moved from fresh development with desirable populations (Grade A) to outdated, damaged development filled with "undesirable" populations (Grade D) (Metzger, 2000). This theory of neighborhood development would evolve over the ensuing decades and guide the so-called urban renewals or "slum clearances" of the 1960s and 1970s, but would still maintain its key assertions that racial minorities and time moves neighborhoods closer to slum-like states (Metzger, 2000). Thus, even though HOLC grades are not causally linked to future racially discriminatory developments, the grades indicated on them serve as place-based proxies which can help unveil how neighborhood life cycle theory and deployments of it in policy have led to modern health disparities within American cities.

HOLC map grades can be used to understand the relationship between neighborhood life cycle theories and modern health outcomes, with this link providing a potential reinterpretation of the otherwise causally confused HOLC literature. However, the potential of HOLC redlining maps goes beyond serving as proxies for antiquated and racist theories of neighborhood development. As noted by Markley (2024) and visible in the data from Nelson and Winling (2023), every HOLC neighborhood discussed in the maps is accompanied by metadata which (to varying levels of specificity) explains why the neighborhood was assigned a given grade and often note some level of sociodemographic makeup for each neighborhood.

While HOLC grades on the maps are a viable proxy for the white spatial imaginary, the map metadata can be used to understand systemic racism. As highlighted by Markley (2024), the HOLC also published metadata about the maps, including discussion of neighborhood characteristics, populations, and any present heterogeneity. Among the metadata published by the HOLC is an indicator of whether the HOLC believed Black populations were present in the neighborhood. In particular, this indicator is about *perception* and not necessarily reality: The HOLC auditors did not necessarily canvas the neighborhoods by foot, instead collating the opinions and ideas of real estate experts in their cities Fishback et al. (2024). Given the explicit racism of many in power in the late 1930s and early 1940s, it is not a stretch to assume that these beliefs were actualized through more avenues than simply redlining, in ways that are likely tailored uniquely to each city. In other words, comparisons between health outcomes in neighborhoods which the HOLC believed had Black population and those in which they believed did not have Black population should indicate the influence of racially discriminatory housing policy in the late 1930s and early 1940s *writ large*, instead of only capturing the influence of a specific instance of redlining policy.

Taken altogether, HOLC maps can be operationalized to capture at least two concepts intimately tied to the built environment: the white spatial imaginary, racial housing policy in housing policy. As traffic crashes are themselves a health outcome closely related to the built environment, these dual interpretations allow the HOLC maps to be leveraged as a tool for understanding how historic ideas of neighborhood progression and systemic racism have influenced modern traffic safety outcomes. Additionally, as the process through which HOLC maps were created varied so heavily from city to city, any such analysis needs to be place based, and treat cities studied as individual units. In order to better understand these relationships, we aim to answer three research questions. First, when adjusting for pretreatment covariates on a per-city basis, to what extent are historic neighborhood development theories and ideas of race related to modern traffic safety outcomes? Secondly, to what extent are historic neighborhood development theories and ideas of race connected to modern physical environment disorder, as measured by select 311 request rates? And finally, what are the potential strengths, limitations, and considerations of these dual HOLC map operationalizations for health inequity research?

3 Data and Methods

We model the impact of two historic neighborhood development theories and ideas of race in 1940's most populous American cities: New York City, Chicago, Los Angeles, Detroit, and Philadelphia. We choose these five largest cities due to data availability. 1940 Census data at the tract level is relatively limited and modern open data portals are expensive to maintain, meaning these large cities tend to have more reliable and available data. Additionally, these five selected cities had notably different developmental pathways since 1940. Some of these five, such as Detroit, lost significant population between 1940 and 2025, while others, such as New York City, grew immensely, increasing the extent to which these five cities are representative of broader trends in the United States. However, even if these cities fail to capture broader trends, they do capture significant portions of the nation's net population, making effects observed in these five cities highly relevant as a standalone result. In the following sections, we conduct an overview of our data sources and modeling choices.

3.1 Historical Census Data

We acquire 1940 Census Tract geographies and all accompanying census variables using the IPUMSR package for R (Version 4.2.3) to use as pre-treatment covariates for our analysis. The HOLC grades we use to proxy spatialized ideas of race were completed in the latter half of the 1930s, making 1940 Census Tracts the best available representation of the pre-treatment conditions present when the maps were created. Usage of 1940 Census Tracts additionally substantially increases the number of study units available, allowing us to better maximize study power (A. Nardone et al., 2021).

We preprocess our retrieved Census data in three ways. First, we collate all gender segregated variables into raw counts, combining counts of women and men with at most a high school degree into a single "population with high school degree" variable, for instance. This process is expected to increase the relevance of each variable, as the outcomes we aim to proxy are not expected to be dependent on gender. Secondly, to increase the comparability of tracts with different total populations, we convert many of our count variables to percentages, creating, for instance, a "percent of population in clerical employment" variable.

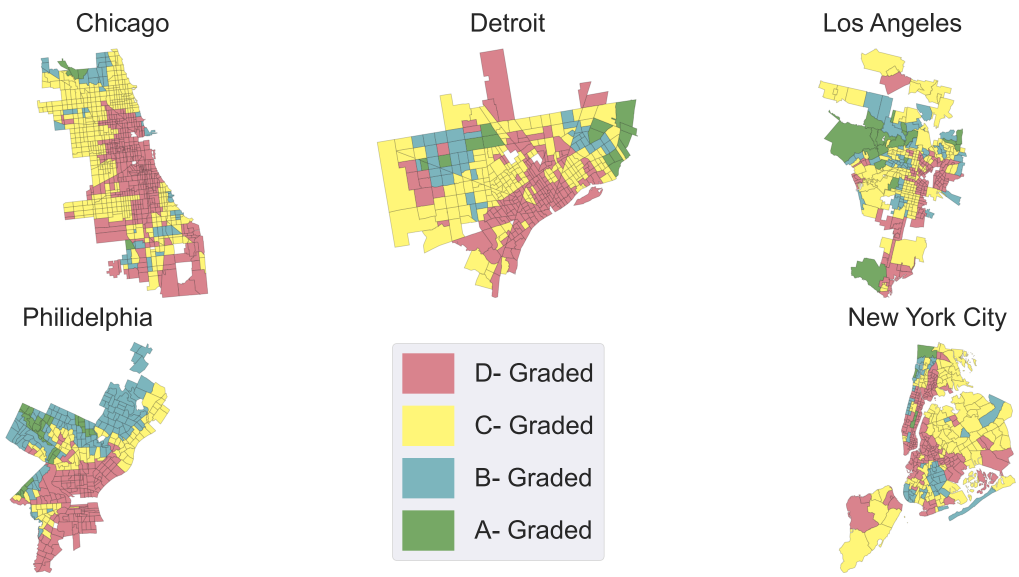

Figure 1: 1940 Census Tracts and Associated HOLC Grade in Target Cities

To assign HOLC grades to each tract, we first retrieve the georeferenced HOLC maps for our five cities from Nelson and Winling (2023). Then, we calculate the percent overlap of each tract with HOLC neighborhoods, before calculating the grade with which it has the highest overlap. That is, if a census tract has a 20% overlap with one D-graded neighborhood, and 20% overlap with a separate D-graded neighborhood, a 30% overlap with a C-graded neighborhood, and a 30% overlap with a B-graded neighborhood, we assign the tract a D- grade. We call this variable HOLC_GRADE. Lastly, the HOLC Maps include metadata that comments on the racial characteristics of neighborhoods. We use this metadata to create an indicator variable RACE which is true if the neighborhoods whose grade was assigned to the tract were indicated as having Black families present. Following with the above example, RACE would be True for the tract if and only if one of the two overlapping D- graded neighborhoods was noted as having Black families present. Lastly, we drop any E or "industrial" graded census tracts. In sum, this process resulted in a total of 2,407 tracts with 65 pretreatment covariates, two treatment indicators (RACE and HOLC_GRADE), and two outcome variables. Pre-treatment covariates themselves are visible in Appendix A.

3.2 City Data Portals

Chicago, Detroit, LA, NYC, and Philadelphia are among the many large cities in the United States which offer open data portals through which researchers and laypeople can access routinely collected data from the city (City of Chicago, 2025; City of Detroit, 2025; City of Los Angeles, 2025; City of New York, 2025; City of Philadelphia, 2025). Using the API of each city's open data portal, we collected all traffic crashes and 311 requests on record in these five cities from January 1st, 2018 at midnight to December 31st, 2022 at 11:59 PM. We intentionally collect this data on a five-year time scale to increase the representativeness of our data with modern outcomes. Additionally, our sample is centered around the COVID-19 pandemic. During the pandemic, lockdown and the shift to remote work would be expected to result in fewer drivers on the road, which would be expected to increase road speeds and likely increase traffic crash severity. Notably, the burden of this impact would be felt most directly by low socioeconomic status communities which are unable to shift away from driving, meaning that the lockdown would be expected to exacerbate preexisting traffic-related health disparities. Thus, by centering on the COVID-19 pandemic we should increase our ability to detect health inequities.

We use our retrieved data to build two outcome variables: count of car crashes per year and count of built environment related 311 requests per year. For our first outcome variable, we consider any collision involving an automobile and resulting in at least one injury or over $1,000 of property damage as a car crash, following the definition used by the open data portals. Due to issues in data comparability, we do not account for crash severity. This results in a collection of 1,545,931 car crashes across our cities and time span.

To measure built environment distress, or the extent to which the built environment in a neighborhood tends to be damaged and infrequently repaired, we use built environment related 311 requests. The count of 311 requests in an area has been used as a measure of built environment distress in prior literature, operating under the assumption that 311 repair requests for potholes, broken streetlights, graffiti, and other factors indicate a more heavily damaged and less routinely repaired built environment (Li et al., 2022). Different cities report 311 requests with differing levels of detail. Chicago, for instance, reports 106 unique request types, whereas Los Angeles reports only 12 different request types. To account for this discrepancy, we only consider built environment repair requests reported by all three cities, which includes broken streetlights, illegal fly dumping, and graffiti removal requests. This filter resulted in a sample of 3,291,664 built environment related 311 requests between our five cities over our study period.

3.3 Statistical Analysis

Attempts to causally infer the effects of historic policies and racial discrimination from the 1940s on modern health outcomes are complicated by multiple factors. First, each of our five cities followed differing historical trajectories and were likely evaluated by differing HOLC evaluators, meaning the treatment effect should be different for different cities. Secondly, the assignment of HOLC grades to tracts was not only contingent on perceptions of race, but also on perceptions of property condition and value, both of which are factors which would impact modern built environment distress and traffic crash totals. Lastly, as we are using 1940 census tracts as our base, we have relatively few observational units.

We account for these issues by undertaking two sets of pooled analyses in which we conduct five observational studies, one for each city. Both analyses proceeded near identically, only differing in terms of treatment chosen. For our first pooled analysis, we created a GRADE indicator from our HOLC_GRADE variable in which we considered a tract with a C- or D- grade as being in the treatment group while tracts with A- or B- grades were in the control group. By dichotomizing, we aim to compare tracts which were considered as "further along" the neighborhood lifecycle with those that were considered young on the lifecycle. For the second pooled analyses, we compared tracts with HOLC noted Black population present to those without HOLC reported Black population present (i.e. we used the RACE variable as a treatment indicator).

For both analyses, we controlled for differing pre-treatment conditions through propensity-score matching, a quasi-experimental approach which identifies and pairs comparable members of the treatment and control groups to better balance their pre-treatment covariates (Hong, 2015). Our propensity matching approach consisted of three steps. First, we used a Decision Tree Classifier from sklearn to identify the top 15 most important 1940 Census derived features (Pedregosa et al., 2011). We only control for 1940 Census features as most future features are expected to be mediators, making them bad controls. Then, we calculated propensity scores using logistic regression and the PsmPy package (Kline & Luo, 2022). Lastly, we paired each treatment tract to a control tract, with replacement, using K-Nearest Neighbors matching. This process was repeated for each of our five cities, resulting in five sets of matched tracts in each treatment case.

We then modeled treatment effect size in each city using a negative binomial regression model. Negative binomial regression is a count regression model akin to Poisson regression but more appropriate for datasets where the variance of the outcome is significantly larger than the mean of the outcome, as was the case with both of our outcome variables (Cameron & Trivedi, 1988). The model is also easily interpretable for multi-year data, as the treatment coefficient captures an incidence rate ratio (IRR), or the ratio of outcome rates in the treatment to outcome rates in the control. Lastly, to calculate the pooled effect across all cities, we utilized the DerSimonian and Liard one-step random effects model (Deeks et al., 2024). This approach is appropriate for cases where we have reason to believe the treatment effect size, but perhaps not direction, differs between cities and where distributions are heterogenous. We then report the results of these analyses in terms of IRRs.

4 Results

Our HOLC assignment process resulted in 67 (2.76%) tracts assigned A- grades, 311 (12.92%) tracts assigned B- grades, 970 (40.299%) tracts assigned C- grades, and 1059 (44.00%) tracts assigned D- grades. As seen in Figure 1, the distribution of these tracts varies by city. In some cities, such as Chicago and Philadelphia, large clusters of D- grade tracts with concentric circles of higher grade tracts as one moves further outwards are apparent. Other cities in our sample, such as LA and NYC, consist of a patchwork of tract grades scattered in small clusters throughout the city. Neither car crashes nor 311s have a clear relationship with tract grade, with C- grade tracts having the highest average quantity of car crashes ($\mu = 733.51$, $\sigma = 983.62$) and 311s ($\mu = 579.74$, $\sigma = 1749.61$), while A- grade tracts have the lowest average crash counts ($\mu = 532.80, \sigma = 901.84$) and 311 request counts ($\mu = 1005.68, \sigma = 1749.61$).

Based on HOLC metadata and our assignment approach, 1471 (61.27%) tracts were believed to not contain Black population by the HOLC, while 931 (38.78%) tracts were listed as having Black population. Distributions of these tracts for Los Angeles and Chicago, as well as distributions of outcome variables, can be found in Figure 5. Based on 1940 Census data, 931 of the 1471 tracts categorized by the HOLC as not having Black population did have at least one Black household, with a median of 0.05% Black population in such tracts. Similarly, Census data indicates that 145 of the 931 tracts listed as having Black population had no Black population. In terms of outcomes, tracts which the HOLC believed had Black population had a lower average quantity of car crashes ($\mu = 579.49, \sigma = 979.60$) and 311 requests ($\mu = 1353.44, \sigma = 2666.64$) than tracts without noted Black population (crashes: $\mu = 700.59, \sigma = 891.48$; 311s: $\mu = 1456.43, \sigma = 3936.27$).

Figure 2: Propensity score balance with GRADE as treatment

Figure 3: Propensity score balance with RACE as treatment

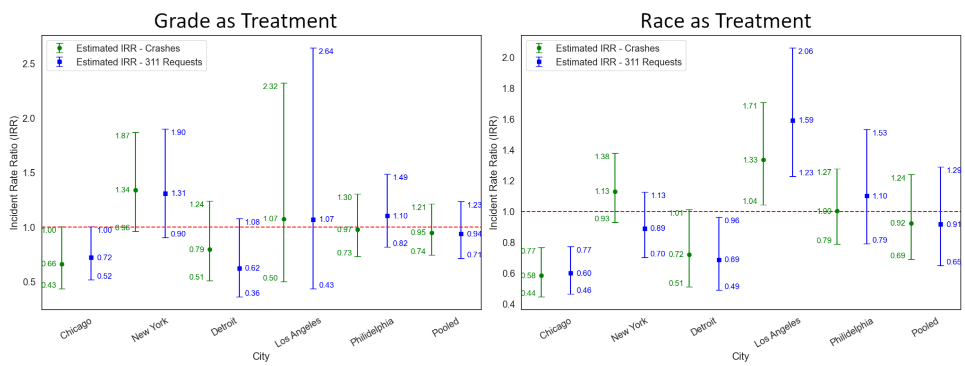

Figure 4: Crash and 311 request IRRs and 95% confidence intervals with GRADE as treatment (left) and RACE as treatment (right) for five American cities

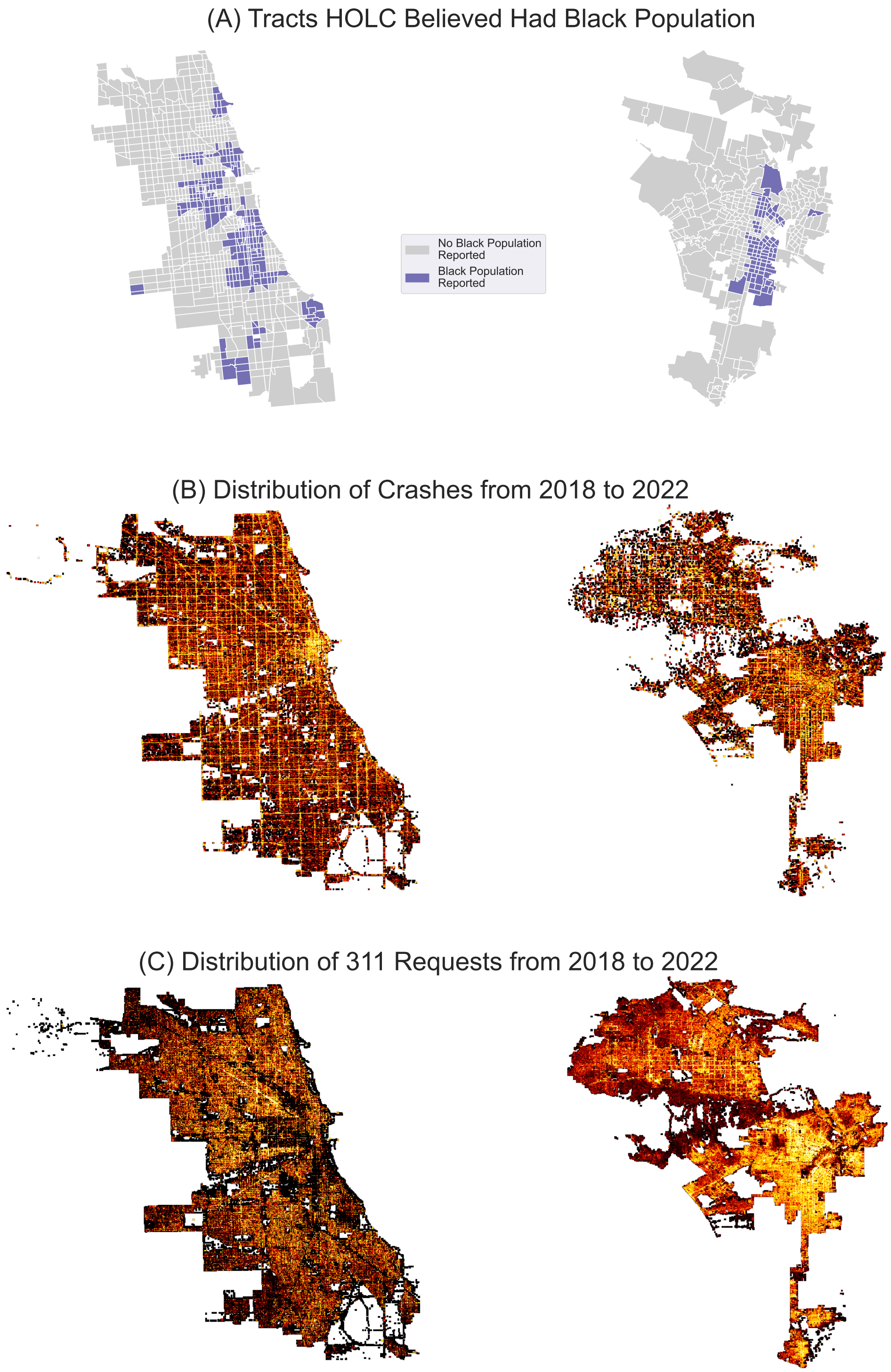

Figure 5: Chicago (left) and LA (right) distribution of tracts which the HOLC believed had Black population (Top), distributions of modern crash counts on 1940 Tracts (center), and distribution of 311 requests on 1940 Census Tracts (bottom).

We propensity matched tracts within each of our five cities for both treatments. The top fifteen pretreatment covariates used for propensity matching can be seen in section 6, while plain english meaning of variable names can be found in section 6. Summary statistics of variables can be found in Table A1. Distributions of propensity scores with GRADE as treatment can be seen in Figure 2, and the distributions of propensity scores with RACE as treatment can be seen in Figure 3. Match characteristics can be found for both treatments in Appendix B, and generally show decreased standardized mean difference across relevant features, although matching resulted in slightly increased standardized mean differences for a few variables in Los Angeles in both treatment cases.

Incident rate ratios were calculated using negative binomial regression for each city and for the overall outcome (Figure 4). When using GRADE as treatment, no individual city had a statistically significant effect, although Chicago and New York City were both close to significance. When using RACE as treatment, statistically significant effects appeared in Chicago (Crash IRR = 0.58, 95% CI: $0.44, 0.77$; 311 IRR = 0.60, 95% CI: $0.46, 0.77$), Detroit (Crash IRR = 0.69; 95% CI: $0.49, 0.96$), and Los Angeles (Crash IRR = 1.33, 95% CI: $1.04, 1.71$; 311 Request IRR = 1.59, 95% CI: $1.23, 2.07$). In order to better understand the robustness of these effects, we manipulated the parameters of our propensity matching analysis and discovered that the effect in Denver disappears if matching is done without replacement, while the effects in Chicago and Los Angeles remain, marking the former as a potentially spurious finding. Lastly, pooled analyses were conducted using the DerSimonian and Laird one-step random effects model, and found no statistically significant effect in either direction.

5 Discussion

Home Owner's Loan Corporation (HOLC) home loan risk maps reflect a dominant theory of the neighborhood life cycle in the 1930s which asserted that neighborhoods marched towards decline over time, with this march being supposedly accelerated by the presence of Black families. Reflected in the grades on HOLC maps, the implementation of these antiquated theories ideas of urban development in racially biased policies have been linked to numerous modern health disparities, ranging from tobacco sales outlet density to green space access to time to viral suppression of HIV (Bassler et al., 2024; A. Nardone et al., 2021; Schwartz et al., 2021). In this study, we aimed to further understand the influence of this historically dominant theory of neighborhood development and the HOLC's accompanying but distinct racialized conception of space on modern traffic safety health outcomes, specifically car crash counts and physical disorder. Our results are unusual within the redlining literature: we find no statistically significant association between HOLC grade assignment and modern traffic safety outcomes, and only find statistically significant and robust associations between conceptions of race held in the 1930s and modern traffic safety outcomes in Los Angeles and Chicago. In the proceeding section, we discuss our findings in more detail, noting three specific implications for future research into the relationship between historic racial discrimination in built environment policy and modern health outcomes.

5.1 HOLC effects are place based

We found three effects in the race as treatment case in the cities of Chicago, Detroit, and Los Angeles. The difference between Chicago and Los Angeles is notable. In Chicago, Census Tracts which the HOLC denoted as having Black population had 23-44% lower traffic crash and 311 request incidence rates, indicating that these tracts tended to have more routinely maintained built environments and fewer traffic crashes. In terms of spatial distribution, crashes in Chicago also tended to occur on either along major roadways or in the Downtown region, and 311 requests in the city tend to cluster slightly north of the city's center. However, in LA, we found that tracts which the HOLC denoted had Black population tended to have between 4-71% more traffic crashes and make 23-106% more 311 requests than tracts the HOLC did denote as having held Black population, indicating higher risk of traffic crash and less routinely maintained built environment. Additionally, traffic crashes in Los Angeles appear to follow a more diverse distribution than in Chicago. In brief, the two cities have opposite trends. In LA, tracts denoted by the HOLC as having Black population have worse outcomes, while the opposite is true in Chicago. In Chicago, traffic crashes have a clear hotspot in the dense downtown, while this is not observed in LA.

This relationship highlights a need which, to the author's knowledge, has not been raised in prior redlining literature: while redlining was a federal policy and the adoption of racially discriminatory policies a nationwide issue, the implementation of these policies is subject to place-based effects which, in the terms of causal inference, should be expected to impact both treatment assignment and outcomes. Treatment assignment had numerous degrees of freedom which should vary from city-to-city. Each city was evaluated by one of the 13 HOLC field agents, and each agent interacted with local real estate experts and officials to varying degrees of success (Michney, 2022). Real estate experts in each city were noted to vary in terms of information available, with smaller operations not necessarily having easy access to the tabulations the HOLC requested, willingness to forward the information to the government, and even varying levels of informational accuracy (Fishback et al., 2024). Field agents were themselves intentionally given vague instructions and numerous degrees of freedom with relatively little oversight, meaning that even the specific reflection of neighborhood lifecycle theories captured by HOLC maps should be presumed to vary from agent to agent (Fishback et al., 2024). Taken altogether, the processes determining both the perceived racial makeup of communities and perceived stage in the neighborhood lifecycle of neighborhoods are subject to significant place-based effects.

Additionally, place-based effects should be expected to influence the outcomes of these treatments as well. Even within our sample of five American cities, the cities chosen have been subject to different developmental pressures over the past decades. These differences in city trajectories can be seen vividly in the cases of Detroit and Los Angeles. In 1940, Detroit was one of the five largest cities in the United States with a population of over 1.5 million, but by 2020 Detroit's population had shrunk to under 700,000 (Manson et al., 2024). Contrarily, Los Angeles saw massive population gains over the past decades, increasing from a population of around 1.5 million in 1940 to a population of over 3.8 million in 2020 (Manson et al., 2024). Although a simplified comparison, these opposing population trajectories indicate differing applications of redlining policies between the two cities.

Taken together with our findings, there is strong evidence that place-based factors should be expected to confound both the application of antiquated neighborhood lifecycle theories and racially discriminatory policies in our five American cities. However, this finding constitutes a potential hole in current HOLC research, which often aggregates results across differing cities with limited amounts of per-city subgroup analysis (Diaz et al., 2021; A. Nardone et al., 2021; A. L. Nardone et al., 2020). Future studies utilizing HOLC maps from multiple cities to draw overarching conclusions about the relationship between systemic racism and modern health outcomes should take potential place-based confounding into account with their methods.

5.2 HOLC metadata can reveal new insights

Studies should additionally consider what specific portions of the HOLC maps and information they utilize. Past literature utilizing the HOLC maps has tended to strictly operationalize them in terms of grades, comparing (e.g.) Grade A- neighborhoods to Grade D- neighborhoods (Bassler et al., 2024; Diaz et al., 2021; Hollenbach et al., 2021; A. Nardone et al., 2021; A. L. Nardone et al., 2020; Schwartz et al., 2021; Swope et al., 2022). While this work has often been framed as investigating specifically racially biased home loan lends and the influence of systemic racism on health outcomes at large, numerous concerns have been raised about the historical validity of this framing (Fishback et al., 2024; Markley, 2024).

In this paper, we have responded to these concerns by reframing HOLC grades as reflections of antiquated ideas of neighborhood development which were themselves implemented into various policies, and further argued that this is a distinct but related phenomenon from racial discrimination in built environment design more broadly. Our results concur with this framing, as we find that trends present when using HOLC maps to proxy for ideas of neighborhood development are not necessarily those observed when more directly proxying for perceived race. Or, in other words, our results change when we use portions of the HOLC metadata as our treatment indicators instead of using the HOLC grades directly.

Looking towards the broader literature, our results do not disqualify or contradict prior work; our results are limited purely to the realm of traffic safety, and our theorization provides a powerful lens through which to interpret studies which only utilize HOLC grades. Nonetheless, the difference in outcomes between out two treatment cases highlight the potential for future research to think more creatively about the HOLC maps as documents, with particular emphasis on the ability to more fully leverage their metadata.

5.3 Redlining is not always to blame

Prior studies have featured a large focus on the influences of redlining policies—or racially biased home loan lending conducted in accordance with neighborhood lifecycle theories—on modern health outcomes. Due in part to the pervasive nature of these policies, ease of access to digitized redlining maps, and possibly some publication bias, we now have a large corpus of health disparities which have been tied to redlining. Given ongoing efforts to digitize and georeference Federal Housing Association (FHA) maps—documents which were directly used for racially discriminatory home loan lending—it is likely that this line of research will increase in prominence in the future ("Redlining Lab", 2023). However, in this study, we find that traffic health disparities are tied to the perceptions of race and space held by governmental entities such as the HOLC, but are not necessarily tied to redlining or other policies derived from neighborhood lifecycle theories. This result highlights a potential limitation of future research, which is that redlining is not always the most relevant culprit.

Although preliminarily, our study does indicate a future potential line of research. In Figure 5, crash count hotspots are observable along the I-94 highway running northwest in Chicago and the I-110 highway running south southwest in Los Angeles. Large numbers of crashes along highways makes intuitive sense, but less intuitive is that highway placement itself may contribute to racial inequities in traffic safety outcomes. Looking towards urban planning research, there is a large amount of evidence that municipal governments intentionally routed roadways and transportation systems to pass through Black and white-working class neighborhoods, usually as part of urban-renewal initiatives intended to improve suburban living (Gioielli, 2011; Retzlaff, 2021). In the case of Baltimore Maryland, Gioielli (2011) notes that these highways were often placed through community resources such as schools and other community resources and forced relocation for some and increasing proximity to highways for those who remained in the area, a trend which may have played out elsewhere. Connections between these racially biased transport planning decisions and modern traffic outcomes have been underexplored so far, but future research into historical determinants of modern traffic safety inequities may benefit from further exploring them further.

5.4 Limitations

Our study has some limitations. In this study, we utilized 1940 census tract geographies to avoid introducing bias to our pretreatment covariates through the use of areal or population weighted interpolation methods. However, by doing so, we restricted our sample size to only 2,400 census tracts. We additionally conducted five separate analyses with these tracts, one for each of five cities, potentially limiting the statistical power of each analysis. Nonetheless, we worked to reclaim some of the lost statistical power through a pooled analysis approach.

Additionally, the traffic crash and 311 request data used in our study are subject to biases and limitations. Our traffic crash dataset in particular is likely incomplete, as it is unlikely that every traffic crash which results in an injury is reported to municipal governments. We used traffic crash counts and built environment 311 request counts per year in order to increase the interpretability of our results. But by using raw counts, we do not adjust for roadway density, frequency of travel on a given roadway, or total size of the census tract in question, all of which could influence our results.

Our study focused on five American cities, all of which had substantial populations in 1940. This limits the generalizability of our results to cities which were smaller in 1940 and smaller today, although the significant variance in urban planning, geographic location, and population trajectories between the five cities helps improve the shortcoming.

Lastly, our study aimed to understand the impact of racial discrimination and neighborhood lifecycle theories on modern traffic outcomes, and hence adopted a quasi-experimental propensity matching approach. Even though propensity matching helped our study control for differences in pretreatment covariates between tracts, it is certain that some unobserved confounders exist, which limits the ability to draw causal conclusions about effect size. However, even if our results are still biased by outside confounders, adopting a propensity matching approach reduces bias which would otherwise be present in a more direct analysis.

6 Conclusion

In this study, we aimed to better understand the relationship between social and political processes from the late 1930s and the modern distribution of traffic safety outcomes in New York City, Los Angeles, Philadelphia, Detroit, and Chicago. To do so, we reframed the Home Owners Loan Corporation (HOLC) maps as multidimensional documents which can be used to proxy both the influence of a now antiquated theory of neighborhood development and neighborhood-level racial discrimination. Our results indicated that neighborhood-level racial discrimination in the late 1930s and early 1940s accounts for some disparities in traffic safety outcomes within Chicago and Los Angeles in particular, but is seemingly less relevant in other cities. We also found no evidence that neighborhood lifecycle theories used to develop the HOLC map are connected to modern traffic safety outcomes in any of our five cities.

Future studies can improve on and build upon this study in numerous ways. Within the traffic safety literature, future studies using HOLC or FHA maps should explore outcomes in a wider variety of cities—including more rural or suburban localities—and with a wider variety of specific outcomes, such as by incorporating measures of crash severity. Future traffic safety studies should also consider other potential historical determinants of health outcomes, including highway construction.

Within the HOLC literature, we found evidence that the relationship between the social and political processes indicated by HOLC maps and modern health outcomes are heavily place-based. Future work can build upon this result by better contextualizing their approaches within cities and through additional subgroup analysis to detect differences in effect size and potentially direction from city to city. Building upon our deployment of indicated race in this study, future studies using HOLC maps should aim to creatively leverage the metadata from the maps to better understand the relevant social processes at play. Modern health disparities were not created through redlining by the HOLC, nor by any single nation-wide policy alone. Understanding the formation of these disparities and repairing them in thus requires taking a nuanced, place-based approach.

Data and Code Availability Statement

Data and code used in this analysis can be found on this GitHub repo. Additionally, please note that data used in this study was retrieved from IPUMS NGHIS (Manson et al., 2024).

References

Azin, B., Ewing, R., Yang, W., Promy, N. S., Kalantari, H. A., & Tabassum, N. (2025). Urban Arterial Lane Width Versus Speed and Crash Rates: A Comprehensive Study of Road Safety [Number: 2 Publisher: Multidisciplinary Digital Publishing Institute]. *Sustainability*, *17*(2), 628. https://doi.org/10.3390/su17020628

Bailey, Z. D., Krieger, N., Agénor, M., Graves, J., Linos, N., & Basset, M. T. (2017). Structural racism and health inequities in the USA: Evidence and interventions. *Lancet*, *389*(10077), 1453–1463. https://doi.org/https://doi.org/10.1016/S0140-6736(17)30569-X

Bassler, J. R., Ostrenga, L., Levitan, E. B., Kay, E. S., Long, D. M., Mugavero, M. J., Nassel, A. F., Parman, M., Tate, M., Rana, A., & Batey, D. S. (2024). Redlining and Time to Viral Suppression Among Persons With HIV [Publisher: American Medical Association]. *JAMA Internal Medicine*, *184*(11), 1329–1337. https://doi.org/10.1001/jamainternmed.2024.5003

Bunn, F., Collier, T., Frost, C., Ker, K., Roberts, I., & Wentz, R. (2003). Traffic calming for the prevention of road traffic injuries: Systematic review and meta-analysis [Publisher: BMJ Publishing Group Ltd Section: Systematic review]. *Injury Prevention*, *9*(3), 200–204. https://doi.org/10.1136/ip.9.3.200

Cameron, C. A., & Trivedi, P. K. (1988). Basic Count Regression. In *Regression Analysis of Count Data*. Cambridge University Press.

City of Chicago. (2025). City of Chicago Data Portal. https://www.chicago.gov/city/en/narr/foia/CityData.html

City of Detroit. (2025). Detroit Open Data Portal. https://data.detroitmi.gov/

City of Los Angeles. (2025). Los Angeles Open Data. https://data.lacity.org/

City of New York. (2025). NYC OpenData. https://opendata.cityofnewyork.us/

City of Philadelphia. (2025). OpenDataPhilly. https://opendataphilly.org/

Das, S., Kong, X., & Tsapakis, I. (2019). Hit and run crash analysis using association rules mining. *Journal of Transportation Safety & Security*, *13*(2). https://doi.org/doi.org/10.1080/19439962.2019.1611682

Das, S., Sun, X., Goel, S., Sun, M., Rahman, A., & Dutta, A. (2022). Flooding related traffic crashes: Findings from association rules [Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/19439962.2020.1734130]. *Journal of Transportation Safety & Security*, *14*(1), 111–129. https://doi.org/10.1080/19439962.2020.1734130

Deeks, J. J., Higgins, J. P., Altman, D. G., McKenzie, J. E., & Veroniki, A. A. (2024, November). Chapter 10: Analysing data and undertaking meta-analyses. In *Cochrane*

Handbook for Systematic Reviews of Interventions version 6.5. Cochrane. Retrieved March 18, 2025, from https://training.cochrane.org/handbook/current/chapter-10

Diaz, A., O'Reggio, R., Norman, M., Thumma, J. R., Dimick, J. B., & Ibrahim, A. M. (2021). Association of Historic Housing Policy, Modern Day Neighborhood Deprivation and Outcomes After Inpatient Hospitalization. *Annals of Surgery*, *274*(6), 985. https://doi.org/10.1097/SLA.0000000000005195

Ding, Y., Zhao, X., Wu, Y., Zhang, X., He, C., & Liu, S. (2023). How psychological factors affect speeding behavior: Analysis based on an extended theory of planned behavior in a Chinese sample. *Transportation Research Part F: Traffic Psychology and Behaviour*, *93*, 143–158. https://doi.org/10.1016/j.trf.2023.01.003

Dinh, D. D., & Kubota, H. (2013). Speeding behavior on urban residential streets with a 30 km/h speed limit under the framework of the theory of planned behavior. *Transport Policy*, *29*, 199–208. https://doi.org/10.1016/j.tranpol.2013.06.003

Dumbaugh, E., Li, Y., Saha, D., & Marshall, W. (2022). Why do lower-income areas experience worse road safety outcomes? Examining the role of the built environment in Orange County, Florida. *Transportation Research Interdisciplinary Perspectives*, *16*, 100696. https://doi.org/10.1016/j.trip.2022.100696

Ellison, A. B., & Greaves, S. P. (2015). Speeding in urban environments: Are the time savings worth the risk? *Accident Analysis & Prevention*, *85*, 239–247. https://doi.org/10.1016/j.aap.2015.09.018

Elvik, R. (2001). Area-wide urban traffic calming schemes: A meta-analysis of safety effects. *Accident Analysis & Prevention*, *33*(3), 327–336. https://doi.org/10.1016/S0001-4575(00)00046-4

Fishback, P., Rose, J., & Snowden, K. (2013). *Well Worth Saving: How the New Deal safeguraded Home Ownership*. The University of Chicago Press.

Fishback, P., Rose, J., Snowden, K. A., & Storrs, T. (2024). New Evidence on Redlining by Federal Housing Programs in the 1930s. *Journal of Urban Economics*, *141*, 103462. https://doi.org/10.1016/j.jue.2022.103462

Gioielli, R. (2011). “We Must Destroy You to Save You”: Highway Construction and the City as a Modern Commons. *Radical History Review*, *2011*(109), 62–82. https://doi.org/10.1215/01636545-2010-015

Hollenbach, S. J., Thornburg, L. L., Glantz, J. C., & Hill, E. (2021). Associations Between Historically Redlined Districts and Racial Disparities in Current Obstetric Outcomes. *JAMA Network Open*, *4*(9), e2126707. https://doi.org/10.1001/jamanetworkopen.2021.26707

Hong, G. (2015). Review of causal inference designs and analytic methods. In *Causality in a Social World: Moderation, Mediation, and Spill-olver* (pp. 40–75). Wiley.

International Transport Forum. (2016). *Zero Road Deaths and Serious Injuries* [Type: doi:https://doi.org/10.1787/9789282108055-en]. https://www.oecd-ilibrary.org/content/publication/9789282108055-en

Kline, A., & Luo, Y. (2022). PsmPy: A Package for Retrospective Cohort Matching in Python, 1354–1357. https://doi.org/10.1109/EMBC48229.2022.9871333

Le, H. T. K., Buehler, R., & Hankey, S. (2018). Correlates of the Built Environment and Active Travel: Evidence from 20 US Metropolitan Areas. *Environmental Health Perspectives*, *126*(7), 077011. https://doi.org/10.1289/EHP3389

Li, Y., Miller, H. J., Root, E. D., Hyder, A., & Lu, D. (2022). Understanding the role of urban social and physical environment in opioid overdose events using found geospatial data. *Health and Place*, *75*. https://doi.org/10.1016/j.healthplace.2022.102792

Link, B. G., & Phelan, J. (1995). Social conditions as fundamental causes of disease. *Journal of Health and Social Behavior*, *Spec No*, 80–94.

Lipsitz, G. (2007). The Racialization of Space and the Spatialization of Race: Theorizing the Hidden Architecture of Landscape [Publisher: Temporary Publisher]. *Landscape Journal*, *26*(1), 10–23. Retrieved March 2, 2025, from https://www.jstor.org/stable/43323751

Manson, S., Schroeder, J., Van Riper, D., Knowles, K., Kugler, T., Roberts, F., & Ruggles, S. (2024). IPUMS National Historical Geographic Information System. https://doi.org/http://doi.org/10.18128/D050.V19.0

Markley, S. (2024). Federal 'redlining' maps: A critical reappraisal [Publisher: SAGE Publications Ltd]. *Urban Studies*, *61*(2), 195–213. https://doi.org/10.1177/00420980231182336

Metzger, J. T. (2000). Planned abandonment: The neighborhood life-cycle theory and national urban policy [Publisher: Routledge _eprint: https://doi.org/10.1080/10511482.2000.9521359]. *Housing Policy Debate*, *11*(1), 7–40. https://doi.org/10.1080/10511482.2000.9521359

Michney, T. M. (2022). How the City Survey's Redlining Maps Were Made: A Closer Look at HOLC's Mortgagee Rehabilitation Division [Publisher: SAGE Publications]. *Journal of Planning History*, *21*(4), 316–344. https://doi.org/10.1177/15385132211013361

Nardone, A., Rudolph, K. E., Morello-Frosch, R., & Casey, J. A. (2021). Redlines and Greenspace: The Relationship between Historical Redlining and 2010 Greenspace across the United States [Publisher: Environmental Health Perspectives]. *Environmental Health Perspectives*, *129*(1), 017006. https://doi.org/10.1289/EHP7495

Nardone, A. L., Casey, J. A., Rudolph, K. E., Karasek, D., Mujahid, M., & Morello-Frosch, R. (2020). Associations between historical redlining and birth outcomes from 2006 through 2015 in California [Publisher: Public Library of Science]. *PLOS ONE*, *15*(8), e0237241. https://doi.org/10.1371/journal.pone.0237241

National Center for Statistics and Analysis. (2022, May). Early estimates of motor vehicle traffic fatalities and fatality rate by sub-categories in 2021. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813298

Nelson, R. K., & Winling, L. (2023). Mapping Inequality: Redlining in New Deal America. https://dsl.richmond.edu/panorama/redlining/contactus

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Peterson, C. M., & Gaugler, J. E. (2021). To speed or not to speed: Thematic analysis of American driving narratives. *Journal of Safety Research*, *78*, 129–137. https://doi.org/10.1016/j.jsr.2021.04.005

Raifman, M. A., & Choma, E. F. (2022). Disparities in Activity and Traffic Fatalities by Race/Ethnicity. *American Journal of Preventive Medicine*, *63*(2), 160–167. https://doi.org/10.1016/j.amepre.2022.03.012

Redlining Lab. (2023). Retrieved March 2, 2025, from https://www.redlininglab.org/

Retzlaff, R. (2021). The Montgomery Bus Boycott and the Racial Basis for Interstate Highways and Urban Renewal [Publisher: SAGE Publications Inc]. *Journal of Urban History*, *47*(6), 1301–1347. https://doi.org/10.1177/0096144220917470

Sarkar, C., Webster, C., & Kumari, S. (2018). Street morphology and severity of road casualties: A 5-year study of Greater London. [Publisher: Taylor & Francis Ltd]. *International Journal of Sustainable Transportation*, *12*(7), 510–525. https://doi.org/10.1080/15568318.2017.1402972

Schwartz, E., Onnen, N., Craigmile, P. F., & Roberts, M. E. (2021). The legacy of redlining: Associations between historical neighborhood mapping and contemporary tobacco retailer density in Ohio. *Health & Place*, *68*, 102529. https://doi.org/10.1016/j.healthplace.2021.102529

Sołowczuk, A. B., & Kacprzak, D. (2022). Effect of Lane Narrowing Implemented on an Urban Dual Carriageway on Speed Reduction and Acoustic Environment [Number: 1 Publisher: Multidisciplinary Digital Publishing Institute]. *Buildings*, *12*(1), 31. https://doi.org/10.3390/buildings12010031

Swope, C. B., Hernández, D., & Cushing, L. J. (2022). The Relationship of Historical Redlining with Present-Day Neighborhood Environmental and Health Outcomes: A Scoping Review and Conceptual Model. *Journal of Urban Health*, *99*(6), 959–983. https://doi.org/10.1007/s11524-022-00665-z

Ukkusuri, S., Miranda-Moreno, L. F., Ramadurai, G., & Isa-Tavarez, J. (2012). The role of built environment on pedestrian crash frequency. *Safety Science*, *50*(4), 1141–1151. https://doi.org/10.1016/j.ssci.2011.09.012

Appendix A: Summary statistics

Feature	Count	Mean	Std. Deviation	Minimum	Maximum
whiteP	2596	92.1261	20.9675	0	100
nonWhtP	2596	7.87389	20.9675	0	100
blackP	2596	7.23378	20.6111	0	100
noSchol	2616	220.411	551.266	0	6303
elmntry	2616	2201.1	2598.9	0	16425
hghSchl	2616	1256.46	1358.38	0	11017
college	2616	427.3	698.249	0	8551
nRprtSc	2616	54.6992	169.692	0	2672
mdMlScY	2616	8.44343	2.75007	0	16
mdFmlSY	2616	8.37798	2.77148	0	13
emplydP	2596	46.7517	7.66052	0	100
sekWrkP	2596	6.85503	4.463	0	100
ntInLbP	2596	44.3834	6.34245	0	92.1
profP	2595	6.48681	6.32419	0	76.33
semPrfP	2595	1.52112	2.4809	0	90.36
propP	2595	9.03259	6.73203	0	100
clerclP	2595	22.6091	9.97946	0	100
craftsP	2595	14.8179	6.78101	0	100
oprtvsP	2595	22.9712	11.4326	0	100
domstcP	2595	3.71203	5.63034	0	80
servicP	2595	10.5867	7.40341	0	100
laborP	2616	136.144	162.166	0	2073
fm1Dtch	2616	467.735	651.259	0	6079
fm1Attc	2616	145.668	451.864	0	4115
fm2SdBS	2616	50.555	88.1872	0	972
fm2Othr	2616	257.861	397.857	0	3386
fam3	2616	111.846	188.921	0	2091
fam4	2616	81.8456	146.804	0	2520
fm1t4WB	2616	74.8754	120.407	0	944
fam5to9	2616	201.919	424.181	0	5488
fm10t19	2616	155.848	415.908	0	4663
fm20pls	2616	416.186	1159.66	0	9780
othrStr	2616	4.41093	11.7836	0	239

Table A1: Summary statistics for pretreatment covariates and outcomes (Part 1).

Feature	Count	Mean	Std. Deviation	Minimum	Maximum
undrP51	2616	481.249	482.545	0	3675
pt51t75	2616	488.081	556.519	0	4384
pt76to1	2616	571.284	682.457	0	4300
pt1t1p5	2616	210.448	308	0	2302
pt1p5t2	2616	67.3394	101.751	0	870
pt2plus	2616	13.8899	26.2208	0	334
nRprtRm	2616	18.695	40.487	0	760
tnUnP51	2616	284.382	358.904	0	3604
tnP5175	2616	352.886	485.591	0	4077
tnPt761	2616	453.041	637.991	0	4241
tnPt115	2616	173.102	288.593	0	2185
tnPt152	2616	59.1563	98.6892	0	865
tnPt2pl	2616	11.82	23.6569	0	303
tnNRprt	2616	15.4358	37.4954	0	758
nMjrRpr	2616	1689.19	1822.79	0	10930
majrRpr	2616	111.736	181.652	0	2052
rprNRpr	2616	167.949	265.803	0	2117
radio	2616	1732.72	1850.53	0	11152
noRadio	2616	62.8093	103.526	0	1107
rdNRprt	2616	55.4587	84.0273	0	852
rfrgMch	2616	1180.86	1504.9	0	10996
refrgIc	2616	529.862	745.966	0	5445
rfrgOth	2616	6.83677	18.1425	0	319
refrgNn	2616	100.937	151.61	0	1296
rfrgNRp	2616	32.4866	60.6473	0	755
htCntrl	2616	1305.71	1820.32	0	11091
htNCntr	2616	509.953	719.129	0	6871
htNRprt	2616	1.89946	5.78481	0	149
n_crashes	2366	652.818	928.008	1	10088
n_311s	2322	1415.86	3497.64	1	61771

Table A2: Summary statistics for pretreatment covariates and outcomes (Part 2).

Appendix B: Standardized Mean Balances

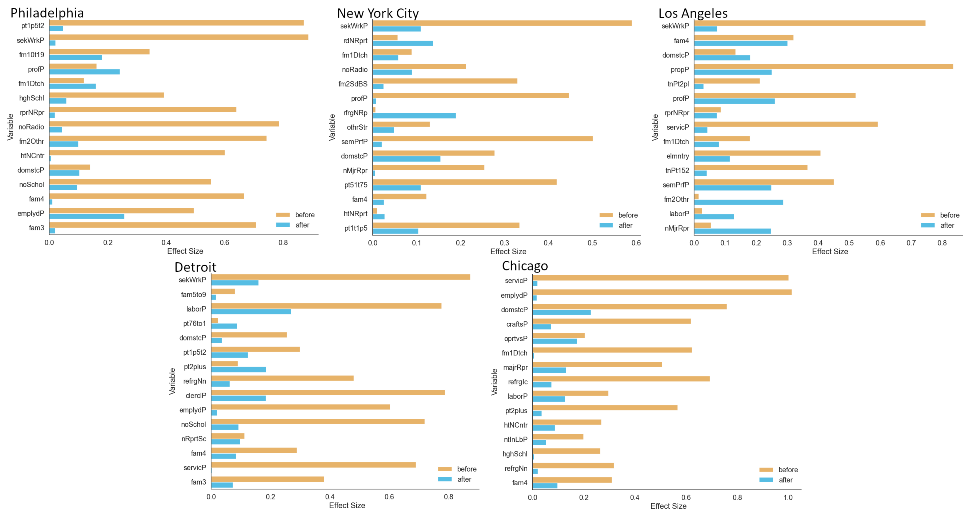

Figure B1: Standardized mean differences before and after matching for top fifteen most predictive variables with RACE as treatment

Figure B2: Standardized mean differences before and after matching for top fifteen variables with GRADE as treatment

Appendix C: Feature Importance Table

Race as Treatment				
Chicago	New York City	Detroit	Los Angeles	Philadelphia
servicP	sekWrkP	sekWrkP	sekWrkP	pt1p5t2
emplydP	rdNRprt	fam5to9	fam4	sekWrkP
domstcP	fm1Dtch	laborP	domstcP	fm10t19
craftsP	noRadio	pt76to1	propP	profP
oprtvsP	fm2SdBS	domstcP	tnPt2pl	fm1Dtch
fm1Dtch	profP	pt1p5t2	profP	hghSchl
majrRpr	rfrgNRp	pt2plus	rprNRpr	rprNRpr
refrgIc	othrStr	refrgNn	servicP	noRadio
laborP	semPrfP	clerclP	fm1Dtch	fm2Othr
pt2plus	domstcP	emplydP	elmntry	htNCntr
htNCntr	nMjrRpr	noSchol	tnPt152	domstcP
ntInLbP	pt51t75	nRprtSc	semPrfP	noSchol
hghSchl	fam4	fam4	fm2Othr	fam4
refrgNn	htNRprt	servicP	laborP	emplydP
fam4	pt1t1p5	fam3	nMjrRpr	fam3
Grade as Treatment				
Chicago	New York City	Detroit	Los Angeles	Philadelphia
propP	mdMlScY	sekWrkP	mdMlScY	pt1p5t2
sekWrkP	clerclP	tnPt152	propP	profP
undrP51	nRprtRm	fm20pls	sekWrkP	ntInLbP
fm1Dtch	tnP5175	nMjrRpr	tnPt761	fam3
ntInLbP	fam5to9	profP	profP	tnPt761
semPrfP	semPrfP	mdMlScY	htCntrl	oprtvsP
domstcP	laborP	propP	hghSchl	sekWrkP
tnPt2pl	oprtvsP	fm1Dtch	majrRpr	domstcP
fm2Othr	tnNRprt	majrRpr	rfrgOth	hghSchl
nRprtSc	nMjrRpr	craftsP	rprNRpr	fm1Dtch
fm10t19	fm1Attc	pt1p5t2	htNRprt	emplydP
noSchol	propP	fm2Othr	semPrfP	servicP
rfrgNRp	tnUnP51	refrgNn	craftsP	nMjrRpr
tnPt115	othrStr	noRadio	htNCntr	rprNRpr
oprtvsP	htNCntr	ntInLbP	tnP5175	tnPt115

Table C1: Top fifteen most important pretreatment covariates for each city in the study, in descending order of importance.

Appendix D: Plain English Meaning of Variable Names

Variable names in this study were converted from their table numbers on the 1940 Census to camel case variable names, but unfortunately the length of these names was limited to at most 10 characters due to the usage of the shapefile format. In this section, we explain each variable featured in this study more clearly.

Variable	Meaning
whiteP	Percent of population which is White
nonWhtP	Percent of population which is not White
blackP	Percent of population which is Black
noSchol	Count of population with no schooling
elmntry	Count of population with at most elementary school education
hghSchl	Count of population with at most high school education
college	Count of population with at least college education
nRprtSc	Count of population with unreported education status
mdMlScY	Median years of schooling of male population over 25
mdFmlSY	Median years of schooling of female population over 25
emplydP	Percent of population 14 years and older which is employed
sekWrkP	Percent of population 14 years and older seeking work
ntInLbP	Percent of population 14 years and older not in the labor pool.
profP	Percent of population 14 years and older in professional employment
semPrfP	Percent of population 14 years and older in semi-professional employment
propP	Percent of population 14 years and older working as proprieters
clerclP	Percent of population 14 years and older in clerical employment
craftsP	Percent of population 14 years and older working as craftspeople
oprtvsP	Percent of population 14 years and older working as operatives
domstcP	Percent of population 14 years and older in domestic employment
servicP	Percent of population 14 years and older in service work
laborP	Percent of population 14 years and older in labor work
fm1Dtch	Count of 1 family detached dwelling units
fm1Attc	Count of 1 family attached dwelling units
fm2SdBS	Count of two family side-by-side dwelling units
fm2Othr	Count of any other two family dwelling unit
fam3	Count of 3 family dwelling units
fam4	Count of 4 family dwelling units
fm1t4WB	Count of 1 to 4 family dwelling units with businesses
fam5to9	Count of 5 to 9 family dwelling units
fm10t19	Count of 10 to 19 family dwelling units
fm20pls	Count of 20+ family dwelling units
othrStr	Count of dwellings otherwise not classified

Table D1: Plain english meaning of variable names

Variable	Meaning
undrP51	Count of occupied dwellings with less than .51 average persons per room
pt51t75	Count of occupied dwellings with between .51 and .75 average persons per room
pt76to1	Count of occupied dwellings with between .76 and 1 average persons per room
pt1t1p5	Count of occupied dwellings with between 1 and 1.5 average persons per room
pt1p5t2	Count of occupied dwellings with between 1.5 and 2 average persons per room
pt2plus	Count of occupied dwellings with over 2 average persons per room
nRprtRm	Count of occupied dwellings with unreported average persons per room.
tnUnP51	Count of tenant-occupied dwellings with less than .51 average persons per room
tnP5175	Count of tenant-occupied dwellings with between .51 and .75 average persons per room
tnPt761	Count of tenant-occupied dwellings with between .76 and 1 average persons per room
tnPt115	Count of tenant-occupied dwellings with between 1 and 1.5 average persons per room
tnPt152	Count of tenant-occupied dwellings with between 1.5 and 2 average persons per room
tnPt2pl	Count of tenant-occupied dwellings with over 2 average persons per room
tnNRprt	Count of tenant-occupied dwellings with unreported average persons per room
nMjrRpr	Count of dwellings not in need of major repairs
majrRpr	Count of dwellings in need of major repairs
rprNRpr	Count of dwellings with unreported repair status
radio	Count of occupied dwelling units with a radio
noRadio	Count of occupied dwelling units without a radio
rdNRprt	Count of occupied dwelling units with unreported radio status
rfrgMch	Count of occupied dwelling units with a mechanical refrigerator
refrgIc	Count of occupied dwelling units with an ice refrigerator
rfrgOth	Count of occupied dwelling units with an otherwise unlisted refrigerator
refrgNn	Count of occupied dwelling units with no refrigerator
rfrgNRp	Count of occupied dwelling units with unknown refrigerator status
htCntrl	Count of dwelling units with central heating
htNCntr	Count of dwelling units with no central heating
htNRprt	Count of dwelling units with unreported central heating status

Table D2: Plain english meaning of variable names (cont.)