Displacement and Infrastructure Provision: Evidence from the Interstate Highway System *

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Abstract

This paper studies the consequences of displacement resulting from the construction of the Interstate Highway System in the United States. It starts by showing that the placement of urban highways was not random. Exploiting cross-sectional variation between neighborhoods in 1950, the last census before the 1956 Federal-Aid Highway Act, I show that tracts with a higher proportion of the city's Black population were more prone to receive a highway, even after controlling for socio-demographic and geographic characteristics of the tract. Subsequently, the paper examines the impact on affected individuals. By geocoding the full-count 1940 census and linking it to administrative mortality records, I track affected individuals before and after highway construction. Exploiting the quasi-random variation in close proximity to highway developments, I show that displaced individuals die at a younger age, exhibit a higher likelihood of relocating from their neighborhood, and lived in neighborhoods with lower socioeconomic characteristics at their time of death. Moreover, although more nuanced, individuals residing near a highway are also negatively impacted. The mortality results are explained by the relocation of individuals into neighborhoods with lower health outcomes. These effects show up in the aggregate. By running an event study design for neighborhoods between 1930 and 2020, I found that highway construction is associated with outmigration, explained by a relative decrease in the Black population. I also find that these effects spill over to adjacent neighborhoods, affecting the demographic dynamics of cities.

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1 Introduction

Since its inception in 1956, the US Interstate Highway System (IHS) has changed the urban landscape in America. Over the second half of the twentieth century, the construction of this extensive network of roads displaced over a million individuals (Schwartz, 1975). Highway construction has also affected and continues to affect families living next to these developments as they are exposed to roadway noise, pollution, and lower amenities overall. Lately, both the urban affairs literature and policymakers have noted that these impacts fall predominantly on low-income and racial minority households. However, the implications of these displacements for individuals and neighborhoods remain largely unexplored. Thus, understanding how urban displacement affects individuals and neighborhoods is crucial for addressing the broader implications of urban development projects.

This paper studies the long-term consequences of urban displacement on individuals and neighborhoods resulting from the construction of the US Interstate Highway System (IHS). The IHS was prompted by the Federal-Aid Highway Act of 1956 to create the first national system of interstate and defense highways. Between 1956 and 1972, this bill triggered the construction of more than 43,000 miles of highways, with approximately a quarter located in metropolitan areas. The Federal Government paid for 90% of the construction costs and presented the states with optional routes, whereas States and local officials had the final word on site selection. During the initial years of highway construction, the program did not provide relocation payments or assistance to displaced households. Researchers have pointed to the disconnect between funding and routing, as well as the lack of support for affected households, as the mechanisms by which local officials used highway construction to carry out local agendas.

The primary data source for this study is the US full count census of 1940, which I geocode to obtain individuals' exact location at the time of the census. I then estimate the distance for each household to the closest interstate highway and to the PR-511, which contains the opening date of each highway segment funded by the Federal Government (Baum-Snow, 2007). To study the long-term consequences of displacement, I link individuals to administrative mortality records from 1988 to 2005 (Goldstein et al., 2023). These records contain, among other characteristics, the nine-digit zip code of residents at their time of death, allowing me to follow individuals in time and space. I supplement this data by digitizing and geocoding maps created by the Bureau of Public Roads in 1955, known informally as the Yellow Book, and linking it to the geocoded individuals in 1940. These maps were created specifically for the Federal-Aid Highway Act and allocated more than 2,000 miles of urban highways to 100 metropolitan areas. Together, these datasets allow me to observe individuals before and after highway construction.

To study the consequences on neighborhoods, I complement this data with a balanced panel of consistent boundary neighborhoods spanning ten census rounds between 1930 and 2020. The spatial information for each decade between 1950 and 2020 is obtained from Manson et al. (2023). I also geocode historical full-count censuses from 1930 to 1940 to retrieve neighborhood-

level information for the years in which spatial data does not exist or in which the coverage is limited. Thus, I can observe the demographic and economic evolution of neighborhoods over the last century.

The empirical analysis examines the determinants of highway location, who was affected by these decisions, and the long-term consequences of displacement. I start by examining the determinants of highway location. Exploiting the cross-sectional variation between census tracts in 1950, I estimate a specification that looks at highway construction and the tracts' geographic and socioeconomic characteristics. I define Black share as the proportion of the city's Black individuals living in the neighborhood. I find that, consistent with qualitative accounts, neighborhoods with a higher proportion of the city's Black residents had a higher probability of having a highway constructed through them. In addition, I find that neighborhoods with a lower median home value and closer to the city center were more likely to receive a highway. On the other hand, I find that the Yellow Book maps were not planned based on the neighborhoods' demographics. When examining the location of federally planned highways in the Yellow Book, I find no evidence that the distribution of Black households in a city predicted the placement of highways in these maps. Proximity to the city center and median home value were the most robust predictors of highway placement in the Yellow Book maps.

With the determinants of highway location established, I turn to the microdata to characterize who was affected by highway placement. In the first years after the Federal-Aid Highway Act of 1956, highway construction displaced more than 130,000 individuals, with more than 4 million affected by the proximity of these developments to their properties. Compared to the rest of the city, these individuals were more likely to be Black, immigrants, or first-generation Americans. They were also less likely to be homeowners and employed, and when employed, they performed occupations with lower occupational scores. These results are consistent with the qualitative accounts that highway construction occurred through marginalized communities.

Having characterized who was affected by highway construction, I then study the long-term consequences of displacement on individuals. I find that highway construction negatively impacted individuals displaced by and residing adjacent to future developments. Exploiting the quasi-random variation of highway placement conditional on the neighborhood, I find that both displaced individuals and those living within 100 meters of future highways are less likely to reside in the same neighborhood at the time of death compared to those living between 100 and 200 meters away, with a stronger effect for displaced individuals. Additionally, displacement is associated with reduced life expectancy, with estimates suggesting a reduction in lifespan by three months for displaced individuals. They are also less likely to survive until the age of 70. Furthermore, both displaced and adjacent individuals tend to die in areas with lower median income and house value, with a larger effect for displaced individuals. These results indicate that highway construction adversely affected individuals' health and economic outcomes.

Which group of individuals drives the long-term results? Using information from the 1940 census, I examine how different groups respond to highway construction. Affected Black indi-

viduals end up in worse neighborhoods than displaced white individuals, though the health of both groups is negatively impacted. Wealth appears to mitigate these negative effects. Proxied by homeownership in 1940, homeowners were more likely to leave the neighborhood without a reduction in life expectancy or relocation to worse neighborhoods. In contrast, renters and households with a college degree bear most of the costs. These findings highlight significant heterogeneity in the consequences of highway construction.

With the effect of displacement on individuals' health established, I turn to understand the underlying mechanisms driving this effect. I find that the negative consequences of highway construction are driven by the lack of support for displaced individuals, which makes them relocate to places with worse health care. I link the matched sample to data on the health characteristics of neighborhoods based on the location of their last residence (CDC, 2019). I find that displaced individuals die in places with a larger share of adults with poor physical and mental health. These findings suggest that inadequate support and relocation to areas with poorer health conditions exacerbate the adverse health effects of displacement.

Then, I turn to the consequences of highway construction on neighborhoods. To do so, I estimate a dynamic differences-in-differences model that uses highway construction as treatment on a battery of demographic and economic outcomes. The dataset comprises a panel of consistent boundary tracts spanning ten census rounds. I compare treated neighborhoods that underwent highway construction to observationally similar untreated neighborhoods. To match each neighborhood to its control, I use nearest-neighbor propensity score matching, following the empirical strategy of Fenizia and Saggio (2023).

The findings indicate that highway construction significantly impacts the racial composition of neighborhoods. Compared to their matched counterfactual, treated tracts experienced a decline in total population over the subsequent three decades. This decline is entirely due to the out-migration of Black individuals, while the White population remained unchanged. The analysis also reveals a decrease in the Black share of the tract. Additionally, the homeownership rate declines after construction while median rent remains constant. These results suggest that highway construction altered the racial composition of the affected tracts without changing land values.

In line with anecdotal evidence, I find that the effect of highway construction spillovers to nearby neighborhoods. Tracts adjacent to treated neighborhoods see an increase in the Black population share and a decrease in the White population, along with declines in homeownership rates and median rent. I also find a heterogeneous effect of highway construction on neighborhoods. The impact on racial composition is more pronounced in tracts with an initially large Black population and those near the city center. These findings highlight the uneven consequences of highway construction on urban demographic dynamics.

The findings of this study contribute to the literature on the long-term consequences of household displacement (Schwank, 2023; Rojas-Ampuero and Barrera, 2023). Deryugina et al.

(2018) find that a few years after Hurricane Katrina, the income of individuals affected by the storm surpassed those with similar characteristics in different cities. Nakamura et al. (2021) find similar results for people displaced by a volcanic eruption in Iceland. I contribute to this literature by exploring the effects of highway-induced displacement carried out by the largest infrastructure project in the US, which displaced more than one million individuals, with millions more affected due to the proximity of these developments to their properties. Further, I study displacement caused by man-made events, which is different from natural disasters like hurricanes and volcanic eruptions.

This study is also relevant to ongoing policy debates. The findings indicate that displaced individuals bear a disproportionate burden of the costs associated with highway construction. Additionally, displaced people and those residing near highway developments are more likely to migrate out of their neighborhoods. Consequently, initiatives like the *Reconnecting Communities and Neighborhoods* program are poised to partially compensate for the negative consequences arising from highway construction. [1] However, a more efficient policy approach would involve targeting individuals directly rather than focusing solely on neighborhoods for compensation.

This paper also contributes to the literature on the economic determinants and consequences of the IHS. First and foremost, this project contributes to this literature by being the first to study the consequences of displacement caused by the construction of the IHS. Also, the findings contribute to the literature on the economic determinants of the IHS by providing new evidence regarding the characteristics predicting highway site selection (Carter, 2023; Brooks and Liscow, 2023). Furthermore, the results add to the broader body of research on the consequences of highway construction, including studies that examine its effects on neighborhoods (Brinkman and Lin, 2022; Brinkman et al., 2023; Bagagli, 2023), segregation in cities (Baum-Snow, 2007; Mahajan, 2023; Weiwu, 2023), and economic factors such as productivity, employment, sector specialization, and travel distances (Duranton et al., 2014; Michaels, 2008; Herzog, 2021; Duranton and Turner, 2012; Chandra and Thompson, 2000; Redding and Turner, 2015; Duranton and Turner, 2011).

Finally, the analysis also complements existing literature that focuses on the history of discriminatory practices carried out by the US government by exploring the uneven burden of displacement faced by Black communities. Prior research has documented how the federal government imposed restrictions on loan access for properties located in historically Black neighborhoods, leading to long-lasting consequences for their residents (Aaronson et al., 2021; Hynsjö and Perdoni, 2022; Rothstein, 2017; Fishback et al., 2022, 2021). Additionally, other studies have examined the relationship between government policies such as zoning and urban renewal and their impact on traditionally Black communities (Lee, 2022; Sood et al., 2019;

[1] *Reconnecting Communities and Neighborhoods* project aims to reconnect neighborhoods divided by highways. It is part of the 2022 Inflation Reduction Act and allocates funds to "remove, retrofit, or mitigate an existing eligible dividing facility to reconnect communities."

LaVoice, 2022). It has also been documented that racial and ethnic minorities face a higher property tax burden for the same level of public goods (Avenancio-León and Howard, 2022). By focusing on displacement caused by highway construction, this article contributes to the existing literature by providing novel insights into the discriminatory practices spearheaded by local governments across the US.

The paper is organized as follows. Section 2 discusses the history of the Interstate Highway System. I describe the data used in the analysis in Section 3. In Section 4, I study where highways were placed and characterize the neighborhoods affected by highway construction. Section 5, analyzes the long-term consequences of highway construction on individuals. In Section 6, I discuss the dynamic implications for those neighborhoods where a highway was built. Finally, Section 7 concludes.

2 The Interstate Highway System

The Interstate Highway System (IHS) was established by the Federal-Aid Highway Act of 1956, signed into law by President Dwight D. Eisenhower. This legislation aimed to enhance the nation's transportation infrastructure by constructing a National System of Interstate and Defense Highways. The bill proposed the construction of over 41,000 miles of highways and allocated 25 billion dollars over twelve years to the project. The Federal Government would cover 90% of the construction costs, while state and local officials determined the routing of the interstates (Rose and Mohl, 2012). To finance the construction without increasing government debt, the legislation created a highway trust fund, which was funded by an increase in the federal gasoline and diesel taxes (Lewis, 2013, pp. 112-118). The enactment of this bill ensured that the United States would develop a modern, interconnected, and transcontinental network of highways, addressing the country's need for a comprehensive transportation system (Murphy, 2009).

A key factor in the approval of the bill was the allocation of over 2,175 miles of interstate routed through into metropolitan areas. The Federal Government proposed the routes and detailed them in a report informally known as the "Yellow Book," which was distributed to every senator before the vote (Lewis, 2013, pp. 119-120).[2] The Yellow Book contained maps outlining the Federal Government's plans for a network of urban highways in 100 metropolitan areas (Rose and Mohl, 2012). Appendix Figure A.1 presents these maps for Atlanta, Detroit, Miami, and New Orleans. By illustrating how the interstates would benefit their districts, the maps helped representatives secure the necessary votes for the bill's passage. However, these proposed routes were not binding. As Rose and Mohl noted, "Congress and President Eisenhower reaffirmed the long-standing principle that the locus of authority in highway programming rested unambiguously in the hands of state highway officials" (Rose and Mohl, 2012,

[2]The official title of the report is "General Location of National System of Interstate Highways, Including All Additional Routes at Urban Areas".

p. 161). This flexibility granted state and local officials the power to determine the location of urban routes, which they often used to serve their own agendas (Rose and Mohl, 2012, p. 97). Figure A.2 plots the planned and built highway networks for Atlanta, Detroit, Miami, and New Orleans, showing that while highway segments typically aligned with the intended origins and destinations, there were variations in the specific locations compared to the initial plans.

Despite the intended benefits of a network of urban highways, the construction of the Interstate Highway System led to widespread displacement of people. City officials often envisioned these new highways as means of clearing "blighted" urban areas, frequently at the expense of residents in predominantly Black neighborhoods. As Alfred Johnson, executive director of the American Association of State Highway Officials, recalled, "Some city officials expressed the view in the mid-1950s that the urban interstates would give them an opportunity to get rid of the local "n*****towns"" (Rothstein, 2017, p. 128). Planning experts in the mid-1960s forecasted that the construction of the interstate network would result in the displacement of more than one million people, primarily African Americans (Rose and Mohl, 2012, p. 96). Moreover, federal and local agencies provided little to no assistance to displaced households in finding new living arrangements. Consequently, highway construction forced these households to relocate to the fringes of cities or emerging "second ghettos" (Rothstein, 2017; Archer, 2020).

One of the most well-documented cases of highway construction used for Black removal occurred in Miami, Florida. State planners routed Interstate 95 directly through the heart of Overtown, a community that was the center of economic and cultural life for the city's Black population. State officials overlooked an alternative route that would have used an abandoned railway right-of-way, resulting in minimal population displacement (Rothstein, 2017). Consequently, Interstate 95's construction displaced approximately ten thousand Black individuals from their homes and communities (Archer, 2020). A similar situation unfolded in Detroit, Michigan, where the predominantly Black neighborhood of Black Bottom was eradicated by the construction of Interstate 75 (Avila, 2014, pp. 89-90). Figure A.3 shows how highways bisected the neighborhood, destroying several hundred homes. In St. Paul, Minnesota, Interstate 94 cut through the city's Black community, displacing one-seventh of St. Paul's African American population. As one critic noted, "very few Black individuals lived in Minnesota, but the road builders found them" (Rose and Mohl, 2012, p. 108).

Initially, the 1956 Federal-Aid Highway Act included no obligations at the federal or state level to assist residents whose homes were demolished or whose homes would be in proximity to new roads. Arthur Burns, chairman of the Council of Economic Advisors in the Eisenhower administration, warned policymakers that compensating people for losing their homes would be too costly, as the highway program was predicted to evict nearly one hundred thousand people a year (Archer, 2020). As a result, no provisions were made to compensate displaced residents or families experiencing air and noise pollution from proximity to a highway (Schwartz, 1975). Thus, during the first decade of highway construction, displaced individuals entered the housing market on their own, bearing the full costs of relocation (Davis, 1965).

As the destructive effects of highway construction became more apparent during the late 1950s, opposition to such projects began to mount. Local opposition movements emerged to defend their communities from the negative consequences of highway building. The first revolt against freeway construction occurred in 1959 in San Francisco, when the city's board of supervisors withdrew their support for any new freeway construction (Rose and Mohl, 2012).[3] Opposition to highway construction quickly spread across the country. By the mid-1960s, local opposition movements had appeared in cities nationwide (Lewis, 2013). The growing discontent with urban interstates soon influenced federal policy. In response to this opposition, Congress passed the Highway Act of 1962, which began to address some of the concerns raised by these movements.

The Highway Act of 1962 was the first federal legislation to allocate funds specifically to mitigate the impact of highway construction. The Act, which came into effect in July 1965, provided a maximum of $200 for residential moves and $3,000 for business relocations. The legislation mandated that transportation projects receiving federal aid must provide support to secure relocation housing for those displaced by road construction (Archer, 2020). However, by the time relocation assistance was integrated into highway construction, much of the damage had already been inflicted. Most urban interstates had been built before housing support became part of highway construction policy.

Albeit late, the assistance provided by the 1962 Act fell short of the needs of displaced individuals. It was not until 1965, almost a decade after the 1956 Federal Highway Act, that the Federal Government required advanced housing relocation for families and businesses displaced by highway construction. By 1967, only 33 states had authorized the payment of relocation costs (US DoT, 1970). As Rose and Mohl (2012) note: *"during most of the expressway-building era, little was done to link the Interstate highway program with public or private housing construction or even with relocation assistance for displaced families, businesses, or community institutions such as churches and schools."* In that line, the Highway Research Board (1967) notes that a small fraction of relocated families found a new home with agency aid. Among the nearly fifty thousand individuals displaced between April 1965 and October 1966, only 37% sought advisory assistance, and a mere 15% were relocated due to this assistance. Also, the average payment made to displaced households was $110, which was insufficient to cover the costs of moving (Highway Research Board, 1967). In addition, the communities affected by highway construction were not given any support to rebuild. The first Federal plan to allocate funds for households and communities affected by their proximity to highways came only under the Biden presidency, more than sixty years after the 1956 Federal Highway (117th Congress, 2022).[4] In sum, up until recent years, assistance for relocation has been scarce, and even when it was

[3]Another example of local highway opposition is the case of Boston. In 1969, thousands of residents stormed the Massachusetts State House to protest the state's highway expansion project (Crockett, 2018). This local opposition led to the construction of the O'Neill and Ted Williams Tunnels, projects known informally as the Big Dig.

[4]The *Reconnecting Communities and Neighborhoods* project, included in the Inflation Reduction Act of

available, it did not give enough support to affected households.

In a highly segregated era for the U.S., highway construction forced households to relocate. Forced relocation has long-term adverse effects on affected individuals' socio-economic welfare and psychological well-being. At the time the IHS was built, housing alternatives for the displaced were largely limited to other racially segregated and economically disadvantaged communities. These options included "emerging second ghettos" or transitioning neighborhoods where working-class Whites predominated (Archer, 2020). Figure A.4 exemplifies these reports. It shows the residence location at the time of death for individuals living in Detroit before and after highway construction. The figure presents stark differences in neighborhood choice among the racial lines. Even fifty years after highway construction began, Black individuals are clustered close to the city center, whereas White individuals are spread across the city. In addition, highway construction impacted individuals' psychological well-being. By looking at families displaced by urban renewal projects in Boston's West End, Fried (2017) finds that most of the interviewees expressed deep grief. The feelings of loss manifest long after the individuals relocate to new living arrangements. These feelings stem from fragmented routines and the loss of personal and social factors (Fried, 2017). Another example of psychological distress caused by forced relocation is the case of urban expressways in New York. Caro (1974) noticed that displaced residents of the Cross-Bronx Expressway were left with a sense of loss and disorientation. Consequently, the forced relocation of households has long-term adverse effects on affected individuals' socio-economic welfare and psychological well-being.

3 Data

To study highway-induced displacement, I needed information regarding where individuals lived before and after highway construction. To know where individuals lived before construction, I use the complete count of U.S. census microdata for the year 1940 (Ruggles et al., 2024). The census collected information on the exact address of each household, which I standardized following the practices recommended by Logan and Zhang (2018), and geocoded to obtain the latitude and longitude of each dwelling. Because this project's scope is on urban displacement, I only focus on urban residents of counties that are part of the 168 Standard Metropolitan Areas (SMA) in 1950. The sample covers 82.16% of the urban residents in the U.S. in 1940, for which I managed to geocode 79.11% of the dwellings or 80.85% of the urban residents. Appendix Section C contains more information about the sample and geocoding process.

To identify which households were displaced by highway construction, I needed information on the exact location of each highway segment with its respective opening date. I obtained this information by linking the PR-511 database used by Baum-Snow (2007) to the actual highway network (OpenStreetMap, 2017). I complement this information with the federal plans' location

2022, aims to reconnect neighborhoods divided by highways. It is part of the 2022 Inflation Reduction Act and allocates funds to "remove, retrofit, or mitigate an existing eligible dividing facility to reconnect communities."

in the Yellow Book (Bureau of Public Roads, US, 1955). This collection included planned urban segments of the IHS for 100 metropolitan areas, which I manually geocoded.

In addition to where individuals lived in 1940, I needed information on individuals after highway construction. I linked the 1940 census to administrative mortality records from 1988 to 2005 (Goldstein et al., 2023). These records include, among other details, the 9-digit zip code of residents at the time of death. The linked dataset enabled me to analyze the long-term impacts of highway construction on urban residents. By leveraging their 1940 addresses, I can accurately identify those who lived in dwellings demolished by highway construction or those close to future developments. Subsequently, using the mortality records, I can track their residence post-construction. The mortality records provide detailed information on age, reliance on social security, and location at the time of death. This data allowed me to infer geographic mobility and changes in socioeconomic status. The characteristics of the database I built make this paper the first to study the long-term consequences of highway-induced displacement.

Furthermore, I also constructed a panel of time-consistent neighborhood definitions from 1930 to 2020.[5] The sample consists of neighborhoods located inside 62 SMAs that had spatial information in 1950. Appendix Table C.1 lists the MSAs used and the number of census tracts available in 1950. Information for the decades between 1950 and 2020 comes from the National Historical GIS census information (Manson et al., 2023). I constructed neighborhood-level information for 1930 and 1940 by aggregating the geocoded complete count censuses. My approach does a good job of matching the historical characteristics of the neighborhoods for the subsample of neighborhoods with spatial data in 1940, as shown in Appendix Figure C.1. Details of the construction of the historical neighborhood characteristics and a benchmarking exercise can be found in Appendix Section C.5.

I supplement the neighborhood-level data with a variety of sources. First, I matched each neighborhood to its geographic characteristics, which come from Lee and Lin (2017). These variables include the tract's average slope in degrees and distance to the closest river. Then I estimated the distance from each tract to the Central Business District (CBD), a proxy for the city center, following the practices recommended by Holian (2019).[6] I calculated the distance from each tract's centroid to the closest railroad network in 1921 (Sequeira et al., 2019). [7] Finally, I included the number of car registrations per 10,000 inhabitants in each state and the

[5]A common challenge while working with neighborhoods over time is that geographic units rarely align across periods. This study addresses this problem by using the crosswalk provided by Lee and Lin (2017) for the years where spatial data is available. The crosswalk uses 2010 census tract definitions. For the census years 1950 to 1960, the crosswalk weighs by overlapping area. From 1970 onwards, it used population weights. More detailed information about the crosswalk can be found on pages vii-viii of the online appendix of Lee and Lin (2017).

[6]First, I use the centroid of the polygon designated as the CBD in the 1982 Trade Census as shown in Fee and Hartley (2013). If the census did not include the city, I used the location of the city hall. That data comes from Wilson (2012). Finally, if the city is not matched in either of the two previous steps, I used the location of the CBD given by Google Maps as in Holian and Kahn (2012).

[7]I used the network available 30 years before the planning to take into consideration that some railroads are not used anymore and were transformed into highways.

state governor's political party for each decade.[8]

4 Motivating Evidence

4.1 Where were highways placed?

Which factors dictate highway construction and, consequently, who gets displaced? I present cross-sectional evidence on the relationship between neighborhood's socioeconomic composition and geographic characteristics with future highway construction. To do this, I exploit variations among census tracts in 1950, the last recorded census before the 1956 Federal-Aid Highway Act that initiated highway construction. The sample size is limited to 62 cities with spatial information in the 1950 census. The estimating equation follows:

$$y_n = \alpha + \lambda_{c(n)} + \gamma_1 \text{DistCBD}_n + \mathbf{S}_n' \gamma_2 + \mathbf{P}_n^{p\prime} \gamma_3 + \mathbf{G}_n' \gamma_4 + \epsilon_n \tag{1}$$

In this equation, n indexes census tracts, and $c(n)$ indexes the metropolitan area in which the census tract was located in 1950. The dependent variable, y_n, takes a value of one if a highway was built through the census tract and zero otherwise. The equation includes a constant term, α, and a city fixed effect, $\lambda_{c(n)}$. The variable DistCBD_n is the distance to the central business district, which is included to account for the fact that highways were built to connect city centers and Black households sorted themselves into city centers (Boustan, 2010). The vector $\mathbf{S}_n$ contains the socioeconomic characteristics of the tract, such as the share of the city's Black population residing in the tract, the median income, the share of the adult population with a high school degree. The vector $\mathbf{P}_n$ contains contols for the (log) median rent, and the (log) median home value. These controls are included to account for the price of land in the neighborhood. The vector $\mathbf{G}_n$ contains geographic and state controls, including (log) average slope in degrees, the (log) area, and the distance to the nearest river, railroad network, number of cars per 10,000 inhabitants, and the governor's political party. The regression results are weighted by the total population of tract n in 1950, and the standard errors are clustered at the city level.

Estimates of Equation 1 are reported in Table 1. Columns (1) to (5) presents the results for the network of highways built. I find that, in equilibrium, highways were built through neighborhoods with lower price of land, larger Black share, and closer to the central business district. The results are similar when using distance to future highway developments as the dependent variable, as seen in Appendix Table D.1. In all specifications, Black households

[8] I draw data on passenger car registrations by state and year from the Federal Highway Administration, table MV-201 (Eli et al., 2022). Data on Governors' political affiliation comes from Inter-University Consortium for Political and Social Research (1995).

reside closer to future highway developments, which can partially be due to political agendas of builders which lead to an unequal placement of highways (Trounstine, 2018). In addition, highways were built in neighborhoods with an initially lower price of land, as it can be see in the negative and significant coefficient of median home value and rent. These results are partially explained by the fact that highways were built to connect city centers, which were experiencing a decline in its economic conditions and an increase in the Black population (Boustan, 2010). However, the results are robust to the inclusion of distance to the central business district.

The socioeconomic results found in this section are consistent with the anecdotal accounts of highway placement. The estimated effects for Black share are large and economically significant. An increase of one standard deviation in the Black share of a neighborhood is equivalent to a decrease in the mean median home value by 18.8% or by $16,836. Compared to median rents, the proposed increase is equivalent to a 25.7% decrease, or by $106, in the mean median rent. [9] These findings underscore the profound impact of racial composition on highway placement. Thus, Black individuals were, on equilibrium, more likely to be displaced by highways than their White counterparts.

One possible explanation for these results is that state planners followed the Federal government's dictates. In column (6) of Table 1, I re-estimate Equation 1 using the Yellow Book maps as the dependent variable. In particular, I use an indicator that takes the value of one if a highway was planned in the neighborhood and zero otherwise. I find that the estimate is not different from zero after including proximity to the city center and the price of land. These results suggest that the racial composition of neighborhoods played a role in the decision of state planners to deviate from the Federal plan.

The results presented in this section demonstrate robust consistency across various robustness checks. Specifically, we have employed alternative definitions of neighborhoods, incorporated nonlinear controls for proximity to the city center, and analyzed unweighted results. Additionally, we conducted leave-one-city-out estimations and applied different clustering techniques as well as Conley standard errors to account for spatial correlation within a 10-kilometer radius. Each of these methodological variations consistently supports our primary findings, underscoring the reliability and robustness of our results. These extensive robustness checks ensure the credibility of our analysis and bolster the validity of our conclusions.

Appendix Section D shows that the results are robust to various checks. Specifically, they are robust to alternative definitions of neighborhoods, incorporated nonlinear controls for proximity to the city center, and analyzed unweighted results. Additionally, the leave-one-city-out estimations suggest that the results are not driven by a single city. Finally, the results are consistent to the use of different clusters as well as Conley standard errors to account for spatial correlation within a 10-kilometer radius.

[9] This estimates comes from $\Delta\%_x = 100 \times (exp\left\{\frac{\sigma_{BS} \times \hat{\beta}_{BS}}{\hat{\beta}_x}\right\} - 1)$ where x denotes median home value or rent and BS denotes Black share.

These results contradict part of the findings of Carter (2023) and Weiwu (2023). They find that the median home value was the most significant predictor of the highway location and that the share of Black individuals did not have a substantial effect. This papers differ in scope and in the way we model neighborhoods' Black share. While they use the share of the tract's population that is Black, I use the share of the city's Black population residing in the tract. Although these two variables are highly correlated, they differ in spirit. Qualitative accounts indicate that highways were constructed "where Black individuals live" (Rose and Mohl, 2012). I argue that the definition used in this paper better reflects this motive. To illustrate, consider a city consisting of two neighborhoods: one with 1,000 Black residents and a total population of 2,000, and a second with a Black and total population of 100. If a highway is constructed through the first neighborhood, then the authors' definition of the Black share will not be statistically significant. However, the highway was built through the neighborhood that housed roughly 90% of the city's Black population.

4.2 Displaced individuals

The previous section provides evidence that highways were built through neighborhoods with lower land prices, closer to the city center, and with a larger Black population share. I now shift my attention to estimate the number of individuals displaced by highway construction, and to describe the characteristics of those displaced. To do this, I use the geocoded 1940 full-count census and explore the characteristics of individuals displaced by highway construction. In particular, I create seven bins: one for individuals displaced by highways, five 100-meter bins, and a final bin for individuals living farther than 500 meters from the highway. Because I only have information from 1940, sixteen years before the 1956 Federal-Aid Highway Act, I focus on the segments opened between 1950 and 1960 to minimize measurement error in the location of households' dwellings.

Before the enactment of the 1962 Federal-Aid Highway Act, highway builders did not systematically collect data on the number of individuals displaced by highway construction. The primary reasons for this lack of data collection were the absence of relocation payments or assistance for displaced individuals and the potential liability that accurate counts might impose on planners and authorities (Schwartz, 1975, pg. 235). As a result, the number of individuals displaced by highway construction, particularly during the first years of construction, is not documented. This paper is the first study to fill this gap by providing an estimate of the number of individuals displaced by highway construction during the first years of highway construction.

Table 2 presents an estimate of the number of individuals displaced by or living in close proximity to future highways, and their characteristics. Panel A presents the estimated number and the corresponding percentage of the population affected by highway construction. I estimate that roughly 10% of the urban population in metropolitan areas in 1940 was either displaced or lived within 500 meters of a future highway. This estimate is a lower bound, as I only manage to

geocode 80% of the individuals in the 1940 census. [10] The total number of individuals displaced by highways constructed between 1950 and 1960 is 131,486. The Federal Highway Act of 1956 was in place only for four years during this decade, this estimate implies that, on average, 32,850 individuals were displaced by highway construction in urban areas each year. This estimate is in line with the official numbers reported in 1967. The Federal Government started collecting data on the number of individuals displaced by highways in 1965. Their official estimate is that an average of 33,070 individuals were relocated by highway construction each year during the period of April 1965 and October 1966 (Highway Research Board, 1967, p. 2). Given my focus on urban areas, and the fact that I was able to geocode only 80% of the individuals in the 1940 census, the estimates suggest that highway construction displaced a significant number of individuals during the first construction years.

Panels B of Table 2 reports the variable averages for individuals in each bin of proximity to highways, whereas Panel C reports household-level averages. The results align with the evidence presented in the previous section: the Black share is larger closer to future developments, with lower high school graduation rates. Individuals living close to future developments are more likely to be part of the labor force but are less likely to be employed. Conditional on employment, individuals living closer to future highways have a lower occupational score. Households are less likely to be homeowners and inhabited in places with lower home values and rents. These results are consistent with the anecdotal evidence that highways were built through neighborhoods with a larger Black share and lower socioeconomic status.

5 Displacement and the Construction of the IHS

This section examines the relationship between highway construction and the long-term outcomes of individuals displaced by or living near future highway developments. I use the geocoded full-count 1940 census linked to mortality records to study the effects on mortality, migration, and neighborhood characteristics.

5.1 Identification Strategy

As shown in Section 3, neighborhoods targeted by local governments for highway construction were not randomly selected, posing a threat to identification. To overcome this threat, I use an inner versus outer ring approach. The logic behind this strategy is that the exact geographic location of the highway site within a broader neighborhood appears to be determined by idiosyncratic characteristics, such as land availability or the connection to other highways. Thus,

[10] Another reason why this estimate is a lower bound is that I can only observe highway openings. If the construction started before 1960 but the opening occurred afterward, I would only observe those displaced households in the following decade. Appendix Table D.7 ameliorates these concerns by providing estimates for all segments opened. The results are consistent with the estimates for highways opened between 1950 and 1960.

the exact location of the highway is as good as random conditional in a short vicinity of the construction site. The strategy is similar to the one used by Diamond and McQuade (2019) to study the spillover effects of social housing construction on nearby neighborhoods. [11]

The identification strategy relies on two assumptions. The first one is that the effect highway proximity has on individuals fades away after some threshold distance. The second assumption is that, conditional on a neighborhood, the exact highway location is as good as random. Together, these assumptions imply that, in the absence of highway construction, the long-term outcomes of individuals affected by construction would have evolved as those living in the same neighborhood but not directly affected by the construction. Thus, I use as the control group those individuals living close to a future highway but not that close to being directly affected by the construction.

The identification strategy, however, leaves the selection of the threshold distance to the research's discretion. I use 100 meters as the threshold distance, making the control group those individuals living within 100 and 200 meters of a future highway. To test the validity of this threshold, I run a regression of a 100-meter distance to the highway bins on the outcomes of interest controlling for city, race, gender at birth, homeownership status, and birth year fixed effects. The results are relative to those individuals living between 2,000 and 2,100 meters of a future highway. Appendix Figure E.1 presents the results for the probability of residing in the same neighborhood, the age at death, the share of high school graduates, and the median home value of the last residence's neighborhood. For all outcomes, the effect of highway proximity fades away after 100 meters. As an additional robustness, I use different distance cutoffs as control groups. Appendix Tables E.2 and E.3 show that the results are robust when using individuals living between 1,000 and 1,100, as well as 2,000 and 2,100 meters of a future highway as a control group. These results suggest that spatial externalities decay rapidly across space, in line with previous results from the literature (Rossi-Hansberg et al., 2010).

The identification strategy assumes that, in close proximity to highway developments, proximity to highways did not depend on individual-level characteristics, conditional on the city they lived. I use individual-level data collected in the 1940 census before highway construction to test this assumption. Table 3 compares the characteristics of individuals in our estimation sample. I find that the inner versus outer ring sample differs in economic characteristics. Both displaced and adjacent individuals have lower employment rates, lived in cheaper houses, and worked in lower status occupations. These differences, however, are not large in magnitude. For example, the difference in the occupational score is around 1% of the mean. I find that the sample is balanced on the other set of variables. I also test the balance of the sample linked to administrative death records, the primary sample of this analysis.

Appendix Table E.1 repeats the exercise using the sub-sample of individuals matched to administrative death records. I find that the sample is more balanced than the full sample. For

[11] The strategy has also been used to study spatial spillovers of housing (Asquith et al., 2021; Autor et al., 2014), bankruptcy (Shoag and Veuger, 2018), startups success (Campusano Garate, 2022), among others.

example, individuals lived in houses with similar home values. Also, the employment status of the individuals is balanced, and the difference in the occupational score is minimal. These findings indicate that the matched sample does not present large and significant differences in the pre-existing characteristics.

5.2 Estimation

After discussing the empirical strategy, I present the estimation of highway construction's effect on individuals' long-term outcomes. The estimating equation follows:

$$y_i = \alpha + \lambda_{c(i,1940)} + \beta_1 Displaced_i + \beta_2 Adjacent_i + \mathbf{X'}_i \mathbf{\Gamma} + \epsilon_i \tag{2}$$

where i denotes individuals. y_i denotes the dependent variables for individual i at their time of death, such as age at death, survival until age 70, migration, or neighborhood socio-economic characteristics. When the outcome is the age of death and survival until age 70, I use the weights developed by Goldstein et al. (2023) to account for the differences in inclusion probabilities by period, age, and demographic characteristics. [12] $\lambda_{c(i,1940)}$ corresponds to a fixed effect controlling for the city where the individual lived in 1940. $Displaced_i$ is an indicator that equals one if individual i lived in 1940 in a dwelling destroyed by highway construction. Conversely, $Adjacent_i$ is an indicator that equals one if individual i lived in 1940 within 100 meters from future developments. $\mathbf{X'}_i$ denotes a vector of individual-level characteristics that includes an indicator if the reported race of the individuals is Black, a gender indicator, indicator if the individual's household owned the property they lived in 1940, and birth year indicators. Standard errors are clustered at the city in 1940 level.

Given that individuals are observed in 1940, sixteen years before the start of highway construction, I use highway segments opened between 1950 and 1960. This helps to overcome part of the classical measurement error in the household location. As Appendix Table E.5 shows, the results do not depend on this sample selection. The coefficients are, as expected, lower in magnitude when using all the highway segments opened, but all have the expected sign. Since I use a modern geocoder to assign the location of the individual at the time of death, I restrict the sample to individuals who died from 1995 onwards. I do this to account for the possibility that ZIP codes could have changed over time. Appendix Table E.6 shows that the results are robust to inclusion of individuals dying before 1995.

[12] The post-stratification weights are constructed using population totals from the Multiple Cause-of-Death (MCOD) mortality data. The purpose of the weights is to adjust for slightly worse coverage of younger ages of death within birth cohorts. Individuals born outside the 48 contiguous states and those without a birthplace are excluded from the weighted sample. More details on the construction of the weights can be found on Breen et al. (2023). Appendix Table E.4 shows that the results do not hinge on the use of weights.

5.3 Displacement Results

This section reports the estimated results for Equation 2. I estimate the effect of highway construction on individual characteristics such as age at death and the probability of survival until age 70, in addition to indicators if the individual resided in the same neighborhood or city as they did in 1940. I also use outcomes from the neighborhood of residence at the time of death. For example, I constructed the share of college-educated adults by race and gender for each neighborhood. Then, I matched it to individuals depending on their residence at the time of death, gender, and race. More information about the geocoded data as well as the linking procedure to the administrative death records can be found in Section 3.

The estimates of equation 2 are reported in Table 4. Column 1 reports estimates where the dependent variable is an indicator that equals one if the individual lives, at the time of their death, in the same neighborhood they lived in 1940. I find evidence that highway construction resulted on out-migration from their neighborhoods from both displaced and individuals living close to future developments, the effect being larger in magnitude for displaced individuals. Column 2 reports estimates that examine if the individual lives in the same city before and after highway construction. I find no statistically significant effect for displaced individuals, whereas adjacent individuals are 1.6% more likely to stay in the same city at their time of death. Column 3 shows that individuals living close to future developments are 0.5% more likely to reside in a redlined neighborhood. Together, these results are consistent with historical accounts that highway changed the social capital of cities (Rose and Mohl, 2012).

These results are relevant to ongoing policy debates. The findings indicate that displaced individuals bear a disproportionate burden of the costs associated with highway construction. Additionally, displaced and those residing near highway developments are more likely to out-migrate from their neighborhoods. Consequently, initiatives like the *Reconnecting Communities and Neighborhoods* program are poised to partially compensate for the negative consequences arising from highway construction. However, a more efficient policy approach would involve targeting individuals directly rather than focusing solely on neighborhoods for compensation.

Highway construction impacted the health of affected individuals. Columns 4 and 5 of Table 4 report estimates for the age at death and at the probability of surviving until 70 years old, respectively. The estimates indicate that displaced individuals die 0.23 years younger whereas individuals living within 100 meters die 0.07 years younger. Individuals living close to future developments also die younger, but the effect is smaller in magnitude compared to displaced individuals. Also, displaced individuals are 1% less likely to live until 70 years old. These results are consistent with historical accounts that mentioned that displaced individuals were forced to move to less desirable neighborhoods, which could have led to worse health outcomes (Archer, 2020).

The mortality effects found are comparable to other effects found for traumatic experiences. For displaced individuals, the magnitude is comparable to a fifth of the effect a divorce has

on the age at death (Sbarra et al., 2011). It also compares to other experiences that affected mortality in the U.S. Black et al. (2015) find that Black individuals born in the U.S. South who migrate to the North have a 5.8% lower probability of surviving until the age of 70. My estimate for displaced people is 1.0%, a 17% of Black et al.'s estimate. These findings highlight the profound impact highway induced displacement had on individuals.

Individuals affected by highway construction also lived in neighborhoods with worse socio-economic characteristics. Archer (2020) notes that relocated individuals were forced to move to "emerging second ghettos" confining them into racially segregated and economically challenged communities. Using neighborhood-level data from the location of the residence at the time of death, I find evidence in line with the historical accounts. Table Table 5 shows that displaced and adjacent individuals resided in neighborhoods that had lower high school, college share, and employment share in the 2000. They also resided in neighborhoods with lower median home value, median income, and lower rent for a two-bedroom apartment. The effects have the same sign for displaced and adjacent individuals, the effect being larger for displaced households.

Different specification As robustness to the main specification, I re-estimate equation 2 using as the control group those individuals living close to planned highways. In particular, I exploit the distance to the Federal highway plans in the Yellow Book, and use individuals living within 100 meters of planned but never built highways as a control group. Table E.7 replicates the results of Table 4 using this alternative approach. I find that the estimates closely mirror the findings using the "inner vs. outer" ring sample. Affected individuals are more likely to move from their neighborhoods, die younger, and are less likely to survive until the age of 70. Table E.8 also finds that affected individuals die in neighborhoods with worse socio-economic characteristics. The estimates are slightly larger that the preferred specification, which is consistent with the historical accounts that mentioned that the local opposition to highway construction was more successful when the communities' connections to local political and economic elites were stronger (Rose and Mohl, 2012).

Placebo Estimations: One possible explanation is that highways were planned, and consequently built, into locations that could impact the long term characteristics. For example, highway could be planned into neighborhoods that were already declining or with geographic characteristics that impact the long term outcomes If that was the casem I would expect that Yellow Book plans would had an independent effect on the long term outcomes of individuals. I test this hypothesis by estimating the effect of living close to a planned highway. This hypothesis is not supported by the data, as shown in Appendix Tables E.9 and E.10. I view the lack of these patterns as evidence against the hypothesis that the results are driven by the location of the highway plans.

Measurement Error in the Geocoding: I geocode addresses collected in 1940, which could have changed the street names or the numbering of the houses. Although there is no clear reason for how this type of error could systematically affect the results, it is possible that the geocoding process could have been more difficult for individuals living in houses destroyed by

highway construction. Thus, the number of individuals living in houses destroyed by highway construction could be underestimated. This could lead to larger confidence intervals in the estimated coefficients. I also drop all observations not geocoded to a unique latitude or longitude and those that are not matched to an address. [13] However, this is a possible explanation, and the results should be interpreted as a lower bound.

A second source could come from the difference in timing between the 1940 census and the start of highway construction. If households were forward-looking, they could have sorted themselves before highway construction started. However, the historical accounts suggest that even in 1940, the exact location of the highway was not clear, alleviating this concern. I restrict the sample to individuals affected by highway segments constructed between 1950 and 1960, which minimizes the number of households who migrate before highway construction. To indirectly test this assumption, I run 2 using individuals born before 1910, who, by their age, are less likely to move. Appendix Table E.11 shows that the results are robust to this restriction. As expected from the attenuation, the coefficients are larger in magnitude.

Finally, we could expect measurement errors coming from the linkage to administrative death records. The linkage is done using Abramitzky et al. (2017), the standard approach in the literature. I only include unique matches between the 1940 census and the death records, ameliorating the false positives. Goldstein et al. (2023) find that these matches are representative of the U.S. population.

5.4 Effects by Birth Cohorts

Forced relocation can have different effects depending on the age at which the person is affected. For example, children could be more affected by the loss of social capital, whereas older individuals could be more affected by the loss of health care or labor access. Nakamura et al. (2021) find that children forced to move by a volcano eruption had higher lifetime earnings, whereas relocation costs fall disproportionately on older individuals. Motivated by these results, I explore if the estimates vary across the life cycle.

I find substantial heterogeneity in the effects across the life cycle. The results are reported in Figure 1. Panel (a) shows displaced individuals are more likely to leave their neighborhoods regardless of their age at displacement. The effect is larger for individuals displaced at older ages, a traditionally less mobile group (Zaiceva, 2014). For individuals living close to future highways, the effect is smaller and statistically insignificant for all groups except the 1920 to 1930 cohorts.

Displaced individuals at both extremes of the age distribution are more likely to die younger. Panel (b) presents the estimates for age at the time of death. When displaced, individuals who were fifteen to twenty-five years old died 0.2 years younger. The effect is larger for individuals

[13] For example, addresses without a street number are geocoded to the middle point of the street.

displaced at older ages. Individuals born before 1910 die 0.65 years younger than the control group. The results control for birth year fixed effect; thus, the estimates can be interpreted as deviations from the cohort average. This highlights the negative consequences of forced relocation on mortality for older individuals. I find no evidence for individuals living close to future highways.

The results also suggest that individuals displaced at younger ages die in worse neighborhoods. Panels (c) and (d) present the estimates for college share and median home value. When looking at the educational distribution of the neighborhood, the results are negative and statistically significant for cohorts born after 1930. The median home value of the neighborhood is also lower. I find that individuals born between 1910 and 1930 living close to future highways die in places with a lower share of college graduates but not with lower home prices. The results show that forced relocation has heterogeneous effects across the life cycle, with significant impacts on both young and old individuals.

5.5 Heterogeneous Effects

Exploiting the rich set of information available in the 1940 census, I study whether displacement had heterogeneous effects on different demographic groups. I estimate a modified version of equation 2 that includes interactions between the treatment and the demographic indicators. In particular, the estimating equation follows:

$$\begin{aligned} y_i = \quad & \alpha + \lambda_{c(i,1940)} + \beta_1 Displaced_i + \beta_1^D Displaced_i \times H_i \\ & + \beta_2 Adjacent_i + \beta_2^D Adjacent_i \times \times H_i + \beta_3 H_i + \mathbf{X}'_i \mathbf{\Gamma} + \epsilon_i \end{aligned} \tag{3}$$

where H_i is an indicator that equals one if the individual belongs to a specific demographic group. The outcomes of interest are age at time of death, an indicator if the individual resides in the same neighborhood or city as they did in 1940, and the median home value of the neighborhood at the time of death. I estimate equation 3 for the following demographic groups: (i) homeownership status in 1940, (ii) race of the individual, (iii) outmigration of the city indicator, (iv) if the household of the individual in 1940 had a college-educated parent, and (v) if the individual resided in 1940 in a redlined neighborhood. The effect for the base level category corresponds to $\hat{\beta}_1$ and $\hat{\beta}_2$, whereas for the demographic group to $\hat{\beta}_1 + \hat{\beta}_1^D$ and $\hat{\beta}_2 + \hat{\beta}_2^D$, respectively.

The results are reported in Figure 2. Homeowners affected are more likely to leave their neighborhoods, whether displaced or living close to future highway developments. They do not, however, die younger nor die in worse neighborhoods. Displaced renters are more likely to leave their neighborhoods, die younger, and die in worse neighborhoods.

I find that white individuals leave their neighborhoods after highway construction, but Black

individuals do not. This result is consistent with the historical accounts that mentioned the lack of housing opportunities in other places of the city (Archer, 2020). Displaced individuals, regardless of their race, die younger, the effect being larger for Black individuals. The results also suggest that White individuals end up in worse neighborhoods, but Black individuals do not. Highway construction downgraded White individuals' neighborhoods by forcing them to move to less desirable neighborhoods. The same effect is not true for Black individuals due to the de facto and de jure restrictions they had on housing opportunities (Rothstein, 2017).

When exploiting differences in human capital, I find that individuals from families without a college education are the ones driving the results. Also, I do not find evidence that individuals who migrated from the city are different from their counterparts. Finally, I find that individuals who live close to future developments and in a redlined area die younger but do not die in worse neighborhoods, nor are they more likely to leave their neighborhoods. These results suggest that redlining might have played a role in the long-term outcomes of individuals living next to a highway, blocking their opportunities to move to a different neighborhood (Aaronson et al., 2022).

5.6 Potential Mechanisms

There are a number of potential mechanisms that could have been damaging to the health of affected individuals. These may include, for example, the loss of social capital due to the destruction of the neighborhood, psychological stress due to the uncertainty of the future, or the loss of access to health care. In this subsection, I will explore the health channel to explain these results.

While I do not have health records or medical expenditure data, I can exploit the health characteristics of the neighborhood in which the individual lived at the time of death. I focus on both mental and physical health. The data comes from the Centers for Disease Control and Prevention (CDC) for the year 2019 and includes the share of adults with poor mental health, the share of adults with poor physical health, and the share of adults with poor health for each census tract (CDC, 2019). I estimate equation 2 using these health characteristics as dependent variables.

Evidence in Table 6 suggests that some of the increased mortality due to displacement or proximity to future highways may be related to a deterioration of the healthcare network. Column (1) shows that both displaced and adjacent individuals live in neighborhoods with a larger obesity share. A similar picture emerges when analyzing the share of adults with a stroke in column (2) and the disability share in column (3). Looking at aggregate measurements of health, I find that individuals who were living close to future highways die in places with worse mental health, physical health, and overall health. Displaced individuals, on the other hand, resided in places with worse physical health and overall health. Together, this evidence suggests that a deterioration of the healthcare network could have been a mechanism through

which highway construction affected the life expectancy of individuals.

6 Highway construction and Neighborhood Dynamics

How do neighborhoods respond after highway construction directly or indirectly causes their residents to outmigrate? In this section, I examine whether the individual estimates from the previous section reflect the aggregate neighborhood dynamics. Specifically, I study the changes in demographic composition and housing values following the construction of a highway. To do this, I use a matched differences-in-differences design, where the treatment is the construction of a highway through the tract. The sample consists of 58 cities with spatial data available from 1930.[14] The analysis focuses on highway openings that occurred between 1950 and 1990. The final sample consists of a balanced panel of tracts with information from 1930 to 2020.

6.1 Matching Algorithm

To estimate the effect of highway construction on neighborhood dynamics, I build a sample of consistent boundary neighborhoods from 1930 to 2020. I utilize nearest-neighbor propensity score matching to pair each census tract where a highway was constructed between 1950 and 1990 with a control census tract. To do so, I first group census tracts based on their standard metropolitan area, a proxy for city, and the decade in which a highway was constructed. Then, I select as potential controls all census tracts that were never treated and were not intended to receive a highway on the Yellow Book maps. I exclude from the potential control group those tracts that were planned to receive a highway, as there is evidence that the expectation of highway construction can affect neighborhood dynamics (Brinkman et al., 2023).[15] Additionally, the control group must be located in a different city than the treatment to avoid contamination from spillover effects. Section 6.6 presents evidence in favor of this assumption To summarize, I match each treated tract with a tract from a different city that was never intended to receive a highway.

Next, I estimate a separate probit model on a cross-sectional sample of tracts consisting of the treated and potential control groups. The probit regressions relate the construction of a highway in the decade of treatment to the proximity of the tract's centroid to the city center, (log) population the three decades prior to construction, (log) White population the decade prior to construction, Black population quartiles before construction, and the (log) median rent in the tract the previous two decades before construction. Finally, using the estimated predicted values as the treatment propensity, each treated tract is matched with the untreated

[14] The 1950 census includes information for only 62 standard metropolitan areas. For these cities, I constructed spatial information for 1930 and 1940 from historical censuses. In Appendix Section C I show that the constructed data does a good job matching historical spatial variation for these decades.

[15] Figure F.9 shows that the results do not depend on this assumption.

tract having the closest propensity score. The matching procedure matches all the 1,562 events in the data, creating a well-balanced sample. A broader discussion of the matched sample can be found in Appendix Section F.1.

6.2 Dynamic Effect of Highway Construction

To study the effect of highway construction on neighborhood characteristics, I estimate the following model:

$$y_{nt} = \alpha_n + \lambda_{c(n)t} + \sum_{k=-2}^{4} \tilde{\theta}_k 1\{t = t_n^* + k\} + \sum_{k=-2}^{4} \theta_k 1\{t = t_n^* + k\} \times HWY_n + u_{nt} \quad (4)$$

where y_{nt} is an outcome variable, such as log Black population, for neighborhood n in decade t. HWY_n is an indicator equal to one if neighborhood n received a highway, the definition of an event, and zero otherwise. I select those highway segments that, once open, remain open until the end of my sample.[16] Thus, highway construction is an absorbing treatment, and the dummy variable takes the value of one for all periods. The variable $1\{t = t_n^* + k\}$ are event time dummies, where t_n^* is the last decade prior a highway opening for neighborhood n.[17] I control for neighborhood fixed effects, α_n, and city-by-decade fixed effects, $\lambda_{c(n),t}$, where $c(n)$ denotes the city associated with neighborhood n. In this specification, I omit the dummy for two decades before the highway opens so that θ_k identifies the changes in outcome y_{nt} between treated and counterfactual neighborhoods relative to the same difference at $k = -1$. I took this decision because I only observe segment openings, but the effect could start showing up when construction begins, which is unobserved in my data. u_{nt} is the error term. The regression results are weighted by the tract population in the decade before highway construction.[18] Standard errors are clustered at the census tract level.

6.3 Validity of the Design

I use a dynamic matched difference-in-differences design to study highway construction's demographic and economic effect on affected neighborhoods, frequently used in the literature (Fenizia and Saggio, 2023; Plotkin, 2024). This research design helps circumvent the known challenges to difference-in-difference when the model only relies on the variation in the timing of treatment and the treatment effect at each period relative to the treatment is not heterogeneous (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille,

[16] Although the movement to tear down highways has gained momentum lately (Lee, 2022), the number of segments that close during the period is low.

[17] Time units will be decades. When using matched tracts, I assign the event time of each treated neighborhood to its matched control. Therefore, the event time dummies are defined for treated and control tracts.

[18] The results are robust to the exclusion of population weights, as shown in Appendix F.

2022; Borusyak et al., 2024) The key identifying assumption is that the outcomes in treated and control tracts should have followed parallel trends in the absence of highway construction. I cannot directly test this assumption, but the research design allows for an indirect test by looking for violations of parallel trends in the pre-periods. Lending credibility to the design, placebo tests show no evidence of differential pre-trends between treated and control tracts over various outcomes. However, even without parallel trend violations, one might still worry that the matched control sample does not represent a valid counterfactual. I discuss some of these concerns below.

Unobserved sudden shocks. The results from the difference-in-difference design are threatened if treated tracts are affected by an unobserved and unrelated shock at the same time as treatment. Fenizia and Saggio (2023) presents evidence of how the research design used in this section ameliorates these concerns. First, highway construction occurred in different decades for different cities, so a single shock to one city/state will only have minimal effect on the estimates. Second, even if unrelated city shocks coincidentally co-vary with highway construction, these shocks are absorbed by city-decade fixed effects. Finally, the effects' timing is inconsistent with shocks triggering highway construction. The population responses do not start to materialize after a decade after the highway opens. It is unlikely that there is a large shock that will trigger highway construction but will only affect the population ten years afterward.

Spillovers from other tracts. As discussed in Section 6.1, I match treated tracts to out-of-city potential census tracts so that the control tracts are not indirectly affected by highway construction. However, one potential threat would occur if the control units may still suffer from spillovers from highway construction occurring in their city. To evaluate this, I drop all tracts within 3 kilometers of any highway built from the pool of potential controls. Figure F.10 shows that the main results are robust to dropping these units.

Differential trends in economic activity. Another potential concern is that an increase in economic activity may induce local governments to trigger the construction of a highway in a certain tract. This could happen if a tract had a boom in manufacturing and the local government decides to connect this place to the rest of the network. There are a few reasons that mitigate this concern. First, recent evidence has shown that the causality is usually reversed: highway construction is the factor that triggers the economic boom to a place (Herzog, 2021; Frye, 2024). Second, these shocks should be reflected in housing prices and homeownership rates, which I do not find any evidence for that. If anything, homeownership rates decrease after highway construction. However, if these economic shocks also have an independent effect on the demographics of the tracts, this would represent a threat to the empirical strategy of this section. I find no evidence consistent with this potential confounder. FiguresF.1, F.2, and F.3 show no systematic differences in the demographic or economic trends between treated and control tracts in the periods leading to treatment.

6.4 Results: Neighborhood Dynamics

Figure 3 reports the event-study coefficients $\hat{\theta}_k$ from Equation 4 on log total population, log Black and log White population, log Black share, log homeownership, and log median rent.

Panel (3a) shows that the log total population in treated tracts closely follows control tracts in the decades leading to highway construction, lending support to the validity of the research design. The log total population decreases modestly in the first decade after highway construction, and the average difference with the control group is not statistically significant. However, the total population decreases in the next three decades following highway construction, plateauing two decades after opening. The total population is 11% lower in the long run for treated tracts.

Who is leaving the neighborhood after highway construction? I run Equation 4 using log Black and log White population as outcomes, the results are shown in Panel (3b) and (3c). Similarly to the log total population, I find that treated and control tracts evolve similarly prior to treatment. Compared to the control tracts, I find that the decrease in total population is due to a decrease in the Black population residing in the tracts. The Black population decreases by 30% in the long run, while the White population remains unaffected. These results decrease the Black share of the treated tracts, as seen in Panel (3d). It is important to note that these results are relative to the control group. As seen in Figure F.1, during the study period, both control and treatment tracts experienced an increase in the Black population and a decrease in total and White population, with the Black share of both groups also increasing.

I study if the demographic changes are accompanied by changes in the housing market. I find that highway construction decreases homeownership rates in the short and long run, as shown in Panel (e). Treated tracts exhibit 10% lower homeownership rates than control neighborhoods. These results hint that highway construction could also impact capital accumulation for individuals living in treated tracts, as there is a strong association between homeownership and wealth (Aneja and Xu, 2021). Panel (3f) presents the results of highway construction on the log median rent. I find that rents modestly decrease after highway construction, with an average decrease of 2% in the three following decades. However, these effects are not statistically significant. Thus, the results suggest that large demographic changes do not affect housing prices, but alter the ownership structure of the neighborhood.

The results for the Black and White population go in a different direction than the findings of Bagagli (2023). Using an event-study design for the city of Chicago, the author finds that the total population decrease associated with highway construction is driven by an increase in the Black share of the tract. These differences arise from the different control group used in the analysis. I match treated tracts to out-of-town control tracts while Bagagli (2023) uses the time variation in treatment for the city of Chicago. My decision to use out-of-town control tracts is motivated by possible spillover effects from treated groups. Both anecdotally and empirically, I find evidence supporting this decision (Archer, 2020). In Figure F.12, I show that the results

are robust to using a potential control group within the same city.

Another paper that studies the effect of highway construction on the Black population is Mahajan (2023). Using an instrumental variables approach, the author finds that between 1970 and 1990, highway construction increased the Black population in neighborhoods with a large initial Black population. To overcome the endogeneity concerns, Mahajan (2023) instruments highway construction with historical highway plans and historical exploration routes, as done previously by Baum-Snow (2007), Duranton and Turner (2011), and Duranton et al. (2014). Thus, the results are a LATE and arise from comparing tracts planned to receive a highway and receive it versus those that did not. I drop from the pool of potential controls those neighborhoods that were planned to receive a highway given the evidence that the expectation of highway construction can change the demographic dynamics (Brinkman et al., 2023). In addition, as discussed in Section 2, local opposition was more effective in stopping highway construction in areas with higher social capital. So, the IV estimates may be conflated by unobserved shocks/amenities to the neighborhood that brought these high social capital residents into the area in the first place.

6.4.1 Robustness

Appendix Section F shows that the results are not sensitive to: (i) using levels instead of logarithms (Figure F.7), (ii) the exclusion of population weights (Figure F.8), (iii) including census tracts that were planned to receive a highway as potential controls (Figure F.9), (iv) dropping potential controls within three kilometers from any highway (Figure F.10), and (v) relaxing the out-of-city restriction for potential controls (Figure F.11).[19]

As an additional robustness check, I also test robustness to matching treated tracts with potential control tracts in the same city. With this procedure, the matching procedure matches only half of the events (772/1,562). Figure F.12 shows that the estimates are noisier and smaller in magnitude, as one would expect with a smaller sample and the presence of spillovers documented in Section 6.6. The results are qualitatively similar: the log total and Black population decreases. Although not statistically significant, the coefficients for the White population are negative. I do not find any effect for the log Black share, homeownership rate, or median rent.

6.5 Heterogeneities

Having documented the effect of highway construction on the tracts demographics, I examine whether the effect was homogeneous across neighborhoods with different characteristics. In particular, I study if the effect varies according to the Black population and the distance from the central business district.

[19]Distance from a tract to a highway is taken from the tract's centroid.

First, I study if the magnitude and direction of the effect vary depending on the number of Black families initially living in the tract before highway construction. The motivation for this analysis comes from the lack of relocation assistance provided by the 1956 Federal Highway Act. So, displaced individuals had to find housing in economically disadvantaged communities (Archer, 2020) In addition, highway construction occurred in the second part of the twentieth century, a period in which a great number of Black families were migrating from the U.S. south to the rest of the country (Althoff and Reichardt, 2024; Boustan, 2012). Thus, the demographic dynamics may vary depending on how many Black individuals lived in the tract before construction as, during the Great Migration period, migrant families sorted themselves into traditional Black communities (Derenoncourt, 2022). I examine this by splitting the sample of matched neighborhoods into two groups: above- and below-median Black population in the last decade before construction.

Figure F.4 reports the event-study coefficients of this analysis. The decrease in total population documented in the previous section comes from neighborhoods with an initial high Black population, as shown in Figure F.4a. These tracts experience a decrease in their White population, with the Black population remaining constant (Panels (b) and (c)), increasing the tract's Black share (Panel e). Neighborhoods with an initial low Black population see their Black population decrease while their White population remains constant, thus decreasing the Black share of the tract. White individuals leaving after highway construction, particularly from places with initially high Black population, is consistent with the "White flight" the literature has documented (Boustan, 2010) The results suggest that homeownership rates decrease in tracts with an initial large Black population but remain constant for those tracts with a lower initial Black population. I find no difference in log median rent for both groups, with an estimated effect not statistically different from zero.

How does the effect vary with distance to the CBD? There is evidence that highways are considered a dis-amenities in neighborhoods close to the CBD because the noise and pollution created by highways offset the gains from connectivity to other places of the city. In contrast, in the suburbs, the opposite effect is true (Brinkman and Lin, 2022). In the twentieth century, neighborhoods close to the CBD disproportionately housed racial minorities given their larger job opportunities (Boustan, 2012). In addition, Baum-Snow (2007) finds that highway construction leads to suburbanization, particularly from White households. Thus, the effect of highway construction is expected to vary with respect to distance to the CBD. I examine this by splitting the sample of matched tracts into quartiles of distance to the CBD.[20]

I find that highway construction leads to suburbanization and lower homeownership rates in neighborhoods closer to the CBD, in the line of Baum-Snow (2007). Figure F.5 reports the

[20]The first quartile consists of all neighborhoods between 0 and 3.3 kilometers from the CBD. The second quartile consists of tracts located from 3.3 to 6 kilometers from the CBD. The third quartile from 6 to 11.8 kilometers. Finally, the fourth quartile consists of all the tracts located further than 11.8 kilometers. Distances are taken from the tract's centroid.

results of the heterogeneity across the distance to the CBD. Highway construction decreases the log total population in tracts close to the city center but increases the total population in the top three quartiles. White households moving in or out of the tract mostly explain the effects on the total population. For tracts in the first quartile, the Black population remains constant for the first decade after construction but decreases in the long run. White households, on the other hand, outmigrates these tracts immediately after construction. The estimated effects for the log Black share are not statistically different from zero, but homeownership rates decrease after construction with no effect on the log median rent.

6.6 Spillovers between Neighborhoods

The 1956 Federal Highway Act did not include relocation provisions for displaced households. Housing alternatives at the time were primarily limited to economically disadvantaged communities (Archer, 2020). Consequently, the effects of highway construction may have spillover to other neighborhoods in the city. I test this hypothesis by examining the effect construction had on tracts next to treated tracts.

The effect of highway construction spread to neighborhoods next to affected tracts. Figure F.6 presents the event-study coefficients for neighborhoods adjacent to tracts where highways were built. For this exercise, treatment is define as the construction of a highway in the adjacent tract. The treatment date in inputed from the treated tract, and the matching procedure is the same. Neighborhoods adjacent to treated tracts saw their total population slightly decrease after construction. The Black population in these tracts increased the two decades after construction, accompanied by a decrease in the White population. As a result, the Black share increases in the two decades following construction, but the effect vanishes in the long run. Both homeownership rates and log median rent respond to these changes in the population. The results suggest that both outcomes decrease following construction. These results present quantitative evidence on the historical accounts that highway construction spillovers to other neighborhoods in the city (Rose and Mohl, 2012).

7 Conclusions

This paper studies whether the racial distribution of a city played a role in the location of highways built after the 1956 Federal-Aid Highway Act of 1956 using data from 62 cities in the US. Recent scrutiny from journalists, policymakers, urbanists, and community leaders has drawn attention to the deliberate efforts of state planners to use highway projects to displace Black Americans from their traditional neighborhoods. The findings provide empirical support for these anecdotal accounts, showing that the proportion of Black residents in a neighborhood is a significant predictor of the location of future highway developments.

The estimated effects are robust to a battery of sensitivity and robustness checks. Fur-

thermore, these results are economically significant, as a one standard deviation increase in the Black share corresponds to an approximate 20% reduction in the mean median land value. Importantly, these results indicate that the placement of highways through Black tracts is not primarily driven by federal initiatives, but rather by deliberate actions taken by state and local officials. However, contrary to some accounts, the evidence suggests that highways were not consistently located between neighborhoods with different racial compositions.

The second set of results shed light on the consequences of highway construction for the affected tracts. Employing matched difference-in-difference model, the analysis reveals that the construction of highways is associated with a subsequent decline in the Black population, while no significant effect is observed for the White population. As a result, the proportion of Black residents in the tract tends to decrease following highway construction. Additionally, the findings indicate that the construction of highways leads to a reduction in homeownership rates, although housing prices remain unaffected.

The third set of results suggest that highway construction negatively impacted individuals displaced by and residing adjacent to future developments. By geocoding the full-count census of 1940 and linking it to mortality records, I exploit the quasi-random variation of highway placement in space within 200 meters of future construction. I find that both displaced and adjacent individuals are less likely to live in the same neighborhood at the time of death compared to individuals living between 100 and 200 meters of a future highway, the effect being stronger for displaced individuals. I also find evidence that highway construction reduces a person's life expectancy.

This paper contributes to the growing literature studying the Interstate Highway System, one of humankind's largest public works. By uncovering the role race played in the location of highways, this paper makes a small step towards understanding how public works, in general, and highways, in particular, impact city dwellers. Collecting and analyzing micro-level data on those relocated by highway developments would be extremely helpful for future research, especially now that the US is in the process of re-thinking its infrastructure.

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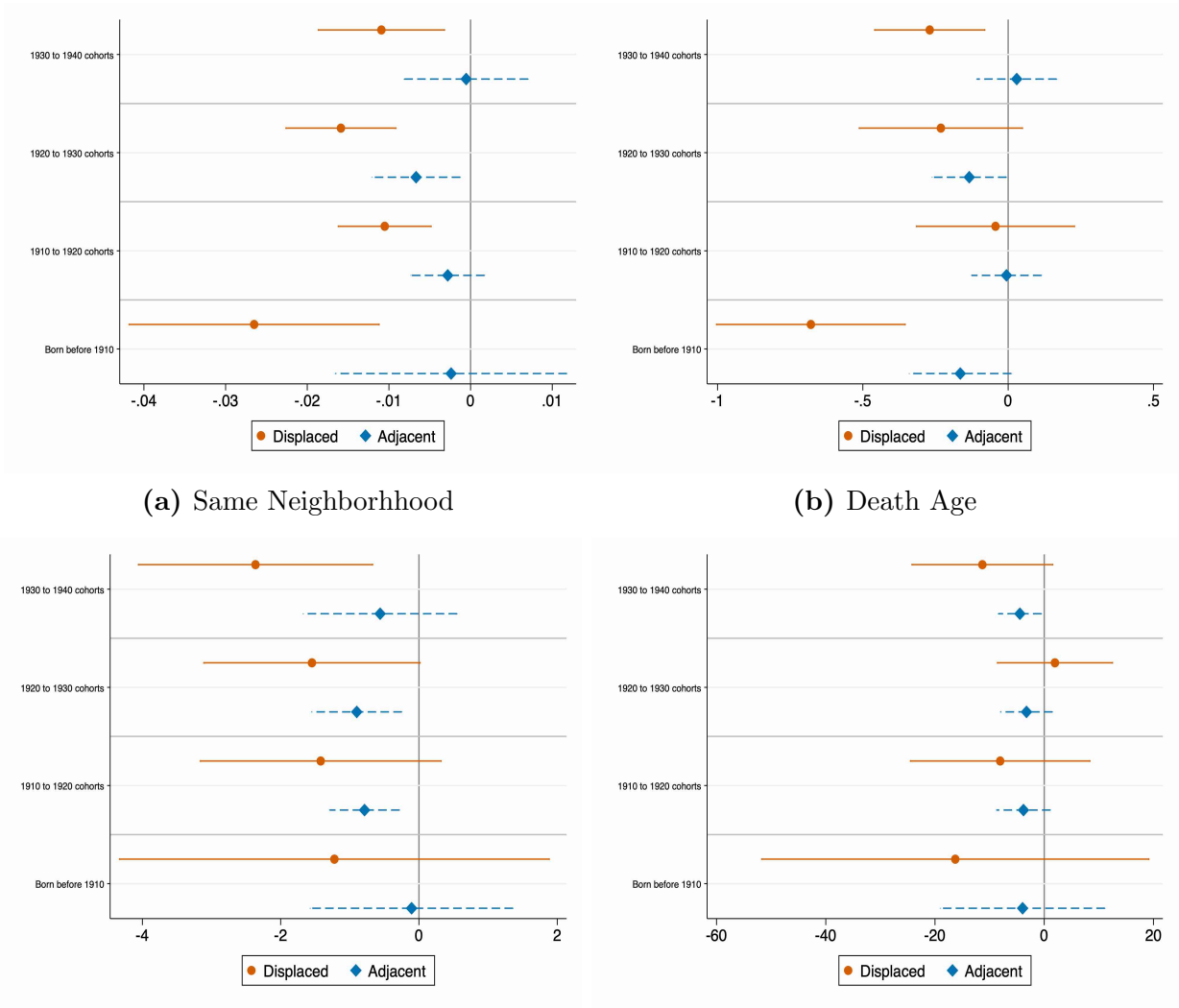
Figures

Figure 1: Effects Across the Life-Cycle



(a) Same Neighborhood

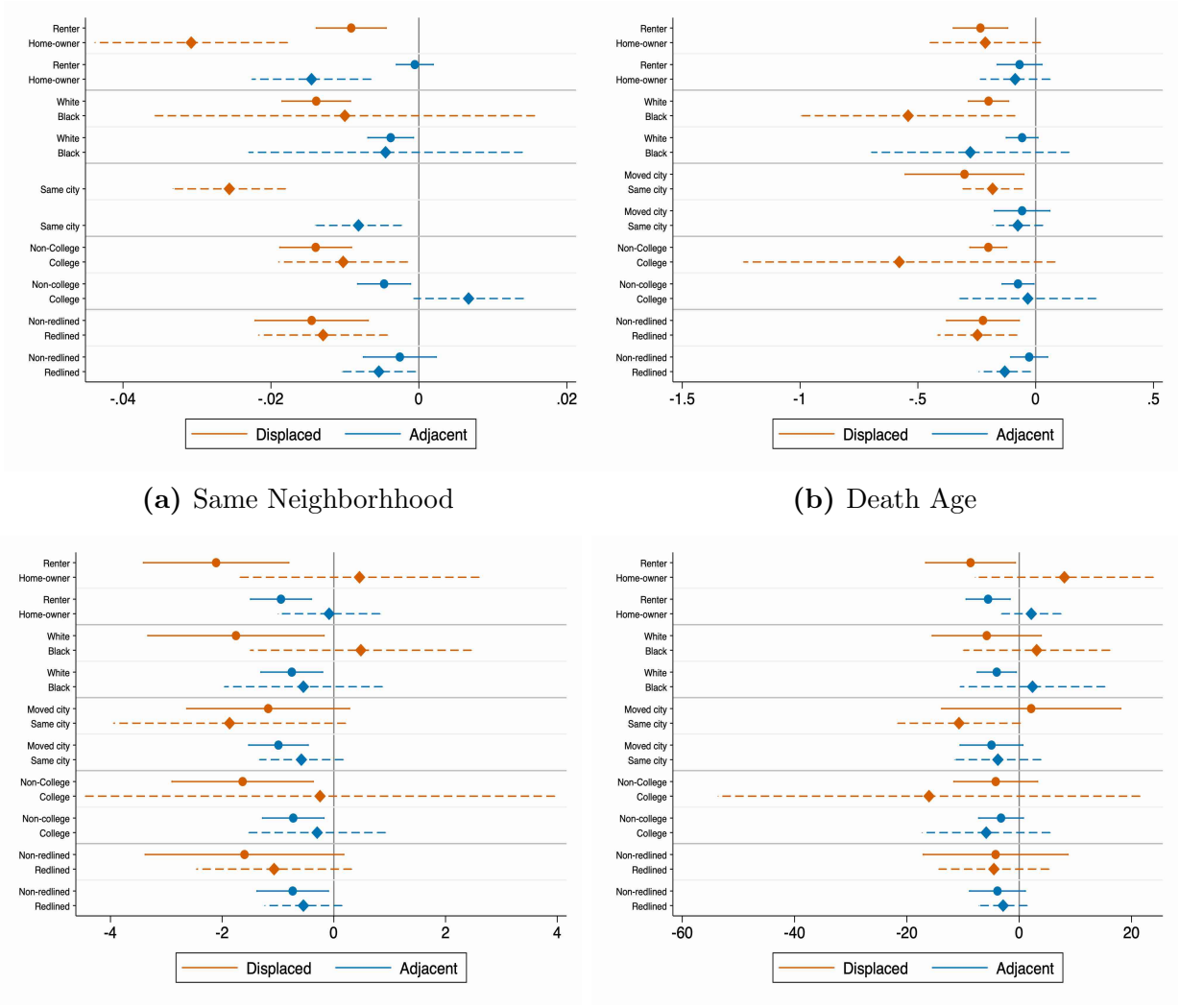
(b) Death Age

(c) College Share

(d) Median Home Value

Note: Highway segments opened between 1950 and 1960 are included in the sample. Each panel presents the coefficients of a different dependent variable. Each row presents the estimates for the corresponding cohort in the y-axis. All panels control for race, gender, homeownership, city, and birth year fixed effects. Standard errors are clustered at the city level.

Figure 2: Heterogeneous Effects



(a) Same Neighborhhood

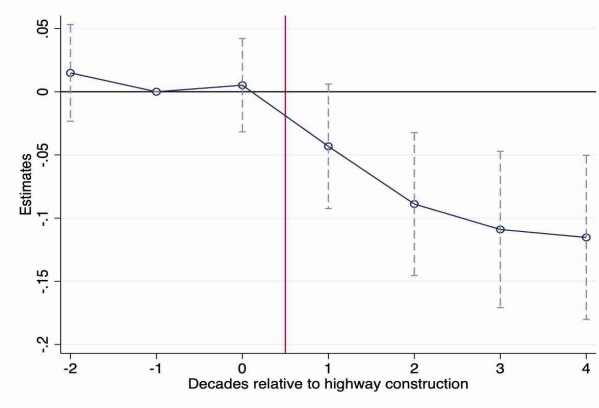
(b) Death Age

(c) College Share

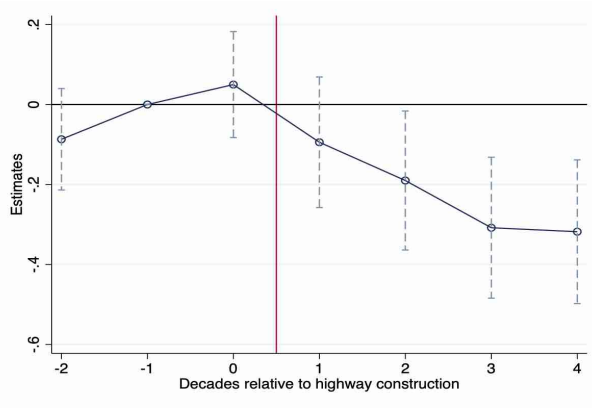
(d) Median Home Value

Note: Highway segments opened between 1950 and 1960 are included in the sample. Each panel presents the coefficients of a different dependent variable. Each row is a different regression with the heterogeneity corresponding to the variable in the y-axis. All panels control for race, gender, homeownership, city, and birth year fixed effects. Standard errors are clustered at the city level.

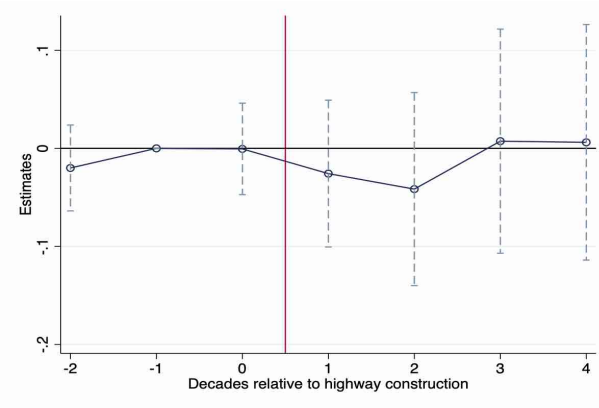
Figure 3: Event-Study Coefficients



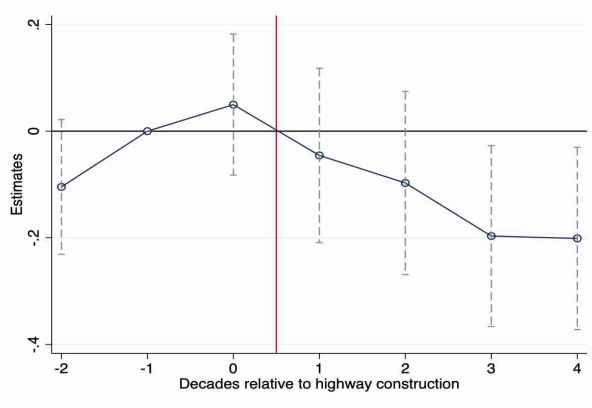
(a) Log Total Population



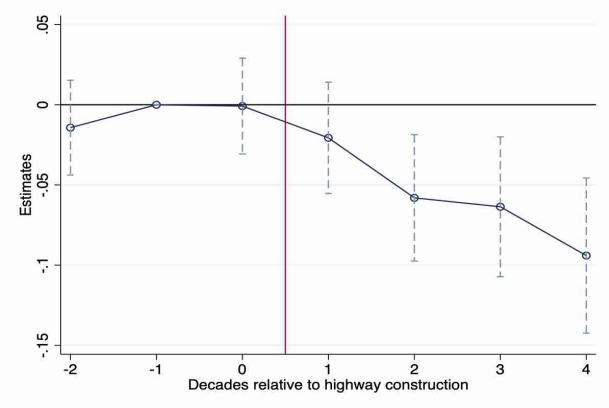
(b) Log Black Population



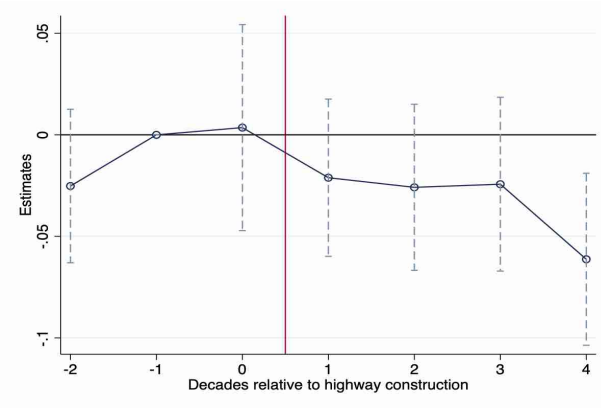
(c) Log White Population



(d) Log Black Share



(e) Log Home-Ownership Share



(f) Log Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. The coefficients at $k = -1$ are normalized to zero. The sample is weighted by the log population of the tract in the decade before highway construction, and standard errors are clustered at the census tract level. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the log total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share of the tract, Panel (e) on the log home-ownership share, and Panel (f) shows the effect on the log median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

Tables

Table 1: Determinants of Highway Placement

	Dependent Variable: Indicator if the tract is crossed by					
	Built highway					Plan
	(1)	(2)	(3)	(4)	(5)	(6)
Black share	1.179[a]	0.996[a]	1.009[a]	0.942[a]	0.902[a]	0.137
	(0.314)	(0.306)	(0.302)	(0.299)	(0.271)	(0.239)
(log) Median income	-0.028[b]	-0.016[c]	-0.009	-0.014	-0.012	-0.007
	(0.012)	(0.009)	(0.016)	(0.013)	(0.010)	(0.011)
High school share	-0.003[b]	-0.001	-0.001	-0.000	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
(log) Median rent		-0.079[a]	-0.064[a]	-0.061[a]	-0.060[a]	-0.005
		(0.025)	(0.022)	(0.021)	(0.018)	(0.035)
(log) Median home value		-0.094[a]	-0.120[a]	-0.112[a]	-0.085[a]	-0.093[a]
		(0.030)	(0.023)	(0.023)	(0.022)	(0.021)
Distance to city center				-0.008[a]	-0.006[a]	-0.008[a]
				(0.001)	(0.001)	(0.002)
Highway planned					0.290[a]	
					(0.042)	
Mean dependent var.	0.214	0.217	0.218	0.218	0.218	0.218
Geo. Controls	No	No	Yes	Yes	Yes	Yes
Obs.	18,242	17,210	16,944	16,944	16,944	16,944
R^2 (Adj.)	0.086	0.094	0.155	0.169	0.239	0.115

Note: Each column corresponds to a different regression. The unit of observation is a census tract. The dependent variable is an indicator if a highway was built or planned through the tract. The vector of controls includes the (log) area and slope of the tract, distance to the nearest river, an indicator if the governor of the state was part of the Republican party, the state (log) number of car registrations per 10k inhabitants, and the distance to the 1921 railroad network. All columns include city fixed effects. Coefficients are reported with standard errors clustered at the city level. [a] indicates the coef. is significant at the 1%, [b] at the 5%, and [c] at the 10%. Regressions are weighted by the census tract's population.

Table 2: Characteristics of Displaced Individuals

	Displaced	Distance to the closest highway					Rest of the city
		0 and 100m	100 and 200m	200 and 300m	300 and 400m	400 and 500m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Number of displaced individuals:							
Total population	131,486	882,590	808,629	844,234	855,238	857,239	40.434m
Population share	0.29%	1.95%	1.79%	1.87%	1.89%	1.90%	89.53%
Panel B: Individual level characteristics:							
Black	0.132	0.098	0.097	0.103	0.095	0.093	0.076
	(0.338)	(0.297)	(0.296)	(0.303)	(0.293)	(0.290)	(0.265)
Immigrant	0.166	0.173	0.175	0.178	0.178	0.178	0.146
	(0.372)	(0.378)	(0.380)	(0.382)	(0.382)	(0.383)	(0.353)
First gen. US born	0.161	0.165	0.165	0.167	0.167	0.165	0.134
	(0.367)	(0.371)	(0.371)	(0.373)	(0.373)	(0.371)	(0.340)
High school share	0.213	0.231	0.246	0.247	0.253	0.264	0.311
	(0.409)	(0.421)	(0.430)	(0.431)	(0.435)	(0.441)	(0.463)
Labor force	0.646	0.642	0.643	0.641	0.640	0.641	0.637
	(0.478)	(0.479)	(0.479)	(0.480)	(0.480)	(0.480)	(0.481)
Employed	0.890	0.894	0.901	0.901	0.903	0.903	0.920
	(0.312)	(0.308)	(0.298)	(0.299)	(0.295)	(0.297)	(0.271)
Occupational score	24.383	25.034	25.344	25.479	25.556	25.659	26.318
	(9.464)	(9.512)	(9.779)	(9.834)	(9.873)	(9.919)	(10.301)
Panel C: Household level characteristics:							
Homeowner	0.218	0.260	0.257	0.258	0.269	0.270	0.353
	(0.413)	(0.439)	(0.437)	(0.437)	(0.443)	(0.444)	(0.478)
Household size	3.439	3.474	3.490	3.500	3.525	3.494	3.493
	(2.027)	(2.043)	(2.034)	(2.019)	(2.033)	(2.027)	(1.952)
Log home value	10.562	10.619	10.660	10.691	10.708	10.733	10.852
	(0.985)	(0.960)	(0.979)	(0.955)	(0.961)	(0.931)	(0.906)
Log rent	5.728	5.811	5.887	5.907	5.936	5.959	6.001
	(0.715)	(0.780)	(0.795)	(0.804)	(0.807)	(0.807)	(0.832)

Note: Each observation corresponds to an individual in the 1940 census. Displacement and the proximity to highways are calculated for all segments opened between 1950 and 1960. Mean values are reported for each variable, with the corresponding standard deviation in parentheses. High school share and labor force are calculated for the sample of individuals aged 25 to 55. Employed is calculated for individuals aged 25 to 55 in the labor force. Occupational score is calculated for individuals aged 25 to 55 and employed. Home value and rent are conditional on ownership status.

Table 3: Balance Test

	Displaced	Adjacent	Mean	Std. Dev.	Obs.
	(1)	(2)	(3)	(4)	(5)
Number of subfamilies in the household	-0.001	-0.006	0.112	0.352	1,161,973
	[0.796]	[0.005]			
Number of own children in the household	0.039	0.026	0.735	1.324	1,161,973
	[0.002]	[0.000]			
Married (indicator)	-0.012	-0.001	0.431	0.495	1,161,973
	[0.001]	[0.437]			
(log) Monthly contract rent	-0.106	-0.057	5.948	0.747	827,965
	[0.022]	[0.000]			
(log) House value	-0.061	-0.034	10.735	0.960	294,688
	[0.049]	[0.049]			
College graduate (indicator)	-0.005	-0.003	0.025	0.157	1,161,973
	[0.012]	[0.000]			
High school graduate (indicator)	-0.028	-0.016	0.184	0.387	1,161,973
	[0.004]	[0.000]			
Middle school graduate (indicator)	-0.018	-0.007	0.727	0.446	1,161,973
	[0.023]	[0.001]			
Employed (indicator)	-0.014	-0.008	0.859	0.348	518,691
	[0.000]	[0.000]			
Labor force participation (indicator)	-0.009	-0.005	0.559	0.496	927,266
	[0.003]	[0.001]			
Occupational score	-0.422	-0.314	24.628	9.181	510,399
	[0.001]	[0.000]			
Born outside the U.S. (indicator)	0.008	0.001	0.196	0.397	1,161,973
	[0.082]	[0.866]			
Same house as 5 years ago	0.003	0.010	0.375	0.484	1,083,998
	[0.572]	[0.006]			
Same community as 5 years ago	0.016	0.007	0.887	0.317	1,083,998
	[0.000]	[0.001]			
Within county mig. in the last 5 years	0.007	-0.006	0.539	0.498	1,083,998
	[0.218]	[0.147]			
Within state mig. in the last 5 years	-0.001	0.000	0.035	0.184	1,083,998
	[0.595]	[0.949]			
Between state mig. in the last 5 years	-0.007	-0.003	0.045	0.206	1,083,998
	[0.000]	[0.006]			

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. Column (1) reports the coefficient of the treatment indicator for the Displaced group. Column (2) reports the coefficient of the treatment indicator for the Adjacent group. The control group corresponds to individuals living between 100 and 200 meters from a future highway. All regressions include city, birth year, homeownership, race, and gender fixed effects.

Table 4: Long-term Effects of Highway Construction

	Same Neigh. (1)	Same City (2)	Redlined Neigh. (3)	Death Age (4)	Survival to age 70 (5)
Displaced	-0.014[a]	0.014	0.005	-0.230[a]	-0.010[a]
	(0.002)	(0.014)	(0.007)	(0.044)	(0.003)
Adjacent	-0.004[b]	0.016[a]	0.005[b]	-0.066[c]	-0.001
	(0.002)	(0.004)	(0.002)	(0.036)	(0.001)
Mean dep. var.	0.022	0.607	0.061	79.077	0.894
R-squared (adj)	0.027	0.019	0.029	0.863	0.526
Observations	35,924	35,924	35,924	33,964	33,964

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died after 1995. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 100 and 200 meters from a future highway. Each column corresponds to a different regression. The dependent variable in column (1) is an indicator that equals one if the individual lives at time of death in the same neighborhood they lived in 1940. In column (2), the dependent variable is an indicator that equals one if the individual lives in the same city they lived in 1940. Column (3) uses an indicator taking value equal to one if the residence at time of death was located in a redlined area as dependent variable. Column (4) use the age at death as dependent variable. Finally, the dependent variable in Column (5) is an indicator if the individual survived until the age of 70. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table 5: Neighborhood Characteristics at Time of Death

	High School Share (1)	College Share (2)	Employment Share (3)	Log Median Income (4)	Log Median Home Value (5)	Log Avg. Rent 2 bedroom (6)
Displaced	-1.011[a]	-1.608[b]	-0.005[a]	-0.018	-0.014	-0.017[b]
	(0.327)	(0.728)	(0.002)	(0.012)	(0.016)	(0.007)
Adjacent	-0.313[b]	-0.757[a]	0.000	-0.010[b]	-0.013[b]	-0.009[a]
	(0.149)	(0.277)	(0.001)	(0.004)	(0.006)	(0.003)
Mean dep. var.	85.026	34.132	0.581	10.975	12.111	6.958
R-squared (adj)	0.146	0.098	0.059	0.120	0.236	0.263
Observations	35,834	35,834	35,922	35,791	35,305	28,312

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died after 1995. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 100 and 200 meters from a future highway. Each column corresponds to a different regression. The dependent variables correspond to the neighborhood-level characteristics of the residence at time of death. The dependent variable in column (1) corresponds to the share of adults living in the neighborhood who have completed high school. In column (2), the dependent variable is the college share. Column (3) uses the employment share as dependent variable. Columns (4) and (5) use the log median income and log median house value, respectively. Finally, column (6) uses the log average rent for a two bedroom apartment as dependent variable. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table 6: Results for Displaced and Adjacent Individuals

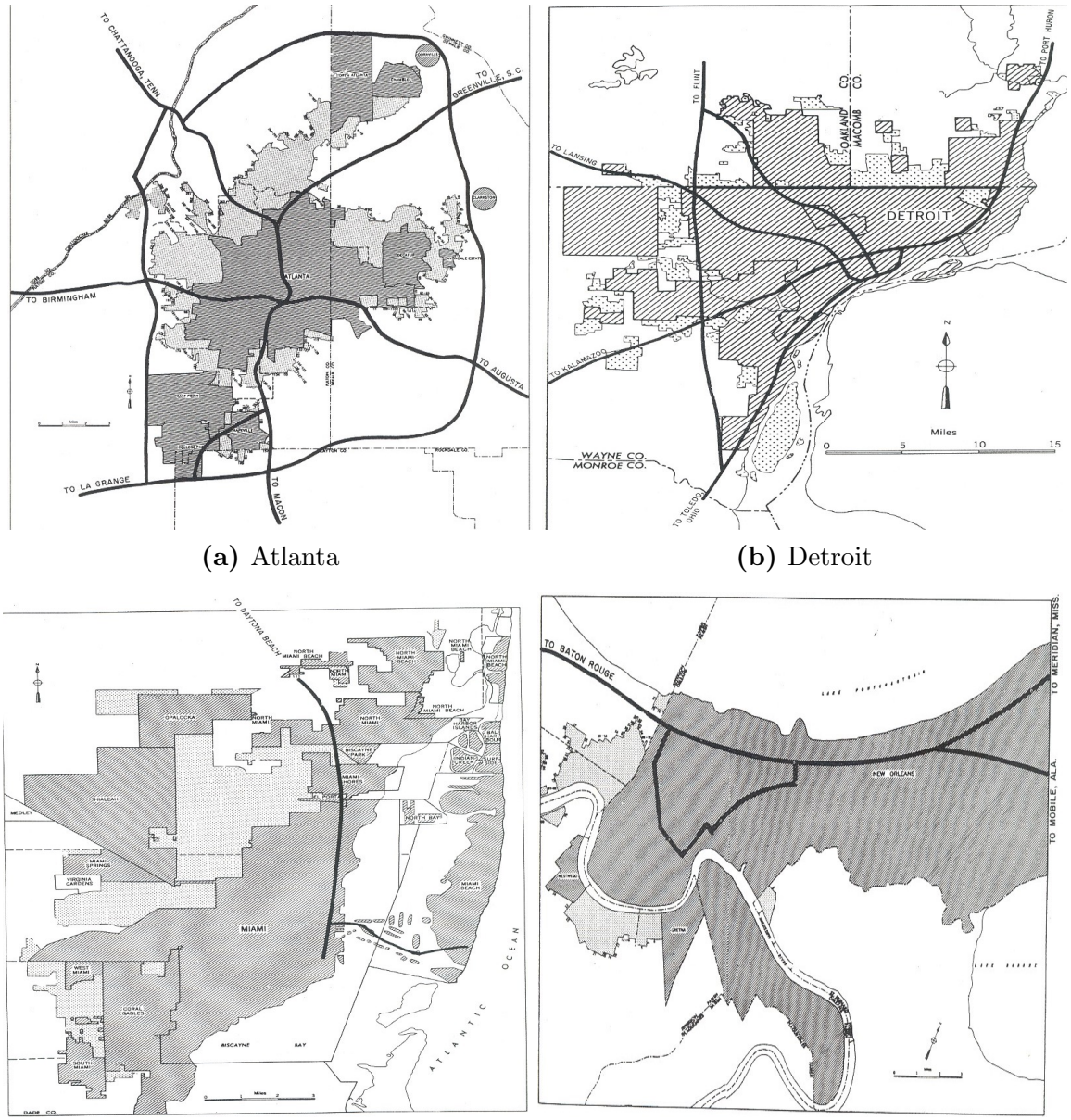
	Obesity Share (1)	Stroke Share (2)	Disability Share (3)	Poor Mental Health Share (4)	Poor Physical Health Share (5)	Poor Health Share (6)
Displaced	0.179	0.031[b]	0.399[b]	0.107	0.154[b]	0.321[b]
	(0.160)	(0.014)	(0.163)	(0.109)	(0.059)	(0.140)
Adjacent	0.125[c]	0.005	0.110[c]	0.093[c]	0.062[a]	0.135[b]
	(0.068)	(0.014)	(0.060)	(0.050)	(0.022)	(0.057)
Mean dep. var.	31.341	3.093	28.125	15.132	11.114	16.092
R-squared (adj)	0.315	0.138	0.159	0.198	0.171	0.199
Observations	32,176	32,176	32,176	32,176	32,176	32,176

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died after 1995. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 100 and 200 meters from a future highway. Each column corresponds to a different regression. The dependent variables correspond to the neighborhood-level characteristics of the residence at time of death. The dependent variable in column (1) corresponds to the share of adults living in the neighborhood who are obese. In column (2), the dependent variable is the share of adults on a tract who had suffered a stroke. Column (3) uses the share of adults with a physical disability. Columns (4) and (5) use the share of adults with poor mental and physical health, respectively. Finally, column (6) uses the share of adults with poor health status as dependent variable. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Appendix and Supplementary Material

A Appendix Figures

Figure A.1: Yellow Book Maps

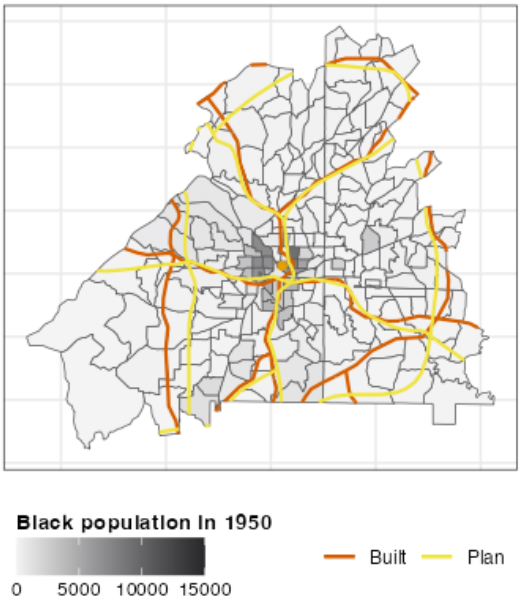


(a) Atlanta **(b)** Detroit

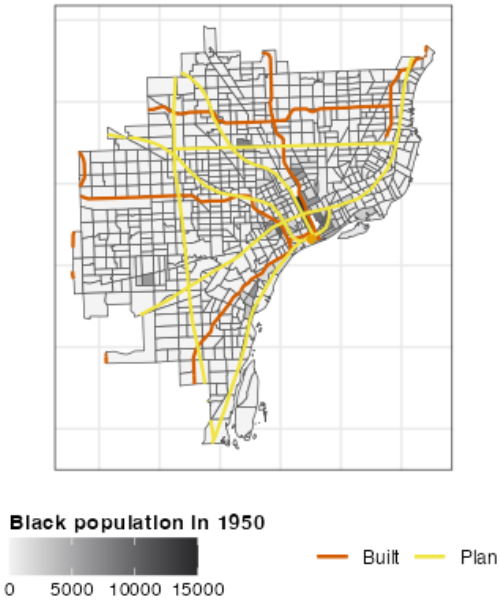
(c) Miami **(d)** New Orleans

Note: The figure includes the maps in the Yellow Book for the cities of Atlanta, Detroit, Miami, and New Orleans.

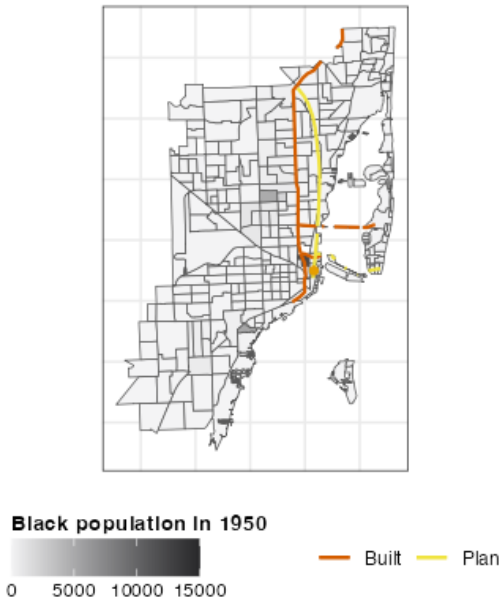
Figure A.2: Racial Distribution, Highways, and Planned Routes



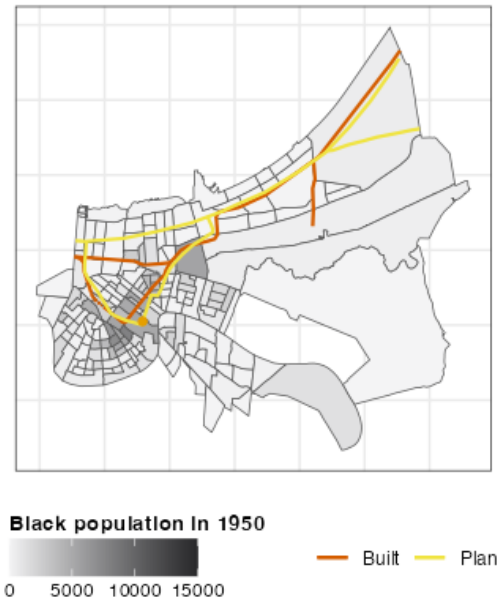
(a) Atlanta



(b) Detroit



(c) Miami



(d) New Orleans

Note: The figure includes maps for Atlanta, Detroit, Miami, and New Orleans. Each observation is a census tract, and its filling corresponds to the number of Black residents in the tract. Depicted in red is the highway network that was built. The network planned in the Yellow Book is presented in yellow. Finally, the city center is plotted in orange.

Figure A.3: Disruptive Effects of Highway Construction

(a) Claiborne before Interstate 10

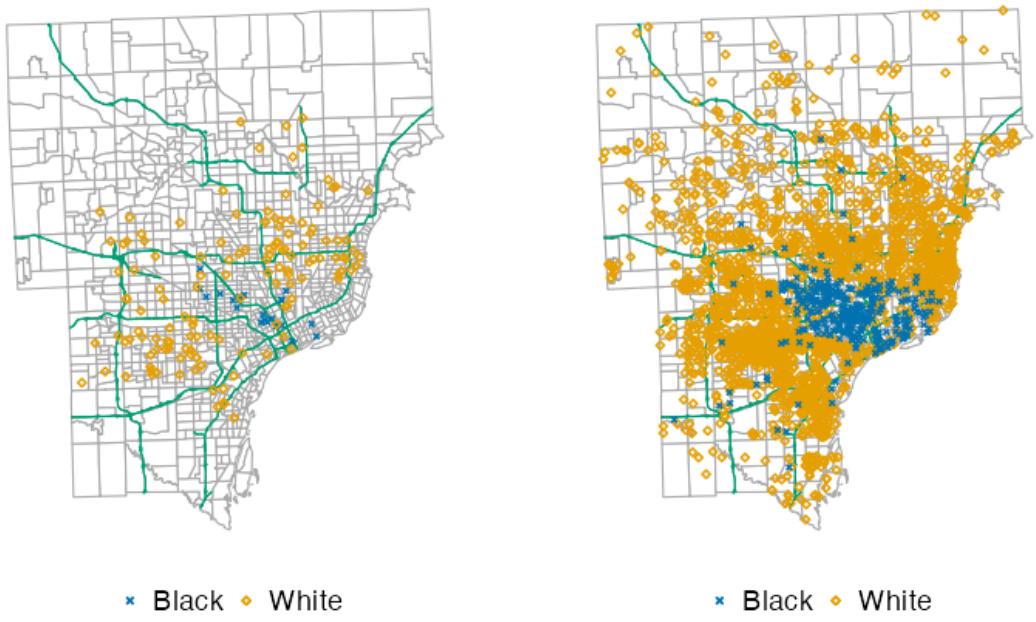
(b) Claiborne after Interstate 10

(c) Black Bottom before Interstate 75

(d) Black Bottom after Interstate 75

Note: The figure presents a visual representation of two neighborhoods, Claiborne in New Orleans and Black Bottom in Detroit, before and after highway construction.

Figure A.4: Location of residents of Detroit in 1940 at their time of death



(a) Displaced **(b)** Adjacent

Note: The observational unit corresponds to the location at the time of death of individuals displaced by or residing close to a future highway in Detroit. The sample consists of individuals residing in Detroit before and after construction, split by the recorded race of the individual. Panel (a) presents the location at the time of death of individuals displaced by highway construction. Pabel (b) presents the location at the time of death of individuals residing within 100 meters of a future highway.

B Appendix Tables

C Data Appendix

C.1 Cleaning historical addresses

I geocode the restricted access full-count censuses from 1930 to 1940 and focus on the 285 counties that contained one of the 168 Standard Metropolitan Areas in 1950. (Ruggles et al., 2024). [21] [22] Rural addresses usually have missing street names and enumeration, introducing inaccurate geocoding. For this reason, I focus only on urban areas in these counties. The sample includes 82.16% of the urban population in the US in 1940. [23] To clean historical addresses, I follow the procedures recommended by Logan and Zhang (2018). In particular, I start by parsing raw addresses and numerations.

To parse the addresses, I assume that enumerators stayed on the same side of the street when moving from building to building and then followed the algorithm described below:

1. *Dwellings IDs:* I work with the dwelling ID provided by IPUMS. Street name and numeration are constant across dwelling IDs. I also keep the state, county, city, and enumeration district.

2. *Extract the street name:* Sometimes it contains additional information. For example, it may include a word like "Cont." or "Rear". In these cases, I consider the street name to be the same as the previous record. In some cases, the street name contains the house number, for example, in large apartment complexes, hotels, or hospitals. In those cases, I store the house number by parsing the street name in the search for street numbers in addition to other keywords such as apartment, hospital, and hotel.

3. *Carrying forward a street name:* Some addresses have a valid house number but no street names. To fill in the missing information, I carry forward the street name from the previous record under two conditions. First, the two records should be on the same enumeration page. Second, the adjacent records should not have a skip in the house number larger than 6, taking into consideration if the numeration is odd or even.

4. *Cleaning house numbers:* There is considerable variation in the way house numbers are recorded. To standardize the records, I set to "missing" any record that includes the following fields:

   (a) A continuation of the previous house number: 'cont', 'con't', 'contd', 'cont'd', etc.

[21] I am waiting for the release of the restricted access full-count 1950 census, which was the last census before the 1956 Federal Highway Act.

[22] Standard Metropolitan Areas are then called Metropolitan Statistical Areas.

[23] New England used a different approach to define urban areas. This sometimes leads to the same county housing two urban areas. To simplify the analysis, I assign the county to the urban area with the largest population. Thus, the total number of SMAs in my sample is 161.

(b) A location relative to the previous house number: 'rear', 'basement', '1/2', 'back', 'front'. Unless the house number is within the text (5147rear), these records are set to missing.

(c) A house number that indicates a floor, indicated by 'floor' or 'fl' in the text.

(d) Apartment numbers indicated by 'apt' in the text.

(e) A combination of numbers and letters that do not follow the standard format of a house number, like '[0-9][ ][a-zA-Z]' or '[0-9][-][a-zA-Z]'. For example: 7-B. These cases are most likely the rooms in a hotel.

5. *Dealing with missing house numbers:* I interpolated missing house numbers in a similar way as I did with missing street names. The only difference is that I take into consideration the side of the street. Some interpolations result in suspicious numbers and are cataloged as missing. For example, the interpolation may result in house numbers far outside the logical range of house numbers. To identify these anomalies, I compare the interpolated house number to the range of house numbers on the same side of the street in the same ED. If the interpolated house number is outside the range or has a skip larger than 6, I set it to missing.

Once the historical addresses are standardized, I proceed to clean them by using the historical addresses for each decade available in *StevenMorse.org*. This website includes addresses for the 1910, 1920, 1930, and 1940 censuses in each enumeration district. This allows me to overcome possible errors in the OCR process of the historical addresses or during the standardization of the data. To do so, I perform a probabilistic match between the standardized street name and the street name in SM's records for each ED. I do a Jaro-Winkler distance match between the standardized street name and the street name in SM's records, with a similarity tolerance of smaller than 0.2. I use the street name in SM's records for those records with a match. If there is no match, due to the similarity being too low or no match, I use the street in the census records.

As a robustness for the address cleaning procedure, I take advantage of the extraordinary job done by Logan et al. (2023), who cleaned and gave a consistent format to street addresses and numeration for 181 cities. Their definition of city differs from mine. They use cities with at least 30 thousand inhabitants in at least one decade between 1910 and 1940, whereas I use the 1950 Standard Metropolitan Areas. I use this data as an additional robustness check for the address-cleaning procedure.

Once I cleaned and standardized, I proceeded to geocode the census addresses. Given that the confidentiality agreement signed with Ruggles et al. (2024) does not allow using cloud geocoding, I rely on ArcGIS Streetmap Premium. The software does the geocoding within your computer, circumventing the use of external geocoders. I dropped all the observations that had suspicious geocoding. In particular, I set the geocoding to missing those records that are

geocoded to different cities, counties, or states, even if the match addresses belong to the same metropolitan areas.[24] I also drop the geocoding for those records with a *match score* equal to or higher than 85 and with a unique address match, as in Hynsjö and Perdoni (2022).[25] In addition, I also drop those matches that do not allow me to identify an address, such as those that only match the street. The cleaning and geocoding procedure leaves me with 45,770,203 geocoded individuals in the 1940 census, which accounts for 80.85% of urban dwellers in the counties I study. Table C.2 shows a breakdown of the number of geocoded dwellings by SMA.

Geocoding historical addresses with modern geocoders could be problematic because street names and numerations may change over time. However, I do not think these concerns invalidate the results. First, I only study those individuals living in dwellings, which the geocoder was able to match, and the match passed all the filters mentioned. If an address is not matched, either because the street is destroyed or the street has changed its name, the record will not be considered in the analysis. This leads to fewer observations to work with, but an accurate geocoding. Second, modern geocoders are equipped to handle missing numeration. This is particularly helpful when the reason behind the missing numeration is highway construction. In this case, the geocoder will match the address to the street segment that is closest to the original address. The geocoder flags this type of match as *StreetAddress*. As a robustness and to minimize measurement errors, I flag those observations with a perfect match score. These observations are the ones that, in addition to passing all the aforementioned filters, have a match score of 100. Thus, these observations' geometry will come from an interpolation at the block level, minimizing the location error. In other words, these observations will be located in the correct block, and their exact location within this block will come from a linear interpolation based on their enumeration.

To study if there is any selection into geocoding, I compare the characteristics of the geocoded individuals with the non-geocoded individuals. Table C.3 presents the results for the 1940 census. The analysis shows some small differences between the geocoded and non-geocoded groups. Black individuals are less likely to be geocoded, and geocoded individuals are more likely to be homeowners. The average home value is larger for the non-geocoded group, whereas rents are higher in the geocoded group. Overall, the differences are small and do not seem to be systematic.

C.2 Highways data

Highway information comes from Open Street Maps (OSM). I download the actual network of highways and their exits from OpenStreetMap (2017) and then link it to the PR-511 database from Baum-Snow (2007) to get the opening date of each highway segment financed by the

[24] For example, the address 24 SW 3rd Ave in Miami was geocoded to 24 SW 3rd Ave in the city of Boca Ratón. These types of matches are not in the final sample.

[25] The match score of a candidate address ranges from 0 to 100. A score of 100 corresponds to a perfect match. The score is penalized according to the number of changes the geocoder needs to do to match the address.

Highways Act. Since I'm interested in the displacement effect of highway construction, I include exits as part of the highway database. The network in OSM is recorded as *Polylines* with negligible width, whereas in reality, highways are polygons. I exploit the information in OSM when possible to convert the polylines into polygons. In particular, I use the number of lanes multiplied by 3.65 meters (12 feet), the average width of an Interstate lane, plus 5 meters to account for the berm (Federal Highway Administration, 2007). When the number of lanes is unavailable, I input the number of lanes to four, which is the median number of lanes a highway has in the sample. The buffer choice was made based on the median number of lanes a highway has in the sample, four, and the minimum lane width recommended by Federal Highway Administration (2007). This buffer is the one used in the subsequent analysis.

C.3 Identifying displacement

I identify displaced individuals as those living in dwellings within the highway buffer. For every individual, I estimate the distance to the nearest highway and flag the record as displaced if the distance to the buffer is zero. As discussed before, modern geocoding engines can interpolate the record's location from the range of addresses nearby. Thus, if highway construction destroys a segment of the street, the geocoder will still match the address to the correct street segment, and hence, I can identify displaced households. I classify an individual as living next to a highway if the dwelling is within 100 meters of the highway buffer.

C.4 Linkage to administrative mortality records

To study the long-term consequences of highway displacement, I use the linkage between the 1940 census and the administrative mortality records from Goldstein et al. (2023). The linkage is done using the algorithm developed by Abramitzky et al. (2017). Table C.4 shows a balance test between those records matched to mortality records and those not. Individuals matched to mortality records are younger due to the double truncated mortality years (1988 to 2005). Consequently, individuals are less likely to be married, have a college degree, or be employed. The matched sample also underrepresents Black individuals and immigrants. The matched sample is similar to the non-matched sample for the rest of the variables. The results suggest that the sample differs from the population in some aspects, but the differences are small and do not present a systematic bias that can confound the results.

C.5 Historical neighborhoods

To study the long-term consequences of highway construction, I use a balanced panel of time-consistent neighborhood definitions from 1930 to 2020. I expand the spatial information available for 1930 and 1940 by aggregating the definitions of the geocoded complete census into 2010 census tracts. I restrict the sample to tracts that are part of the 62 SMA with spatial

information available in 1950. [26] To avoid bias coming from the geocoding process, I drop tracts whose population increased or decreased by a factor of ten in consecutive census years.

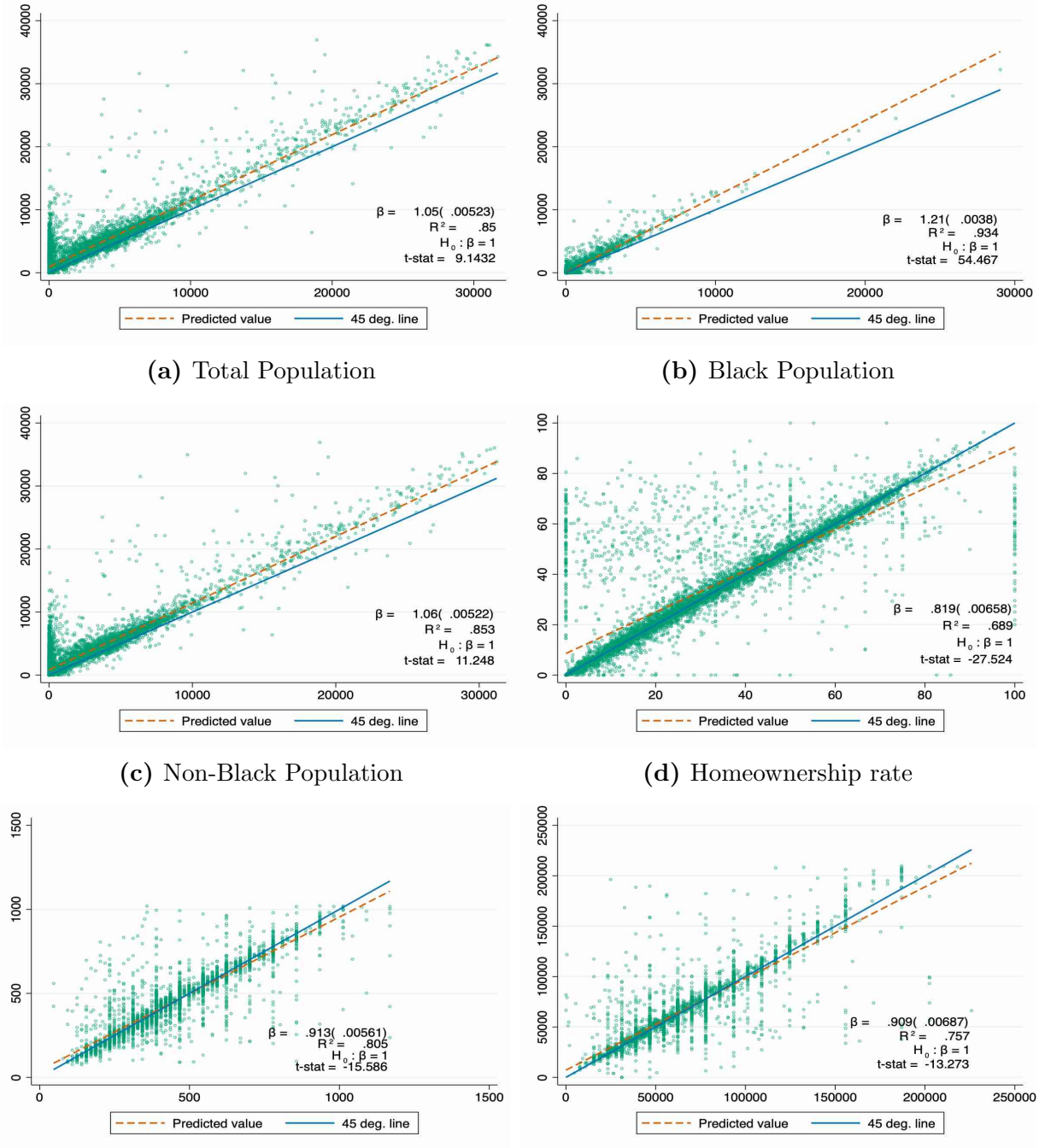
Because census tract definitions change over the decades, I cannot observe the official estimates for the 2010 census tracts in 1940 (or 1930). However, for a sample of 42 cities, I observe the 1940 census tract definition. To test the quality of the geocoding process, I aggregate the geocoded individuals into the 1940 census tracts and compare my estimates to the demographics and economic characteristics available in IPUMS (Manson et al., 2023). Figure C.1 shows that all the estimates are very close to each other, with a $\hat{\beta}$ close to one and a R^2 greater than 0.69 for all the variables of the study. The results suggest that the geocoding process does a very good job matching total, white population, median rent and median home value. The procedure seems to undercount Black individuals in large census tracts ($\hat{\beta} = 1.2$) and to underestimate the homeownership rate ($\hat{\beta} = 0.82$).

As an additional comparison, I benchmark the geocoding estimates to the enumeration district values for 1930 and 1940. By construction, population estimates will lie above the 45-degree line, as the geocoded sample is a subsample of the population in the ED. On the other hand, median home value, median rent, and homeownership rates are a function of the population, so their values could lie above or below the 45-degree line. Figures C.3 and C.2 present the results for the 1930 and 1940 censuses, respectively. Similar to the census tracts, the estimates for the geocoded ED do a good job of matching the variation in ED's socioeconomic characteristics.

[26] Once the complete count of the 1950 census is released, I will expand the sample to the 169 SMA in 1950.

C.6 Additional figures

Figure C.1: Benchmarking 1940 geocoding: census tracts



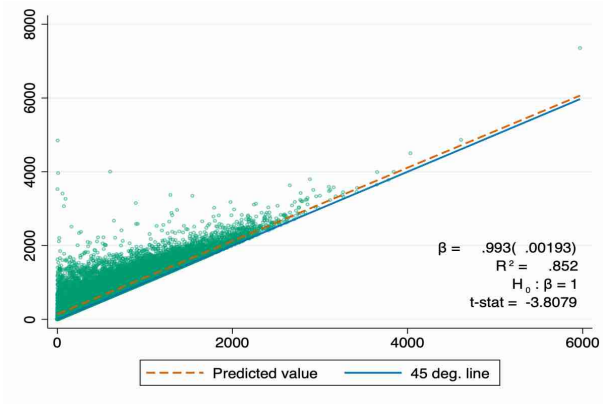
(a) Total Population **(b)** Black Population

(c) Non-Black Population **(d)** Homeownership rate

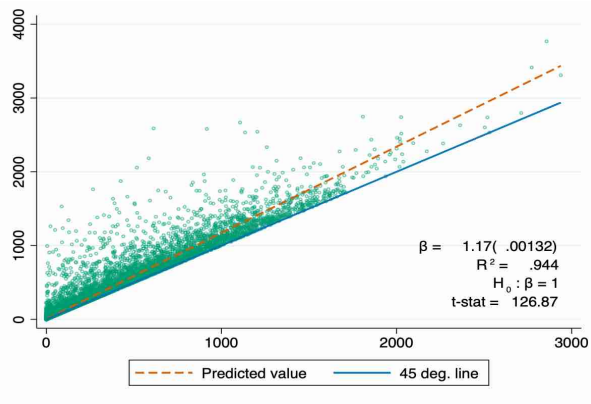
(e) Median Rent **(f)** Median Value

Note: Each observation corresponds to a 1940 census tract. The x-axis shows the estimates from the geocoded 1940 census. The y-axis shows the estimates from IPUMS (Manson et al., 2023).

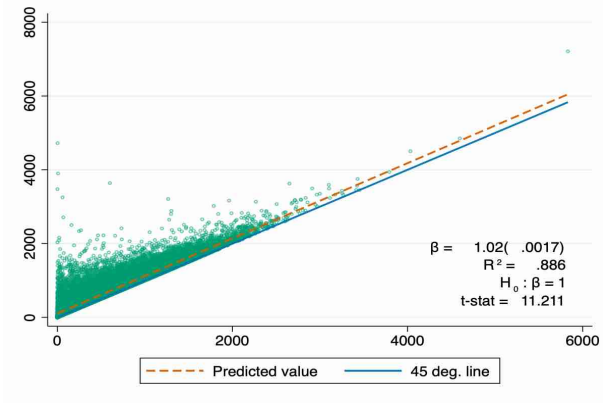
Figure C.2: Benchmarking 1940 geocoding: enumeration districts



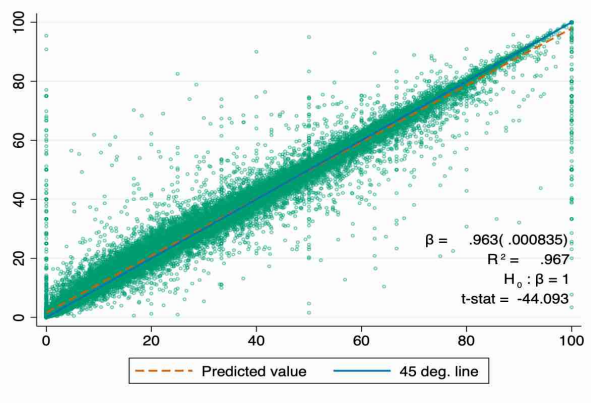
(a) Total Population



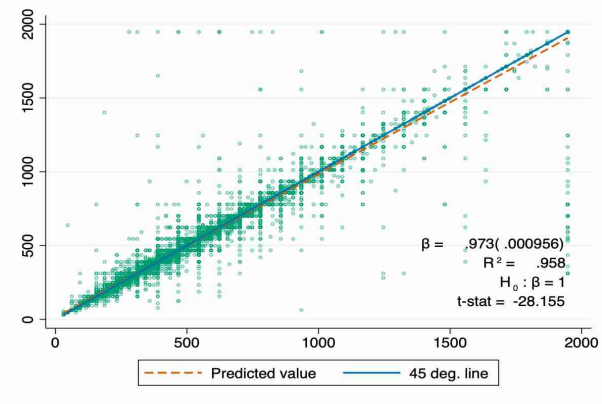
(b) Black Population



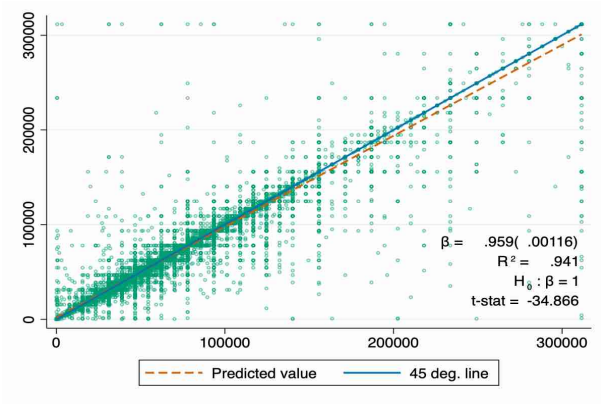
(c) Non-Black Population



(d) Homeownership rate



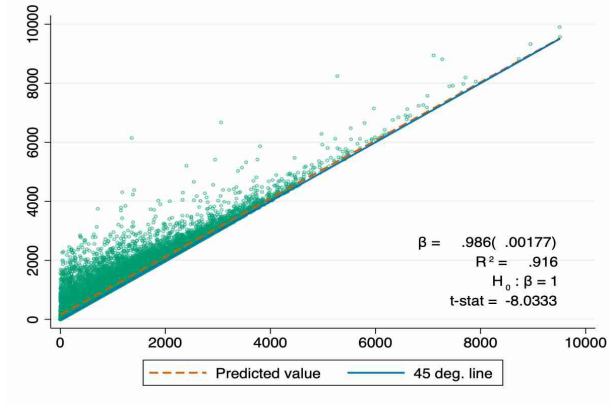
(e) Median Rent



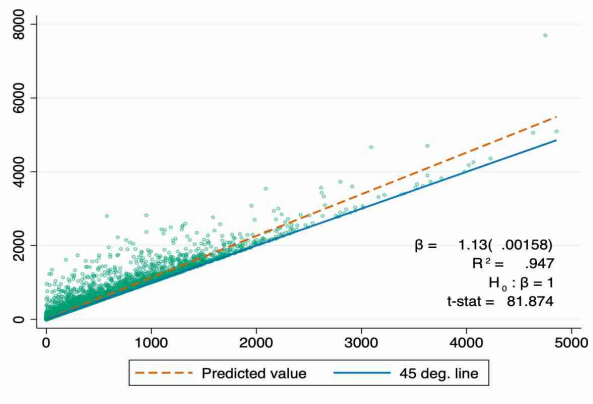
(f) Median Value

Note: Each observation corresponds to a 1940 enumeration district. The x-axis shows the estimates from the geocoded 1940 census. The y-axis shows the estimates from the 1940 census.

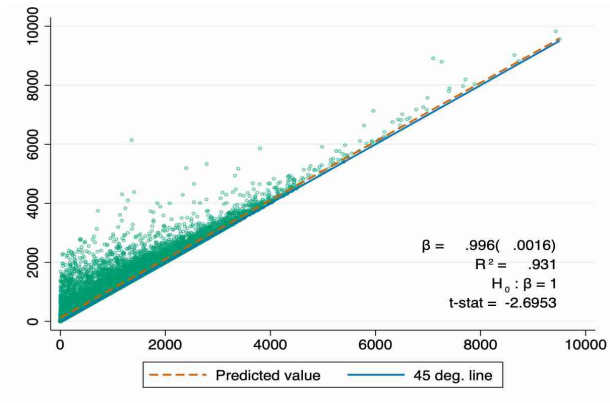
Figure C.3: Benchmarking 1930 geocoding: enumeration districts



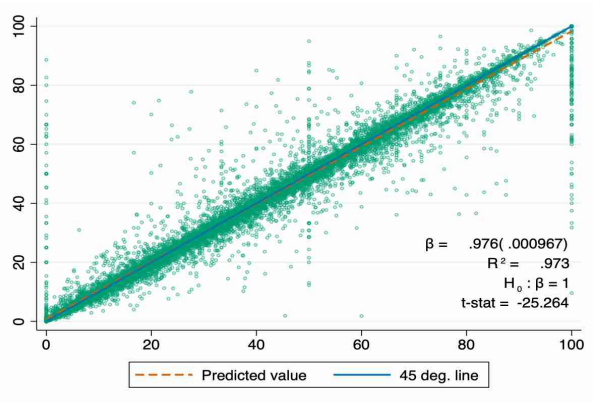
(a) Total Population



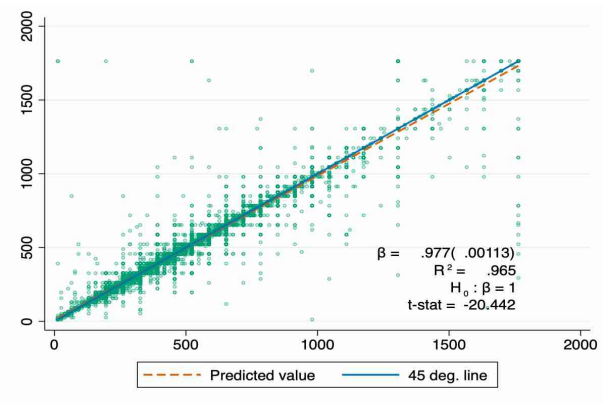
(b) Black Population



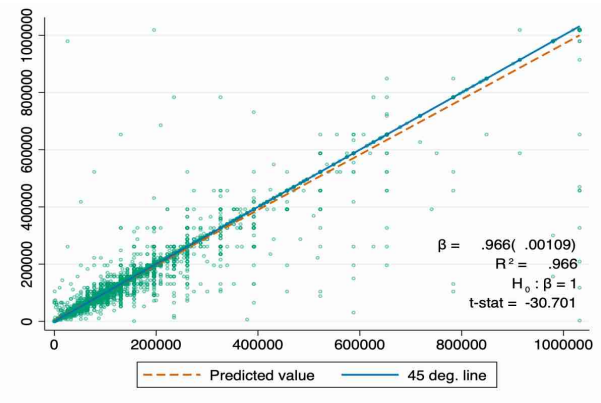
(c) Non-Black Population



(d) Homeownership rate



(e) Median Rent



(f) Median Value

Note: Each observation corresponds to a 1930 enumeration district. The x-axis shows the estimates from the geocoded 1930 census. The y-axis shows the estimates from the 1930 census.

C.7 Additional tables

Table C.1: List of MSAs Used in the Analysis

Metropolitan Area Name	State	Code	# tracts in 1950	Yellow Book
Akron	OH	80	95	No
Atlanta	GA	520	228	Yes
Austin	TX	640	71	No
Baltimore	MD	720	476	Yes
Birmingham	AL	1000	70	Yes
Boston	MA	1120	596	Yes
Bridgeport	CT	1160	70	No
Brockton	MA	1200	57	No
Buffalo	NY	1280	188	Yes
Chattanooga	TN-GA	1560	50	Yes
Chicago	IL-IN	1600	1547	Yes
Cincinnati	OH-KY	1640	233	Yes
Cleveland	OH	1680	473	Yes
Columbus	OH	1840	284	Yes
Dallas	TX	1920	205	Yes
Dayton	OH	2000	126	No
Denver	CO	2080	126	Yes
Detroit	MI	2160	748	Yes
Duluth-Superior	MN-WI	2240	36	No
Durham	NC	2280	60	No
Flint	MI	2640	113	Yes
Fort Worth	TX	2800	131	Yes
Greensboro-High Point	NC	3120	119	No
Hartford	CT	3280	108	Yes
Houston	TX	3360	785	Yes
Indianapolis	IN	3480	186	Yes
Kalamazoo	MI	3720	46	No
Kansas City	MO-KS	3760	136	Yes
Los Angeles	CA	4480	2348	Yes
Louisville	KY-IN	4520	85	Yes
Memphis	TN	4920	93	Yes
Miami	FL	5000	286	Yes
Milwaukee	WI	5080	297	Yes
Minneapolis-St. Paul	MN	5120	329	Yes
Nashville	TN	5360	86	Yes
New Haven	CT	5480	41	No
New Orleans	LA	5560	183	Yes
New York-Northeastern NJ	NY-NJ	5600	2491	Yes
Norfolk-Portsmouth	VA	5720	85	Yes
Oklahoma City	OK	5880	144	Yes
Omaha	NE-IA	5920	73	Yes
Philadelphia	PA-NJ	6160	1300	Yes
Pittsburgh	PA	6280	420	Yes
Portland	OR-WA	6440	117	Yes

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Table C.1 – *Continued from previous page*

Metropolitan Area Name	**State**	**Code**	**# tracts in 1950**	**Yellow Book**
Providence	RI	6480	53	Yes
Richmond	VA	6760	71	Yes
Rochester	NY	6840	106	Yes
Sacramento	CA	6920	318	No
St. Louis	MO-IL	7040	348	Yes
San Diego	CA	7320	406	No
San Francisco-Oakland	CA	7360	421	Yes
San Jose	CA	7400	47	No
Seattle	WA	7600	283	Yes
Spokane	WA	7840	50	No
Springfield-Holyoke	MA-CT	8000	86	Yes
Syracuse	NY	8160	140	Yes
Tacoma	WA	8200	149	No
Toledo	OH-MI	8400	77	Yes
Trenton	NJ	8480	35	No
Utica-Rome	NY	8680	34	Yes
Washington	DC-MD-VA	8840	266	Yes
Wichita	KS	9040	56	Yes
Total			18,687	

Table C.2: Number of Geocoded Dwellings by SMA

Metropolitan Area Name	State	Code	N. of Dwellings	Geocoded	Share (%)
Akron	OH	80	83,654	70,753	84.58%
Albany-Schenectady-Troy	NY	160	109,436	94,583	86.43%
Albuquerque	NM	200	11,100	7,821	70.46%
Allentown-Bethlehem	NJ-PA	240	77,579	59,077	76.15%
Altoona	PA	280	27,778	24,228	87.22%
Amarillo	TX	320	16,245	13,441	82.74%
Asheville	NC	480	15,331	12,017	78.38%
Atlanta	GA	520	102,697	74,634	72.67%
Atlantic City	NJ	560	31,161	23,515	75.46%
Augusta	GA-SC	600	22,409	15,384	68.65%
Austin	TX	640	29,208	19,666	67.33%
Baltimore	MD	720	258,356	198,428	76.80%
Baton Rouge	LA	760	9,896	6,441	65.09%
Bay City	MI	800	13,098	10,085	77.00%
Beaumont-Port Arthur	TX	840	30,852	25,758	83.49%
Binghamton	NY	960	35,387	28,891	81.64%
Birmingham	AL	1000	89,889	74,081	82.41%
Boston	MA	1120	510,083	291,597	57.17%
Brockton	MA	1200	18,827	17,286	91.81%
Buffalo	NY	1280	223,401	193,466	86.60%
Canton	OH	1320	46,950	41,752	88.93%
Cedar Rapids	IA	1360	21,089	18,606	88.23%
Charleston	SC	1440	21,765	17,694	81.30%
Charleston	WV	1480	27,065	16,680	61.63%
Charlotte	NC	1520	28,128	19,995	71.09%
Chattanooga	GA-TN	1560	38,199	29,474	77.16%
Chicago	IL-IN	1600	1,346,533	1,141,562	84.78%
Cincinnati	KY-OH	1640	216,362	153,677	71.03%
Cleveland	OH	1680	357,514	265,703	74.32%
Columbia	SC	1760	21,999	12,819	58.27%
Columbus	AL-GA	1800	19,106	15,073	78.89%
Columbus	OH	1840	106,097	86,854	81.86%
Corpus Christi	TX	1880	18,188	11,920	65.54%
Dallas	TX	1920	98,091	78,808	80.34%
Davenport-Rock Island-Moline	IA-IL	1960	52,089	42,591	81.77%
Dayton	OH	2000	72,350	59,161	81.77%
Decatur	IL	2040	17,879	14,150	79.14%
Denver	CO	2080	116,679	71,191	61.01%
Des Moines	IA	2120	51,787	45,715	88.28%
Detroit	MI	2160	592,206	454,455	76.74%
Duluth-Superior	MN-WI	2240	55,852	43,060	77.10%
Durham	NC	2280	16,574	11,775	71.05%
El Paso	TX	2320	26,861	21,541	80.19%
Erie	PA	2360	37,826	31,662	83.70%

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Table C.2 – *Continued from previous page*

Metropolitan Area Name	State	Code	N. of Dwellings	Geocoded	Share (%)
Evansville	IN	2440	28,670	25,358	88.45%
Flint	MI	2640	43,354	33,979	78.38%
Fort Wayne	IN	2760	36,765	30,690	83.48%
Fort Worth	TX	2800	56,813	50,361	88.64%
Fresno	CA	2840	23,612	19,610	83.05%
Gadsen	AL	2880	10,974	7,879	71.80%
Galveston	TX	2920	21,577	16,623	77.04%
Grand Rapids	MI	3000	51,643	43,188	83.63%
Green Bay	WI	3080	15,077	12,434	82.47%
Greensboro-High Point	NC	3120	25,593	16,954	66.24%
Greenville	SC	3160	10,855	8,371	77.12%
Hamilton-Middleton	OH	3200	24,398	21,563	88.38%
Harrisburg	PA	3240	46,334	34,392	74.23%
Houston	TX	3360	126,074	100,742	79.91%
Huntington-Ashland	KY-OH-WV	3400	37,055	29,457	79.50%
Indianapolis	IN	3480	122,486	100,279	81.87%
Jackson	MI	3520	14,975	11,601	77.47%
Jackson	MS	3560	18,386	13,833	75.24%
Jacksonville	FL	3600	50,322	40,327	80.14%
Johnstown	PA	3680	33,753	22,920	67.91%
Kalamazoo	MI	3720	18,841	12,407	65.85%
Kansas City	KS-MO	3760	181,166	159,427	88.00%
Kenosha	WI	3800	13,349	12,440	93.19%
Knoxville	TN	3840	34,425	19,649	57.08%
Lancaster	PA	4000	27,550	22,882	83.06%
Lansing	MI	4040	26,891	19,369	72.03%
Laredo	TX	4080	8,969	7,703	85.88%
Lexington	KY	4280	17,260	11,603	67.22%
Lima	OH	4320	14,495	12,228	84.36%
Lincoln	NE	4360	26,508	22,995	86.75%
Little Rock-North Little Rock	AR	4400	35,620	27,072	76.00%
Lorain-Klyria	OH	4440	22,277	19,492	87.50%
Los Angeles	CA	4480	859,418	672,334	78.23%
Louisville	IN-KY	4520	107,216	90,186	84.12%
Lubbock	TX	4600	10,831	8,856	81.77%
Macon	GA	4680	17,295	8,014	46.34%
Madison	WI	4720	22,142	18,196	82.18%
Manchester	NH	4760	22,710	19,673	86.63%
Memphis	TN	4920	90,103	76,715	85.14%
Miami	FL	5000	67,235	54,624	81.24%
Milwaukee	WI	5080	208,231	157,514	75.64%
Minneapolis-St. Paul	MN	5120	267,304	225,713	84.44%
Mobile	AL	5160	23,956	18,277	76.29%
Montgomery	AL	5240	22,749	10,489	46.11%
Muncie	IN	5280	15,867	12,920	81.43%

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Table C.2 – *Continued from previous page*

Metropolitan Area Name	State	Code	N. of Dwellings	Geocoded	Share (%)
Nashville	TN	5360	49,121	39,490	80.39%
New Britain-Bristol	CT	5440	74,925	63,188	84.33%
New Orleans	LA	5560	148,288	122,205	82.41%
New York- Northeastern New Jersey	NJ-NY	5600	3,210,862	2,581,327	80.39%
Norfolk-Portsmouth	VA	5720	64,668	37,196	57.52%
Ogden	UT	5840	12,832	11,456	89.28%
Oklahoma City	OK	5880	67,797	53,530	78.96%
Omaha	IA-NE	5920	80,834	71,472	88.42%
Orlando	FL	5960	13,936	10,765	77.25%
Peoria	IL	6120	44,068	22,235	50.46%
Philadelphia	NJ-PA	6160	767,116	593,790	77.41%
Phoenix	AZ	6200	25,144	17,931	71.31%
Pittsburgh	PA	6280	412,566	269,883	65.42%
Pittsfield	MA	6320	13,746	11,676	84.94%
Portland	ME	6400	30,529	25,212	82.58%
Portland	OR-WA	6440	125,876	107,588	85.47%
Providence	MA-RI	6480	208,857	187,181	89.62%
Pueblo	CO	6560	19,254	13,490	70.06%
Racine	WI	6600	20,385	17,143	84.10%
Raleigh	NC	6640	14,359	8,182	56.98%
Reading	PA	6680	41,414	30,500	73.65%
Richmond	VA	6760	56,901	44,642	78.46%
Roanoke	VA	6800	21,360	12,502	58.53%
Rochester	NY	6840	110,896	93,085	83.94%
Rockford	IL	6880	26,719	21,995	82.32%
Sacramento	CA	6920	37,488	31,134	83.05%
Saginaw	MI	6960	23,322	18,259	78.29%
St. Joseph	MO	7000	26,962	20,979	77.81%
St. Louis	IL-MO	7040	363,030	289,852	79.84%
Salt Lake	UT	7160	50,546	40,863	80.84%
San Angelo	TX	7200	7,879	6,801	86.32%
San Antonio	TX	7240	76,845	61,520	80.06%
San Bernardino	CA	7280	30,547	25,011	81.88%
San Diego	CA	7320	90,377	67,076	74.22%
San Francisco-Oakland	CA	7360	467,825	401,332	85.79%
San Jose	CA	7400	35,838	30,555	85.26%
Savannah	GA	7520	27,806	20,568	73.97%
Scranton	PA	7560	68,280	47,516	69.59%
Seatle	WA	7600	143,821	128,787	89.55%
Shreveport	LA	7680	28,655	23,602	82.37%
Sioux city	IA	7720	25,234	19,971	79.14%
Sioux falls	SD	7760	12,513	11,118	88.85%
South Bend	IN	7800	37,525	31,818	84.79%
Spokane	WA	7840	44,019	38,681	87.87%
Springfield	IL	7880	23,260	19,258	82.79%

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Table C.2 – *Continued from previous page*

Metropolitan Area Name	**State**	**Code**	**N. of Dwellings**	**Geocoded**	**Share (%)**
Springfield	MO	7920	19,520	16,650	85.30%
Springfield	OH	7960	20,865	18,901	90.59%
Springfield-Holyoke	MA	8000	84,401	68,560	81.23%
Stamford-Norwalk	CT	8040	66,071	55,425	83.89%
Stockton	CA	8120	26,214	17,655	67.35%
Syracuse	NY	8160	66,930	59,433	88.80%
Tacoma	WA	8200	40,904	35,000	85.57%
Tampa-St. Petersburg	FL	8280	61,391	48,641	79.23%
Terre Haute	IN	8320	21,738	18,702	86.03%
Toledo	OH	8400	89,533	76,475	85.42%
Topeka	KS	8440	21,602	18,052	83.57%
Trenton	NJ	8480	39,097	32,489	83.10%
Tulsa	OK	8560	47,464	39,052	82.28%
Utica-Rome	NY	8680	56,283	42,215	75.00%
Waco	TX	8800	17,893	15,363	85.86%
Washington D.C.	DC-MD-VA	8840	224,652	171,150	76.18%
Waterbury	CT	8880	72,557	63,379	87.35%
Waterloo	IA	8920	18,455	15,202	82.37%
Wheeling-Steubenville	OH-WV	9000	56,634	43,667	77.10%
Wichita	KS	9040	37,485	32,966	87.94%
Wichita Falls	TX	9080	16,130	13,888	86.10%
Wilkes-Bare-Hazleton	PA	9120	80,591	52,535	65.19%
Wilmington	DE-NJ	9160	39,268	33,131	84.37%
Winston-Salem	NC	9220	22,167	15,295	69.00%
Worcester	MA	9240	55,988	48,472	86.58%
York	PA	9280	24,087	19,545	81.14%
Youngstown	OH-PA	9320	86,165	74,368	86.31%
			16,783,010	13,276,985	79.11%

Table C.3: Sample selection: Geocoded

	Geocoded	Non-Geocoded	Mean Diffs.
	(1)	(2)	(3)
Black (indicator)	0.0784	0.0952	0.0168
	(0.2688)	(0.2935)	[0.000]
Female (indicator)	0.5126	0.5021	-0.0105
	(0.4998)	(0.5000)	[0.000]
Age	32.5461	32.3638	-0.1823
	(19.4842)	(19.3879)	[0.000]
Married (indicator)	0.4435	0.4147	-0.0287
	(0.4968)	(0.4927)	[0.000]
Home owner (indicator)	0.3085	0.3013	-0.0072
	(0.4619)	(0.4588)	[0.000]
Home value (000)	70.1813	74.1869	4.0056
	(57.4663)	(64.2508)	[0.000]
Rent (000)	0.9553	0.9124	-0.0429
	(4.2648)	(4.1162)	[0.000]
College degree (indicator)	0.0389	0.0420	0.0031
	(0.1933)	(0.2006)	[0.000]
High school degree (indicator)	0.2358	0.2380	0.0022
	(0.4245)	(0.4258)	[0.000]
Middle school degree (indicator)	0.7631	0.7474	-0.0157
	(0.4252)	(0.4345)	[0.000]
Immigrant (indicator)	0.1491	0.1399	-0.0092
	(0.3562)	(0.3469)	[0.000]
First gen. immigrant (indicator)	0.1372	0.1233	-0.0139
	(0.3441)	(0.3288)	[0.000]
Same house last 5 years	0.3856	0.3724	-0.0132
	(0.4867)	(0.4834)	[0.000]
Within county migration last 5 years	0.5129	0.4989	-0.0140
	(0.4998)	(0.5000)	[0.000]
Within state migration last 5 years	0.0429	0.0575	0.0146
	(0.2027)	(0.2328)	[0.000]
Between state migration last 5 years	0.0536	0.0661	0.0125
	(0.2252)	(0.2485)	[0.000]
Employed (indicator)	0.8881	0.8894	0.0013
	(0.3152)	(0.3136)	[0.000]
Labor force participation (indicator)	0.5551	0.5529	-0.0022
	(0.4969)	(0.4972)	[0.000]
Occupational score	25.2746	24.8657	-0.4089
	(9.9995)	(10.3155)	[0.000]
Observations	45,161,046	10,699,634	

Note: Each observation is an individual in the 1940 census living in the urban centers in the sample of counties. Column (1) reports the mean and standard error for geocoded individuals. Column (2) reports the mean and standard error for non-geocoded individuals. Column (3) reports the mean difference and the two-sided p-value of the difference

Table C.4: Sample selection: Matched to administrative mortality records

	Matched	Non-Matched	Mean Diffs.
	(1)	(2)	(3)
Black (indicator)	0.0519	0.0799	0.0279
	(0.2219)	(0.2711)	[0.000]
Female (indicator)	0.5303	0.5116	-0.0187
	(0.4991)	(0.4999)	[0.000]
Age	19.3770	33.2718	13.8948
	(9.2257)	(19.6413)	[0.000]
Married (indicator)	0.2634	0.4534	0.1899
	(0.4405)	(0.4978)	[0.000]
Home owner (indicator)	0.3187	0.3079	-0.0108
	(0.4660)	(0.4616)	[0.000]
Home value (000)	68.6802	70.2633	1.5831
	(55.3883)	(57.5766)	[0.000]
Rent (000)	0.9053	0.9581	0.0529
	(4.1120)	(4.2732)	[0.000]
College degree (indicator)	0.0337	0.0392	0.0055
	(0.1804)	(0.1940)	[0.000]
High school degree (indicator)	0.2989	0.2323	-0.0666
	(0.4578)	(0.4223)	[0.000]
Middle school degree (indicator)	0.7973	0.7612	-0.0361
	(0.4020)	(0.4264)	[0.000]
Immigrant (indicator)	0.0400	0.1551	0.1151
	(0.1959)	(0.3620)	[0.000]
First gen. immigrant (indicator)	0.2394	0.1316	-0.1078
	(0.4267)	(0.3380)	[0.000]
Same house last 5 years	0.3712	0.3864	0.0151
	(0.4831)	(0.4869)	[0.000]
Within county migration last 5 years	0.5143	0.5128	-0.0015
	(0.4998)	(0.4998)	[0.000]
Within state migration last 5 years	0.0501	0.0425	-0.0075
	(0.2181)	(0.2018)	[0.000]
Between state migration last 5 years	0.0613	0.0532	-0.0081
	(0.2398)	(0.2244)	[0.000]
Employed (indicator)	0.8446	0.8901	0.0455
	(0.3623)	(0.3127)	[0.000]
Labor force participation (indicator)	0.5132	0.5573	0.0440
	(0.4998)	(0.4967)	[0.000]
Occupational score	23.4902	25.3535	1.8632
	(8.2732)	(10.0617)	[0.000]
Observations	2,358,731	42,802,315	

Note: Each observation is a geocoded individual in the 1940 census living in the urban centers in the sample of counties. Column (1) reports the mean and standard error for matched individuals. Column (2) reports the mean and standard error for non-matched individuals. Column (3) reports the mean difference and the two-sided p-value of the difference

D Placement Appendix

D.1 Robustness of the Placement Results

In this section I present evidence that the results are robust to alternative specifications. A potential concern is the use of the 2010 census tract definition. Evidence suggests that state and city officials had detailed micro-data about neighborhood racial composition in 1950 (Caro, 1974, p.968), which is more disaggregated than any available census tract definition. In the previous analysis, I used the 2010 definition of census tracts because its geographic unit is smaller than the 1950 definition. However, it relies on area-weighted interpolation to convert the 1950 census tracts into the 2010 definition. To check the extent to which the results rely on this interpolation, I re-estimate Equation 1 using the 1950 definition. In Tables D.2 and D.3, I present the results for both the discrete and continuous dependent variables. The results, however, remain virtually unchanged. Therefore, for the rest of the paper, I will use the 2010 census tract definition, the standard in the urban economics literature (Weiwu, 2023; Brinkman and Lin, 2022; Brinkman et al., 2023; Lee and Lin, 2017; Couture et al., 2023).

A second potential concern is that controlling for proximity to the city center linearly may partially account for the city's socioeconomic distribution. In particular, including a linear term on proximity to the city center may not account for the fact that Black households tended to reside in city centers (Boustan, 2010), which were the main targets of urban highways. This is particularly important given the recent findings in Brinkman and Lin (2022), which show that highways in central parts of the city were most likely to deviate from the plan. Hence, a linear measure may not accurately capture the intended effect. To investigate this possibility, I re-estimate Equation 1 using the log distance to the city center. As displayed in Appendix Table D.4, the results remain robust to the alternative definition of proximity to the city center.

Another potential concern arises regarding the use of population as weights. In the 1950s, tracts closer to the city center had a larger population, which may have led to tracts that were more likely to receive an urban highway. To address this, I test the sensitivity of the estimates by excluding weights. As presented in Table D.5, the data does not support this critique. In fact, the estimated effect appears to be even larger without using weights.

One possibility is that the results are driven by a few cities, and the results do not reflect the widespread behavior of US builders. To test this possibility, I re-estimated Equation 1 while leaving one city out of the sample each time. The estimated effects for the Black share, log median home value, log median rent, and distance to the city center are reported in Figure D.1. The estimated coefficients remain similar in magnitude and statistical significance.

The final check examines the robustness of the results to various methods of calculating standard errors. In particular, I cluster by city, clustering by state, by census tract in 1950,

and allow for spatial correlation within 10 kilometers of a tract's centroid. [27] As reported in Appendix Table D.6, the magnitude of the standard error and the statistical significance of the estimates is similar in each case.

[27] To calculate spatial standard errors, I use Colella et al.'s 2019 implementation of Conley (1999).

D.2 Additional Tables

Table D.1: Determinants of Highway Placement: Continuous Dependent Variable

	Dependent Variable: Distance to the closest					
	Built highway					Plan
	(1)	(2)	(3)	(4)	(5)	(6)
Black share	-4.268[a]	-3.596[a]	-3.678[a]	-2.656[a]	-1.744[b]	-1.537
	(0.956)	(1.026)	(0.985)	(0.957)	(0.705)	(1.113)
(log) Median income	-0.184	-0.225	-0.174	-0.107	0.072[c]	-0.330
	(0.262)	(0.254)	(0.194)	(0.121)	(0.037)	(0.227)
High school share	0.032[a]	0.023[c]	0.013	-0.004	-0.005	0.003
	(0.011)	(0.012)	(0.011)	(0.007)	(0.003)	(0.012)
(log) Median rent		-0.097	-0.058	-0.100	0.200	-0.648[b]
		(0.337)	(0.230)	(0.152)	(0.155)	(0.295)
(log) Median home value		0.712[b]	0.544[a]	0.429[b]	0.248[b]	0.457[c]
		(0.294)	(0.166)	(0.174)	(0.117)	(0.241)
Distance to city center				0.128[a]	0.011	0.217[a]
				(0.026)	(0.008)	(0.056)
Distance to the planned route					0.536[a]	
					(0.038)	
Mean dependent var.	3.207	3.100	3.104	3.104	3.031	3.031
Geo. Controls	No	No	Yes	Yes	Yes	Yes
Obs.	18,242	17,210	16,944	16,944	15,416	15,416
R^2 (Adj.)	0.115	0.120	0.227	0.319	0.596	0.389

Note: Each column corresponds to a different regression. The unit of observation is a census tract. The dependent variable is the distance to the closest highway/planned segment. The vector of controls includes the (log) area and slope of the tract, distance to the nearest river, an indicator if the governor of the state was part of the Republican party, the state (log) number of car registrations per 10k inhabitants, and the distance to the 1921 railroad network. All columns include city fixed effects. Coefficients are reported with standard errors clustered at the city level. [a] indicates the coef. is significant at the 1%, [b] at the 5%, and [c] at the 10%. Regressions are weighted by the census tract's population.

Table D.2: 1950 Census Tract Definition

	Dependent Variable: Indicator if the tract is crossed by					
	Built highway					Plan
	(1)	(2)	(3)	(4)	(5)	(6)
Black share	0.306	0.253	0.268	0.275	0.374[c]	-0.313
	(0.274)	(0.271)	(0.252)	(0.254)	(0.220)	(0.203)
(log) Median income	-0.009	0.055[c]	-0.067[c]	-0.059	-0.055[c]	-0.011
	(0.030)	(0.029)	(0.038)	(0.037)	(0.029)	(0.035)
High school share	-0.114	0.056	-0.053	-0.020	0.034	-0.172
	(0.094)	(0.104)	(0.096)	(0.086)	(0.073)	(0.134)
(log) Median rent		-0.120[a]	-0.084[a]	-0.082[a]	-0.073[a]	-0.028
		(0.034)	(0.025)	(0.023)	(0.023)	(0.029)
(log) Median home value		-0.065	-0.073[b]	-0.077[a]	-0.062[b]	-0.049[b]
		(0.041)	(0.028)	(0.029)	(0.027)	(0.019)
Distance to city center				-0.007[a]	-0.005[a]	-0.006[a]
				(0.001)	(0.001)	(0.002)
Highway planned					0.317[a]	
					(0.054)	
Mean dependent var.	0.233	0.237	0.238	0.238	0.238	0.238
Geo. Controls	No	No	Yes	Yes	Yes	Yes
Obs.	9,968	9,566	9,439	9,439	9,439	9,439
R^2 (Adj.)	0.063	0.070	0.162	0.170	0.251	0.125

Note: Each column corresponds to a different regression. The unit of observation is a census tract, using the 1950 census tract definition. The dependent variable is an indicator if a highway was built or planned through the tract. The vector of controls includes the (log) area of the tract, distance to the nearest river, an indicator if the governor of the state was part of the Republican party, the state (log) number of car registrations per 10k inhabitants, and the distance to the 1921 railroad network. All columns include city fixed effects. Coefficients are reported with standard errors clustered at the city level. [a] indicates the coef. is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table D.3: 1950 Census Tract Definition and Continuous Dependent Variable

	Dependent Variable: Distance to the closest					
	Built highway					Plan
	(1)	(2)	(3)	(4)	(5)	(6)
Black share	-1.238	-0.937	-1.850[c]	-1.960[c]	-2.265[b]	-1.005
	(0.930)	(0.948)	(1.015)	(0.985)	(1.022)	(1.192)
(log) Median income	0.802[a]	0.675[b]	-0.058	-0.199	0.194	-0.823[c]
	(0.263)	(0.334)	(0.358)	(0.342)	(0.189)	(0.445)
High school share	1.597	1.310	0.452	-0.084	-0.616	0.966
	(0.996)	(1.039)	(0.902)	(0.795)	(0.380)	(1.279)
(log) Median rent		-0.120	-0.015	-0.058	0.185	-0.504
		(0.325)	(0.223)	(0.156)	(0.181)	(0.395)
(log) Median home value		0.498[c]	0.395[b]	0.463[a]	0.173	0.670[a]
		(0.268)	(0.182)	(0.168)	(0.110)	(0.235)
Distance to city center				0.123[a]	0.021[c]	0.191[a]
				(0.024)	(0.012)	(0.044)
Distance to the planned route					0.532[a]	
					(0.044)	
Mean dependent var.	2.398	2.434	2.439	2.439	2.424	2.424
Geo. Controls	No	No	Yes	Yes	Yes	Yes
Obs.	9,968	9,566	9,439	9,439	8,430	8,430
R^2 (Adj.)	0.119	0.121	0.205	0.270	0.577	0.286

Note: Each column corresponds to a different regression. The unit of observation is a census tract, using the 1950 census tract definition. The dependent variable is the distance to the closest highway/planned segment. The vector of controls includes the (log) area of the tract, distance to the nearest river, an indicator if the governor of the state was part of the Republican party, the state (log) number of car registrations per 10k inhabitants, and the distance to the 1921 railroad network. All columns include city fixed effects. Coefficients are reported with standard errors clustered at the city level. [a] indicates the coef. is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table D.4: Determinants of Highway Placement: Log Distance to CBD

	Dependent Variable: Indicator if the tract is crossed by					
	Built highway					Plan
	(1)	(2)	(3)	(4)	(5)	(6)
Black share	1.179[a]	0.996[a]	1.009[a]	0.720[b]	0.735[a]	-0.052
	(0.314)	(0.306)	(0.302)	(0.295)	(0.262)	(0.245)
(log) Median income	-0.028[b]	-0.016[c]	-0.009	-0.002	-0.003	0.003
	(0.012)	(0.009)	(0.016)	(0.013)	(0.010)	(0.011)
High school share	-0.003[b]	-0.001	-0.001	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(log) Median rent		-0.079[a]	-0.064[a]	-0.048[b]	-0.050[a]	0.006
		(0.025)	(0.022)	(0.020)	(0.017)	(0.035)
(log) Median home value		-0.094[a]	-0.120[a]	-0.101[a]	-0.077[a]	-0.084[a]
		(0.030)	(0.023)	(0.023)	(0.022)	(0.021)
(log) Distance to city center				-0.110[a]	-0.083[a]	-0.096[a]
				(0.017)	(0.014)	(0.015)
Highway planned					0.284[a]	
					(0.041)	
Mean dependent var.	0.214	0.217	0.218	0.218	0.218	0.218
Geo. Controls	No	No	Yes	Yes	Yes	Yes
Obs.	18,242	17,210	16,944	16,944	16,944	16,944
R^2 (Adj.)	0.086	0.094	0.155	0.177	0.243	0.119

Note: Each column corresponds to a different regression. The unit of observation is a census tract. The dependent variable is an indicator if a highway was built or planned through the tract. The vector of controls includes the (log) area and slope of the tract, distance to the nearest river, an indicator if the governor of the state was part of the Republican party, the state (log) number of car registrations per 10k inhabitants, and the distance to the 1921 railroad network. All columns include city fixed effects. Coefficients are reported with standard errors clustered at the city level. [a] indicates the coef. is significant at the 1%, [b] at the 5%, and [c] at the 10%. Regressions are weighted by the census tract's population.

Table D.5: Determinants of Highway Placement: Unweighted

	Dependent Variable: Indicator if the tract is crossed by					
	Built highway					Plan
	(1)	(2)	(3)	(4)	(5)	(6)
Black share	1.298[a]	1.143[a]	1.390[a]	1.269[a]	1.118[a]	0.472[c]
	(0.299)	(0.304)	(0.311)	(0.295)	(0.263)	(0.237)
(log) Median income	-0.007	-0.004	0.002	-0.002	-0.002	-0.001
	(0.006)	(0.006)	(0.008)	(0.006)	(0.005)	(0.004)
High school share	-0.001[c]	-0.000	-0.000	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(log) Median rent		-0.072[a]	-0.039[b]	-0.041[b]	-0.038[b]	-0.009
		(0.023)	(0.018)	(0.016)	(0.015)	(0.016)
(log) Median home value		-0.050[c]	-0.063[b]	-0.072[a]	-0.064[a]	-0.027
		(0.028)	(0.027)	(0.024)	(0.021)	(0.018)
Distance to city center				-0.008[a]	-0.005[a]	-0.007[a]
				(0.001)	(0.001)	(0.001)
Highway planned					0.321[a]	
					(0.040)	
Mean dependent var.	0.214	0.217	0.218	0.218	0.218	0.218
Geo. Controls	No	No	Yes	Yes	Yes	Yes
Obs.	18,242	17,210	16,944	16,944	16,944	16,944
R^2 (Adj.)	0.048	0.052	0.093	0.111	0.194	0.087

Note: Each column corresponds to a different regression. The unit of observation is a census tract. The dependent variable is the distance to the closest highway/planned segment. The vector of controls includes the (log) area and slope of the tract, distance to the nearest river, an indicator if the governor of the state was part of the Republican party, the state (log) number of car registrations per 10k inhabitants, and the distance to the 1921 railroad network. All columns include city fixed effects. Coefficients are reported with standard errors clustered at the city level. [a] indicates the coef. is significant at the 1%, [b] at the 5%, and [c] at the 10%.

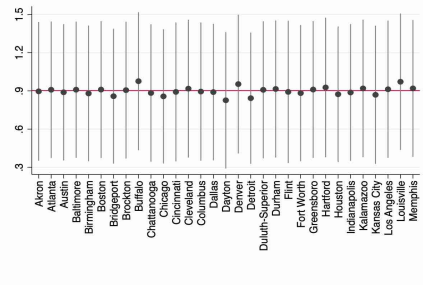
Table D.6: Determinants of Highway Placement: Different standard errors

	Dep. var.: Indicator if the tract is crossed by					
	Built Highway					Plan
	(1)	(2)	(3)	(4)	(5)	(6)
Black share	1.179	0.996	1.009	0.942	0.902	0.137
	(0.314)[a]	(0.306)[a]	(0.302)[a]	(0.299)[a]	(0.271)[a]	(0.239)
	[0.239][a]	[0.239][a]	[0.232][a]	[0.227][a]	[0.212][a]	[0.188]
	{0.297}[a]	{0.295}[a]	{0.291}[a]	{0.287}[a]	{0.261}[a]	{0.229}
(log) Median income	-0.028	-0.016	-0.009	-0.014	-0.012	-0.007
	(0.012)[b]	(0.009)[c]	(0.016)	(0.013)	(0.010)	(0.011)
	[0.005][a]	[0.006][a]	[0.006]	[0.005][b]	[0.005][b]	[0.005]
	{0.007}[a]	{0.007}[b]	{0.008}	{0.008}[c]	{0.006}[c]	{0.007}
High school share	-0.003	-0.001	-0.001	-0.000	0.000	-0.002
	(0.001)[b]	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	[0.001][a]	[0.001][b]	[0.001][b]	[0.001]	[0.001]	[0.001][a]
	{0.001}[a]	{0.001}	{0.001}	{0.001}	{0.001}	{0.001}[c]
(log) Median rent		-0.079	-0.064	-0.061	-0.060	-0.005
		(0.025)[a]	(0.022)[a]	(0.021)[a]	(0.018)[a]	(0.035)
		[0.021][a]	[0.020][a]	[0.019][a]	[0.018][a]	[0.020]
		{0.029}[a]	{0.026}[b]	{0.026}[b]	{0.022}[a]	{0.033}
(log) Median home value		-0.094	-0.120	-0.112	-0.085	-0.093
		(0.030)[a]	(0.023)[a]	(0.023)[a]	(0.022)[a]	(0.021)[a]
		[0.020][a]	[0.019][a]	[0.019][a]	[0.018][a]	[0.020][a]
		{0.029}[a]	{0.025}[a]	{0.026}[a]	{0.024}[a]	{0.028}[a]
Distance to city center				-0.008	-0.006	-0.008
				(0.001)[a]	(0.001)[a]	(0.002)[a]
				[0.001][a]	[0.001][a]	[0.001][a]
				{0.001}[a]	{0.001}[a]	{0.001}[a]
Highway planned					0.290	
					(0.042)[a]	
					[0.013][a]	
					{0.032}[a]	
Geo. Controls	No	No	Yes	Yes	Yes	Yes
Obs.	18,242	17,210	16,944	16,944	16,944	16,944
R^2 (adj.)	0.089	0.098	0.158	0.173	0.242	0.118

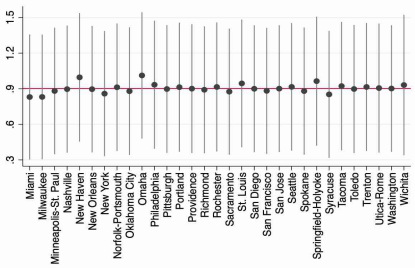
Note: Each column corresponds to a different regression. The unit of observation is a census tract. The dependent variable is an indicator if a highway was built or planned through the tract. The vector of controls includes the (log) area and slope of the tract, distance to the nearest river, an indicator if the governor of the state was part of the Republican party, the state (log) number of car registrations per 10k inhabitants, and the distance to the 1921 railroad network. All columns include city fixed effects. Regressions are weighted by the census tract's population. Standard errors clustered at the city level in parentheses. Standard errors clustered at the census tract in 1950 level in squate brackets. Standard errors allowing for spatial correlation within 10 kilometers of a census tract's centroid in curly brackets. [a] indicates the coef. is significant at the 1%, [b] at the 5%, and [c] at the 10%.

D.3 Additional Figures

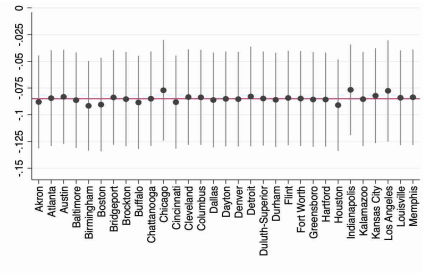
Figure D.1: Leave-one-out Analysis



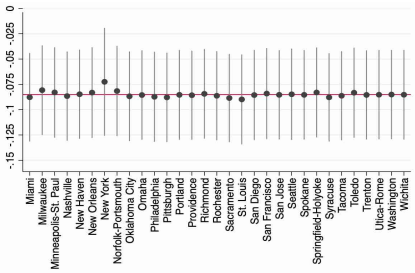
(a) Black share (1/2)



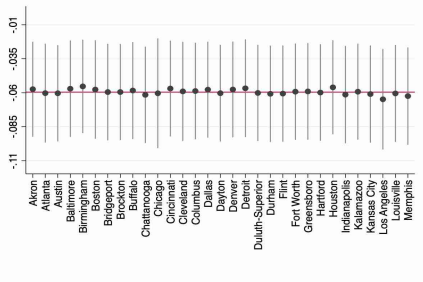
(b) Black share (2/2)



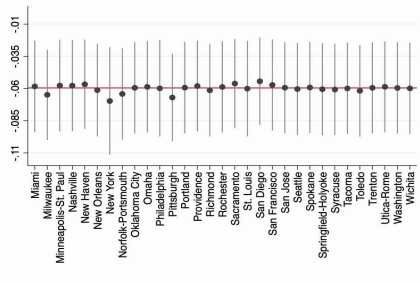
(c) Log median home value (1/2)



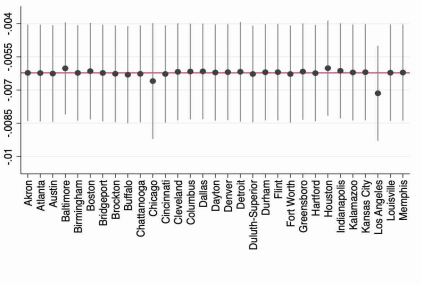
(d) Log median home value (2/2)



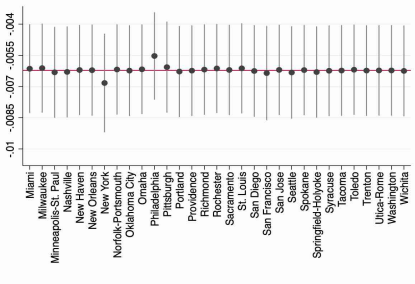
(e) Log median rent (1/2)



(f) Log median rent (2/2)



(g) Distance to city center (1/2)



(h) Distance to city center (2/2)

Note: Each figure present the results of estimating Equation 1 while leaving one city out of the sample each time. The first two panels show the estimated coefficients for the Black share of the city's population residing in the tract. The second two panels show the estimated coefficients for the log median home value. The third two panels show the estimated coefficients for the log median rent. The last two panels show the estimated coefficients for the distance to the city center. All regressions include city fixed effects, Black share, high school share, log median income, log median rent, log median home value, log area, log slope, log distance to the nearest river, log number of cars per 10k inhabitants, and an indicator if the governor was a Republican. Standard errors are clustered at the city level and observations are weighted by the tract's total population.

Table D.7: All Segments

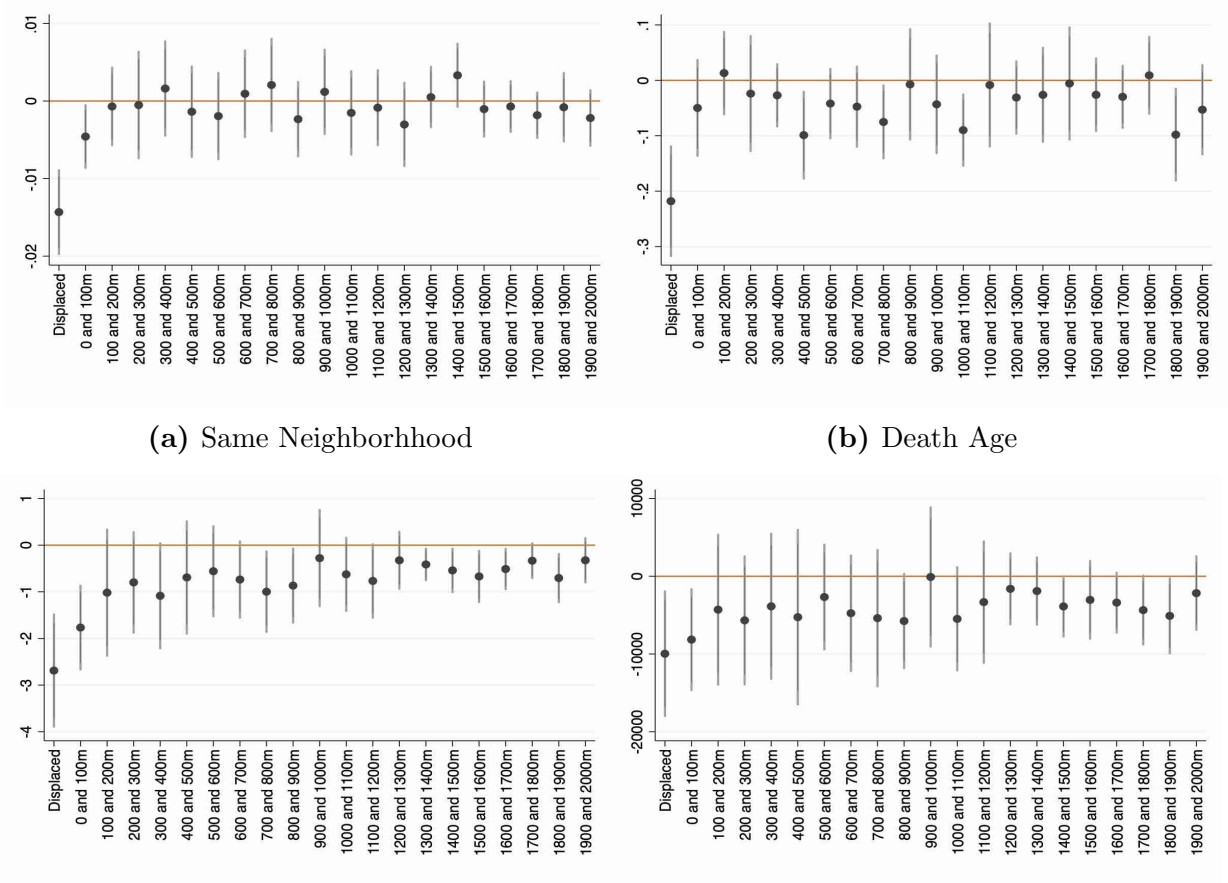
	Displaced	Distance to the closest highway					Rest of the city
		0 and 100m	100 and 200m	200 and 300m	300 and 400m	400 and 500m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Number of displaced individuals:							
Total population	356,314	2,318,919	2,150,826	2,202,002	2,197,029	2,119,511	33.816m
Population share	0.79%	5.13%	4.76%	4.88%	4.86%	4.69%	74.88%
Panel B: Individual level characteristics:							
Black	0.129	0.112	0.103	0.101	0.094	0.090	0.071
	(0.335)	(0.315)	(0.304)	(0.301)	(0.292)	(0.286)	(0.257)
Immigrant	0.155	0.159	0.163	0.166	0.167	0.165	0.144
	(0.362)	(0.366)	(0.370)	(0.372)	(0.373)	(0.371)	(0.351)
First gen. US born	0.137	0.145	0.146	0.146	0.147	0.144	0.135
	(0.344)	(0.352)	(0.353)	(0.353)	(0.354)	(0.351)	(0.341)
High school share	0.236	0.247	0.265	0.271	0.275	0.282	0.317
	(0.425)	(0.431)	(0.441)	(0.444)	(0.446)	(0.450)	(0.465)
Labor force	0.660	0.648	0.649	0.647	0.646	0.648	0.635
	(0.474)	(0.478)	(0.477)	(0.478)	(0.478)	(0.478)	(0.482)
Employed	0.894	0.901	0.906	0.907	0.907	0.909	0.923
	(0.308)	(0.299)	(0.292)	(0.290)	(0.290)	(0.288)	(0.267)
Occupational score	24.463	24.965	25.336	25.502	25.577	25.637	26.507
	(9.926)	(9.781)	(10.056)	(10.167)	(10.086)	(10.054)	(10.303)
Panel C: Household level characteristics:							
Homeowner	0.217	0.271	0.268	0.268	0.277	0.285	0.368
	(0.412)	(0.444)	(0.443)	(0.443)	(0.447)	(0.451)	(0.482)
Household size	3.362	3.458	3.444	3.452	3.451	3.451	3.508
	(2.110)	(2.071)	(2.088)	(2.051)	(2.059)	(2.031)	(1.925)
Log home value	10.583	10.626	10.684	10.720	10.743	10.774	10.872
	(0.985)	(0.943)	(0.957)	(0.949)	(0.945)	(0.929)	(0.899)
Log rent	5.755	5.828	5.900	5.940	5.959	5.963	6.020
	(0.778)	(0.822)	(0.831)	(0.836)	(0.838)	(0.831)	(0.827)

Note: Each observation corresponds to an individual in the 1940 census. Displacement and the proximity to highways are calculated for all segments of the IHS. Mean values are reported for each variable, with the corresponding standard deviation in parentheses. High school share and labor force are calculated for the sample of individuals aged 25 to 55. Employed is calculated for individuals aged 25 to 55 in the labor force. Occupational score is calculated for individuals aged 25 to 55 and employed. Home value and rent are conditional on ownership status.

E Displacement Appendix

E.1 Additional Figures

Figure E.1: Spatial Decay of Highway Effects



(a) Same Neighborhhood **(b)** Death Age

(c) College Share **(d)** Log Black Share

Note: Highway segments opened between 1950 and 1960 are included in the sample. Each panel presents the coefficients of a dependent variable. Each coefficient corresponds to a different bin of distance to the highway. The base coefficient is the one corresponding to the bin of distance 2,000 and 2,100 meters. All panels control for race, gender, homeownership, city, and birth year fixed effects. Standard errors are clustered at the city level.

E.2 Additional Tables

Table E.1: Balance Test – CENSOC Sample

	Displaced	Adjacent	Mean	Std. Dev.	Obs.
	(1)	(2)	(3)	(4)	(5)
Number of subfamilies in the household	0.006	-0.003	0.101	0.332	44,233
	[0.333]	[0.299]			
Number of own children in the household	0.027	0.022	0.273	0.786	44,233
	[0.015]	[0.000]			
Married (indicator)	-0.007	0.005	0.233	0.422	44,233
	[0.394]	[0.042]			
(log) Monthly contract rent	-0.108	-0.046	5.946	0.720	31,997
	[0.029]	[0.000]			
(log) House value	-0.026	-0.036	10.716	0.930	11,189
	[0.690]	[0.158]			
College graduate (indicator)	-0.001	-0.002	0.023	0.150	44,233
	[0.798]	[0.277]			
High school graduate (indicator)	-0.030	-0.014	0.250	0.433	44,233
	[0.002]	[0.000]			
Middle school graduate (indicator)	0.004	0.003	0.780	0.415	44,233
	[0.345]	[0.071]			
Employed (indicator)	-0.018	-0.010	0.810	0.392	16,952
	[0.084]	[0.047]			
Labor force participation (indicator)	0.010	-0.006	0.532	0.499	31,842
	[0.324]	[0.339]			
Occupational score	-0.273	-0.323	23.373	7.830	15,688
	[0.329]	[0.006]			
Born outside the U.S. (indicator)	0.002	-0.002	0.048	0.213	44,233
	[0.521]	[0.363]			
Same house as 5 years ago	0.007	0.014	0.370	0.483	41,592
	[0.576]	[0.009]			
Same community as 5 years ago	0.012	0.008	0.876	0.329	41,592
	[0.020]	[0.023]			
Within county mig. in the last 5 years	0.000	-0.009	0.536	0.499	41,592
	[0.993]	[0.115]			
Within state mig. in the last 5 years	-0.001	0.001	0.039	0.193	41,592
	[0.764]	[0.641]			
Between state mig. in the last 5 years	-0.006	-0.005	0.051	0.220	41,592
	[0.259]	[0.020]			

Note: OLS estimates are reported. Individuals in the 1940 full count census matched to administrative mortality records are included in the sample. Only segments opened between 1950 and 1960 are included in the sample. Column (1) reports the coefficient of the treatment indicator for the Displaced group. Column (2) reports the coefficient of the treatment indicator for the Adjacent group. The control group corresponds to individuals living between 100 and 200 meters from a future highway. All regressions include city, birth year, homeownership, race, and gender fixed effects.

Table E.2: Long-term Effects of Highway Construction – Control Group 1km

	Same Neigh. (1)	Same City (2)	Redlined Neigh. (3)	Death Age (4)	Survival to age 70 (5)
Displaced	-0.014[a]	0.021	0.009	-0.148[a]	-0.008[a]
	(0.002)	(0.015)	(0.008)	(0.040)	(0.002)
Adjacent	-0.004[b]	0.021[a]	0.010[a]	0.034	0.001
	(0.002)	(0.007)	(0.002)	(0.033)	(0.002)
Mean dep. var.	0.023	0.608	0.061	79.074	0.893
R-squared (adj)	0.023	0.018	0.037	0.864	0.526
Observations	37,960	37,960	37,960	35,919	35,919

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died after 1995. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 1,000 and 1,100 meters from a future highway. Each column corresponds to a different regression. The dependent variable in column (1) is an indicator that equals one if the individual lives at time of death in the same neighborhood they lived in 1940. In column (2), the dependent variable is an indicator that equals one if the individual lives in the same city they lived in 1940. Column (3) uses an indicator taking value equal to one if the residence at time of death was located in a redlined area as dependent variable. Column (4) use the age at death as dependent variable. Finally, the dependent variable in Column (5) is an indicator if the individual survived until the age of 70. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table E.3: Long-term Effects of Highway Construction – Control Group 2km

	Same Neigh. (1)	Same City (2)	Redlined Neigh. (3)	Death Age (4)	Survival to age 70 (5)
Displaced	-0.016[a]	0.031[c]	0.013	-0.212[a]	-0.009[a]
	(0.003)	(0.018)	(0.012)	(0.045)	(0.003)
Adjacent	-0.006[a]	0.031[b]	0.013[b]	-0.043	0.000
	(0.002)	(0.015)	(0.005)	(0.044)	(0.001)
Mean dep. var.	0.024	0.607	0.059	79.115	0.895
R-squared (adj)	0.025	0.019	0.032	0.864	0.528
Observations	33,847	33,847	33,847	31,990	31,990

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died after 1995. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 2,000 and 2,100 meters from a future highway. Each column corresponds to a different regression. The dependent variable in column (1) is an indicator that equals one if the individual lives at time of death in the same neighborhood they lived in 1940. In column (2), the dependent variable is an indicator that equals one if the individual lives in the same city they lived in 1940. Column (3) uses an indicator taking value equal to one if the residence at time of death was located in a redlined area as dependent variable. Column (4) use the age at death as dependent variable. Finally, the dependent variable in Column (5) is an indicator if the individual survived until the age of 70. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table E.4: Long-term Effects of Highway Construction – Unweighted

	Same Neigh. (1)	Same City (2)	Redlined Neigh. (3)	Death Age (4)	Survival to age 70 (5)
Displaced	-0.014[a]	0.014	0.005	-0.126[b]	-0.010[a]
	(0.002)	(0.014)	(0.007)	(0.051)	(0.003)
Adjacent	-0.004[b]	0.016[a]	0.005[b]	-0.038	-0.001
	(0.002)	(0.004)	(0.002)	(0.038)	(0.002)
Mean dep. var.	0.022	0.607	0.061	78.256	0.848
R-squared (adj)	0.027	0.019	0.029	0.862	0.641
Observations	35,924	35,924	35,924	35,924	35,924

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died after 1995. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 100 and 200 meters from a future highway. Mortality variables are not weighted. Each column corresponds to a different regression. The dependent variable in column (1) is an indicator that equals one if the individual lives at time of death in the same neighborhood they lived in 1940. In column (2), the dependent variable is an indicator that equals one if the individual lives in the same city they lived in 1940. Column (3) uses an indicator taking value equal to one if the residence at time of death was located in a redlined area as dependent variable. Column (4) use the age at death as dependent variable. Finally, the dependent variable in Column (5) is an indicator if the individual survived until the age of 70. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table E.5: Long-term Effects of Highway Construction – All Highway Segments

	Same Neigh. (1)	Same City (2)	Redlined Neigh. (3)	Death Age (4)	Survival to age 70 (5)
Displaced	-0.014[a]	0.013	0.002	-0.049	-0.004[a]
	(0.002)	(0.013)	(0.005)	(0.043)	(0.002)
Adjacent	-0.005[a]	0.011[a]	0.000	-0.059[a]	-0.003[a]
	(0.001)	(0.004)	(0.002)	(0.022)	(0.001)
Mean dep. var.	0.028	0.600	0.058	79.094	0.892
R-squared (adj)	0.026	0.027	0.037	0.864	0.533
Observations	85,877	85,877	85,877	81,153	81,153

Note: OLS estimates are reported. All highway segments are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 100 and 200 meters from a future highway. Each column corresponds to a different regression. The dependent variable in column (1) is an indicator that equals one if the individual lives at time of death in the same neighborhood they lived in 1940. In column (2), the dependent variable is an indicator that equals one if the individual lives in the same city they lived in 1940. Column (3) uses an indicator taking value equal to one if the residence at time of death was located in a redlined area as dependent variable. Column (4) use the age at death as dependent variable. Finally, the dependent variable in Column (5) is an indicator if the individual survived until the age of 70. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table E.6: Long-term Effects of Highway Construction – All Death Years

	Same Neigh. (1)	Same City (2)	Redlined Neigh. (3)	Death Age (4)	Survival to age 70 (5)
Displaced	-0.016[a]	0.010	0.003	-0.127[c]	-0.010[a]
	(0.002)	(0.015)	(0.008)	(0.069)	(0.004)
Adjacent	-0.005[a]	0.014[a]	0.003	-0.029	0.000
	(0.002)	(0.004)	(0.002)	(0.035)	(0.002)
Mean dep. var.	0.023	0.616	0.064	77.537	0.825
R-squared (adj)	0.029	0.018	0.029	0.782	0.546
Observations	44,005	44,005	44,005	44,005	44,005

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died between 1988 and 2005. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 100 and 200 meters from a future highway. Each column corresponds to a different regression. The dependent variable in column (1) is an indicator that equals one if the individual lives at time of death in the same neighborhood they lived in 1940. In column (2), the dependent variable is an indicator that equals one if the individual lives in the same city they lived in 1940. Column (3) uses an indicator taking value equal to one if the residence at time of death was located in a redlined area as dependent variable. Column (4) use the age at death as dependent variable. Finally, the dependent variable in Column (5) is an indicator if the individual survived until the age of 70. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table E.7: Long-term Effects of Highway Construction – Yellow Book

	Same Neigh. (1)	Same City (2)	Redlined Neigh. (3)	Death Age (4)	Survival to age 70 (5)
Displaced	-0.015[a]	0.020	0.004	-0.145[a]	-0.008[a]
	(0.003)	(0.019)	(0.007)	(0.043)	(0.003)
Adjacent	-0.005[b]	0.021[a]	0.005[b]	0.024	0.001
	(0.002)	(0.008)	(0.002)	(0.022)	(0.001)
Mean dep. var.	0.024	0.612	0.061	79.133	0.895
R-squared (adj)	0.023	0.021	0.027	0.864	0.525
Observations	46,118	46,118	46,118	43,714	43,714

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died between 1995 and 2005. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 0 and 100 meters from a highway planned in the Yellow Book maps. Each column corresponds to a different regression. The dependent variable in column (1) is an indicator that equals one if the individual lives at time of death in the same neighborhood they lived in 1940. In column (2), the dependent variable is an indicator that equals one if the individual lives in the same city they lived in 1940. Column (3) uses an indicator taking value equal to one if the residence at time of death was located in a redlined area as dependent variable. Column (4) use the age at death as dependent variable. Finally, the dependent variable in Column (5) is an indicator if the individual survived until the age of 70. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table E.8: Neighborhood Characteristics at Time of Death – Yellow Book

	High School Share (1)	College Share (2)	Employment Share (3)	Log Median Income (4)	Log Median Home Value (5)	Log Avg. Rent 2 bedroom (6)
Displaced	-1.154[a]	-1.967[a]	-0.005[a]	-0.015	-0.017	-0.011
	(0.359)	(0.739)	(0.001)	(0.010)	(0.018)	(0.008)
Adjacent	-0.462[a]	-1.096[a]	0.000	-0.007	-0.017[b]	-0.003
	(0.138)	(0.240)	(0.001)	(0.004)	(0.008)	(0.004)
Mean dep. var.	85.288	34.597	0.581	10.981	12.119	6.965
R-squared (adj)	0.132	0.094	0.052	0.103	0.233	0.254
Observations	46,003	46,003	46,112	45,955	45,237	36,219

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died after 1995. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 0 and 100 meters from a highway planned in the Yellow Book maps. Each column corresponds to a different regression. The dependent variables correspond to the neighborhood-level characteristics of the residence at time of death. The dependent variable in column (1) corresponds to the share of adults living in the neighborhood who have completed high school. In column (2), the dependent variable is the college share. Column (3) uses the employment share as dependent variable. Columns (4) and (5) use the log median income and log median house value, respectively. Finally, column (6) uses the log average rent for a two bedroom apartment as dependent variable. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

Table E.9: Long-term Effects of Yellow Book plans

	Same Neigh. (1)	Same City (2)	Redlined Neigh. (3)	Death Age (4)	Survival to age 70 (5)
Displaced	0.002	-0.007	-0.004	0.040	0.001
	(0.002)	(0.007)	(0.003)	(0.041)	(0.004)
Adjacent	0.000	0.000	-0.000	-0.018	-0.001
	(0.001)	(0.004)	(0.002)	(0.022)	(0.001)
Mean dep. var.	0.028	0.613	0.060	79.177	0.897
R-squared (adj)	0.024	0.025	0.033	0.864	0.516
Observations	57,515	57,515	57,515	54,436	54,436

Note: OLS estimates are reported. Only highways planned in the Yellow Books are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died between 1995 and 2005. Displaced corresponds to individuals living in 1940 in houses potentially destroyed by planned highways. Adjacent corresponds to individuals living in 1940 within 100 meters from a planned highway. The control group are individuals living between 100 and 200 meters from a planned highway. Each column corresponds to a different regression. The dependent variable in column (1) is an indicator that equals one if the individual lives at time of death in the same neighborhood they lived in 1940. In column (2), the dependent variable is an indicator that equals one if the individual lives in the same city they lived in 1940. Column (3) uses an indicator taking value equal to one if the residence at time of death was located in a redlined area as dependent variable. Column (4) use the age at death as dependent variable. Finally, the dependent variable in Column (5) is an indicator if the individual survived until the age of 70. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. ^{a} indicates the coefficient is significant at the 1%, ^{b} at the 5%, and ^{c} at the 10%.

Table E.10: Neighborhood Characteristics at Time of Death

	High School Share (1)	College Share (2)	Employment Share (3)	Log Median Income (4)	Log Median Home Value (5)	Log Avg. Rent 2 bedroom (6)
Displaced	0.020	-0.054	-0.002	-0.003	-0.006	-0.006
	(0.162)	(0.266)	(0.001)	(0.004)	(0.007)	(0.005)
Adjacent	0.098	-0.043	0.001	-0.000	-0.005	-0.003
	(0.092)	(0.136)	(0.001)	(0.003)	(0.004)	(0.002)
Mean dep. var.	85.351	34.692	0.583	10.973	12.090	6.950
R-squared (adj)	0.141	0.103	0.056	0.109	0.242	0.255
Observations	57,366	57,366	57,500	57,287	56,396	45,087

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died after 1995. Displaced corresponds to individuals living in 1940 in houses potentially destroyed by planned highways. Adjacent corresponds to individuals living in 1940 within 100 meters from a planned highway. The control group are individuals living between 100 and 200 meters from a planned highway. Each column corresponds to a different regression. The dependent variables correspond to the neighborhood-level characteristics of the residence at time of death. The dependent variable in column (1) corresponds to the share of adults living in the neighborhood who have completed high school. In column (2), the dependent variable is the college share. Column (3) uses the employment share as dependent variable. Columns (4) and (5) use the log median income and log median house value, respectively. Finally, column (6) uses the log average rent for a two bedroom apartment as dependent variable. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. ^{a} indicates the coefficient is significant at the 1%, ^{b} at the 5%, and ^{c} at the 10%.

Table E.11: Long-term Effects of Highway Construction on Cohorts Born Before 1910

	Same Neigh. (1)	Same City (2)	Redlined Neigh. (3)	Death Age (4)
Displaced	-0.025[a]	-0.110[a]	-0.009	-0.645[a]
	(0.008)	(0.035)	(0.015)	(0.165)
Adjacent	-0.004	0.022	0.008	-0.170[c]
	(0.007)	(0.018)	(0.006)	(0.092)
Mean dep. var.	0.033	0.592	0.058	92.063
R-squared (adj)	0.044	0.007	0.031	0.433
Observations	2,615	2,615	2,615	2,516

Note: OLS estimates are reported. Only segments opened between 1950 and 1960 are included in the sample. An observation is an individual in the 1940 full count census matched to administrative mortality records. The sample consists of individuals who died after 1995 and were born before 1910. Displaced corresponds to individuals living in 1940 in houses destroyed by highway construction. Adjacent corresponds to individuals living in 1940 within 100 meters of future development. The control group are individuals living between 100 and 200 meters from a future highway. Each column corresponds to a different regression. The dependent variable in column (1) is an indicator that equals one if the individual lives at time of death in the same neighborhood they lived in 1940. In column (2), the dependent variable is an indicator that equals one if the individual lives in the same city they lived in 1940. Column (3) uses an indicator taking value equal to one if the residence at time of death was located in a redlined area as dependent variable. Column (4) use the age at death as dependent variable. All regressions control for race, gender at birth, homeownership, city, and birth year fixed effects. Coefficients are reported with standard errors clustered at the city where the individual lived in 1940 level. [a] indicates the coefficient is significant at the 1%, [b] at the 5%, and [c] at the 10%.

F Event Study Appendix

F.1 Matched Sample Statistics

Table F.1 reports the summary statistics of the matched sample in the last decade before highway opening. Column (1) reports statistics on the full-matched sample. Columns (2) and (3) display the statistics for treated and control census tracts, respectively. Finally, column 4 presents the p-value of an OLS regression between the variable and an indicator that takes the value one if a highway was built through the tract and zero otherwise.

The average census tract has a log total population of 8.28 (3944 inhabitants) and its population is mostly White. The average tract in the sample has a Black share of 12.3%, and most of their population does not own the property where they live. Tracts in the sample are located at similar distances from the city center, with no significant difference between treated and control tracts. Differences in Black share, home-ownership rate, and median home value notwithstanding, covariates are relatively well balanced between treated and control groups. The algorithm matches well variables that were not used in the procedure, such as other race populations, home-ownership, and Black population.

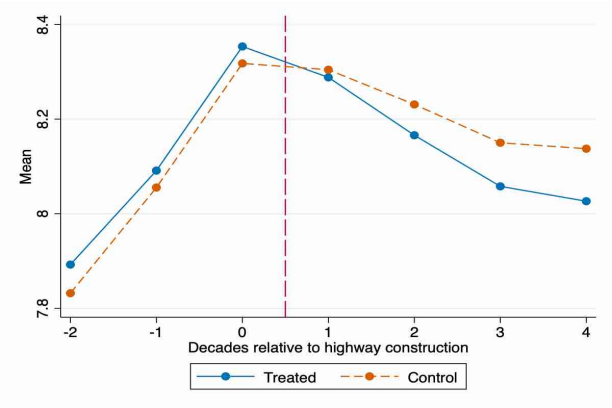
Figure F.1 presents the evolution of the population raw means relative to highway construction. The matched sample has had a similar evolution in the decades leading up to treatment for both control and treatment tracts. Figure F.1a and Figure F.1b show that the total population decreases in absolute terms for both groups in the sample. However, a different picture arises when we split the sample between the Black and White populations. Figure F.1c and Figure F.1d suggest that the Black population is increasing over time for treatment and control tracts. The White population, on the other hand, is decreasing over the sample as shown by Figure F.1e and Figure F.1f. Thus, the Black share in both groups is increasing (Figure F.3b).

Now, I turn my attention to the evolution of the median rent, home value, and home-ownership rate. Figure F.2 presents these plots. We can see that prices go up after highway construction. Panels (a) - (d) show an upward evolution of both the level and the log level of the mean of median rent and median home value. Finally, we observe that the home-ownership rate decreases after highway construction, as seen in Figure F.3d. It is worth pointing out that the matching procedure accurately matches the evolution of the variables excluded from the matching procedure (median home value, home ownership, the Black share) before treatment.

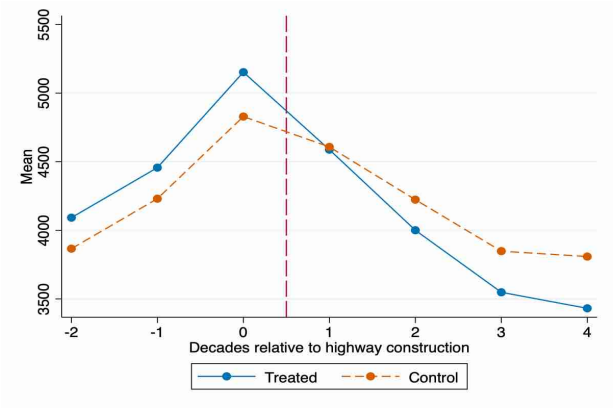
F.2 Additional Figures

In this section, I present additional figures for the event-study section.

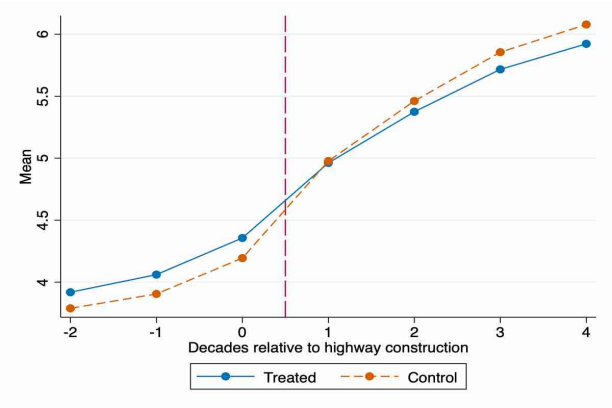
Figure F.1: Raw Means Evolution



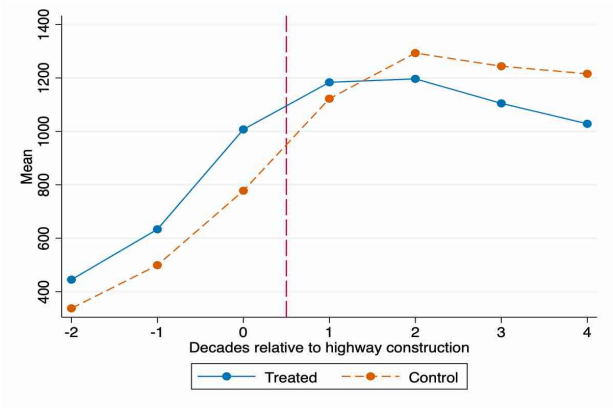
(a) Log Total Population



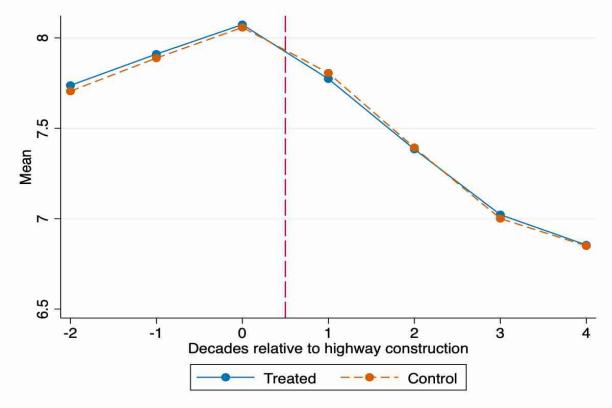
(b) Total Population



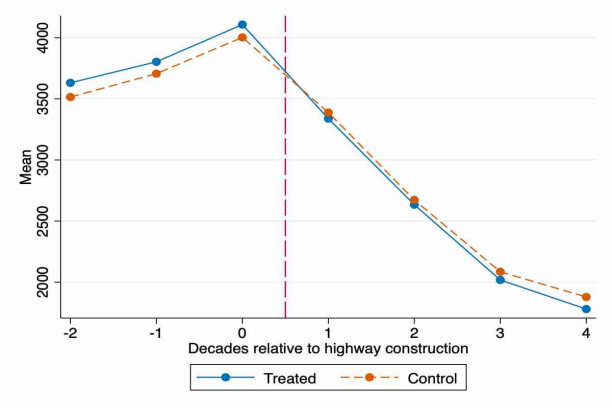
(c) Log Black Population



(d) Black Population



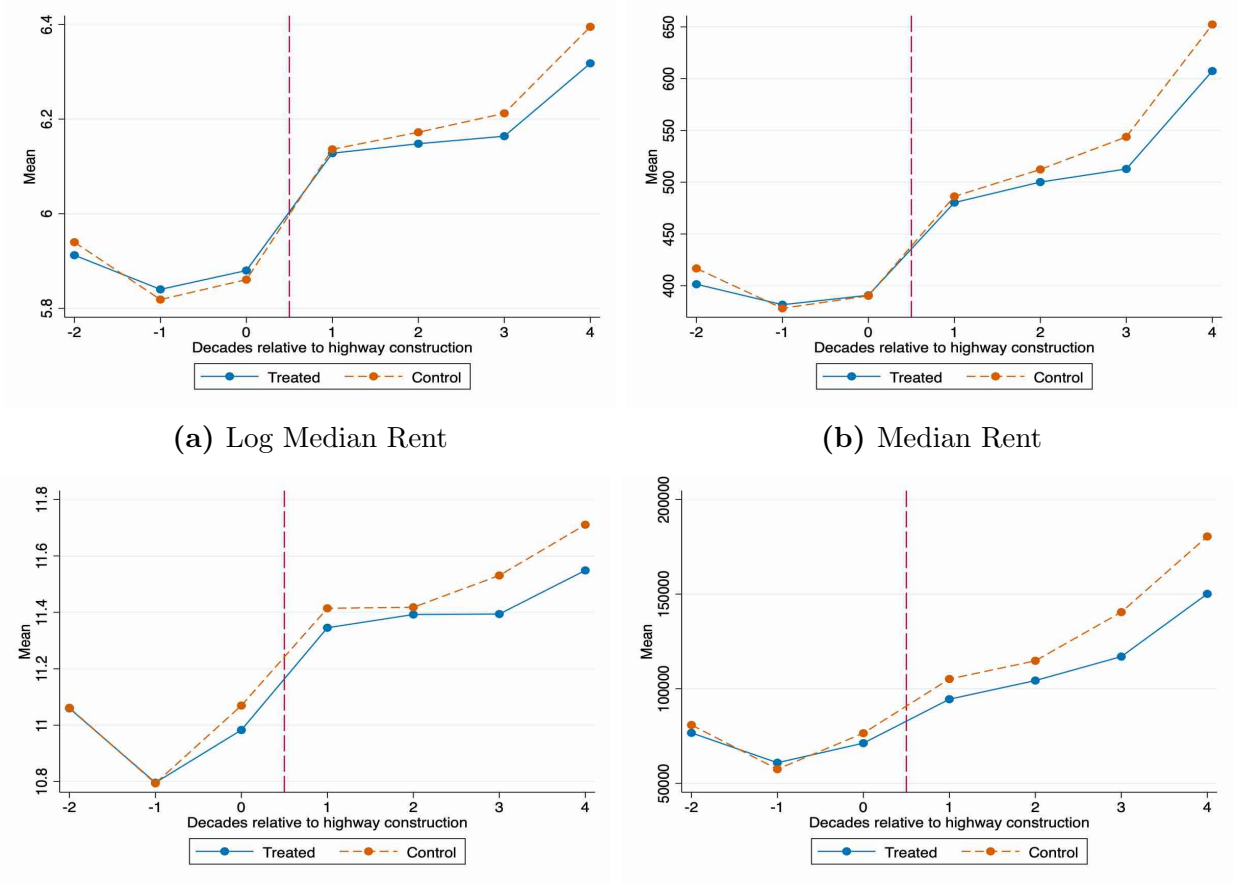
(e) Log White Population



(f) White Population

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. All panels display the raw means of treated and control tracts relative to the treatment decade. The sample is weighted by the log population of the tract in the decade before highway construction. Panel (a) shows the log total population raw mean, whereas Panel (b) presents the evolution of the total population. Panel (c) shows the log Black population raw mean, whereas Panel (d) presents the evolution of the Black population. Panel (e) shows the log White population raw mean, whereas Panel (f) presents the evolution of the White population. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

Figure F.2: Raw Means Evolution *(continued)*



(a) Log Median Rent

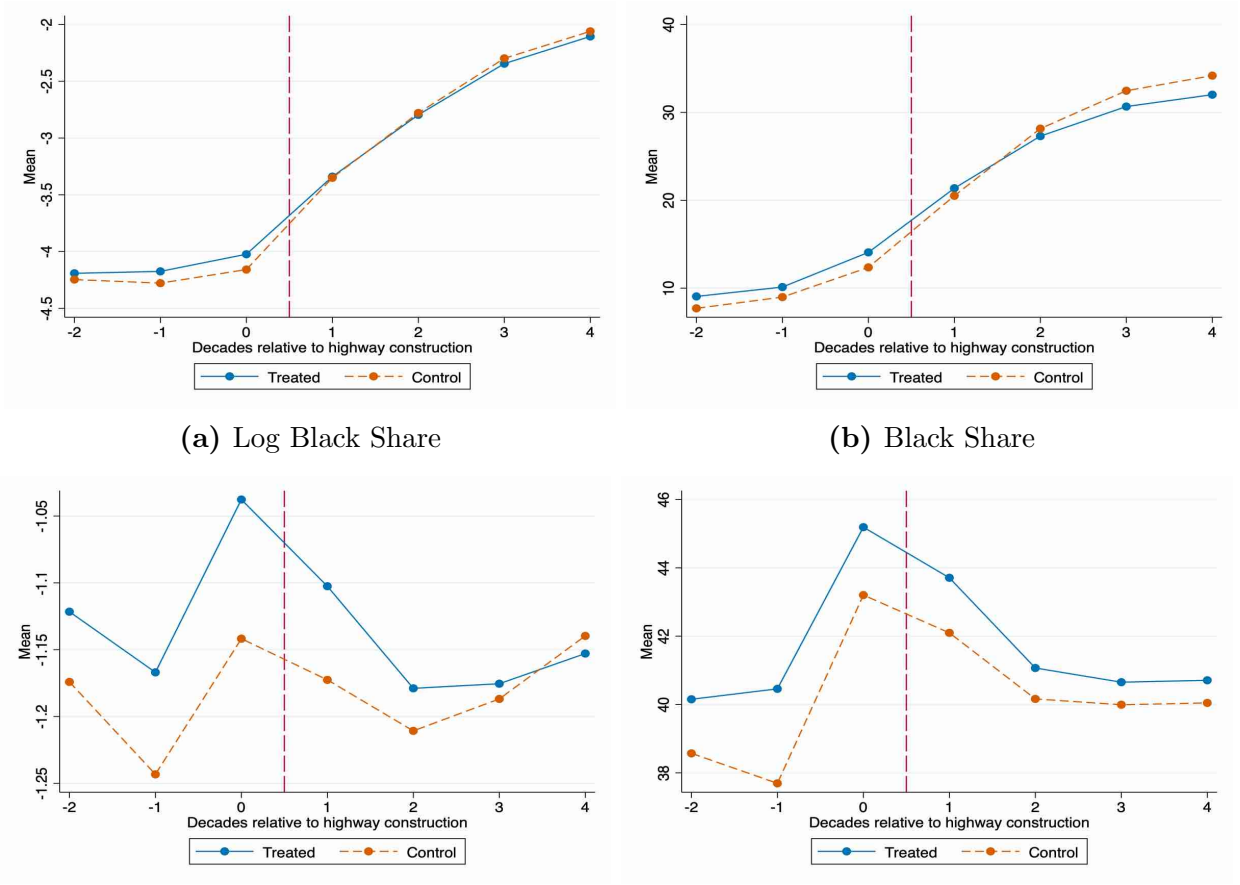
(b) Median Rent

(c) Log Median Home Value

(d) Median Value

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. All panels display the raw means of treated and control tracts relative to the treatment decade. The sample is weighted by the log population of the tract in the decade before highway construction. Panel (a) shows the evolution of the log median rent raw mean, whereas Panel (b) presents the evolution of the level. Panel (c) shows the evolution of the log median home value raw mean, whereas Panel (b) presents the evolution of the level in the tract's median home value. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

Figure F.3: Raw Means Evolution *(continued)*



(a) Log Black Share

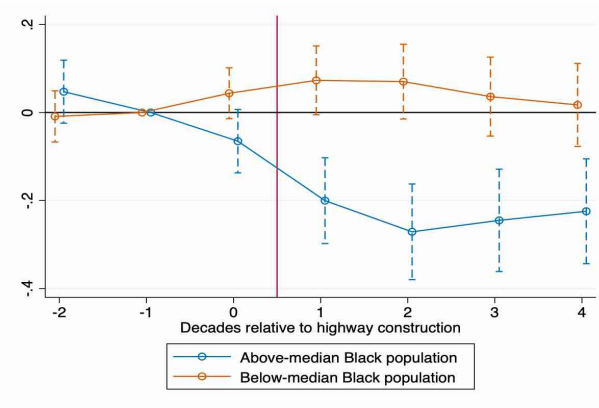
(b) Black Share

(c) Log Home-ownership Share

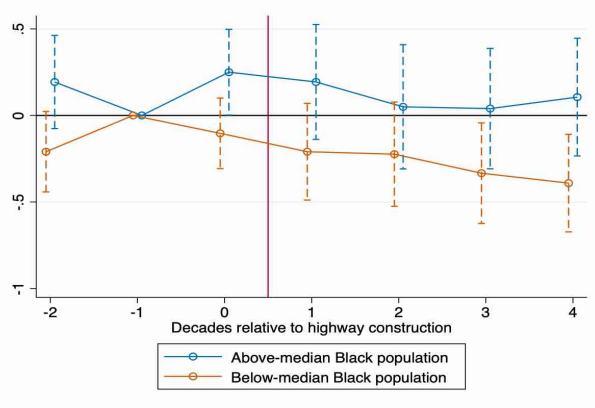
(d) Home-ownership Share

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. All panels display the raw means of treated and control tracts relative to the treatment decade. The sample is weighted by the log population of the tract in the decade before highway construction. Panel (a) shows the evolution in the log Black share raw mean, whereas Panel (b) presents the evolution of the level. Panel (c) presents the evolution in the log home-ownership rate, whereas Panel (d) presents the evolution of the level. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

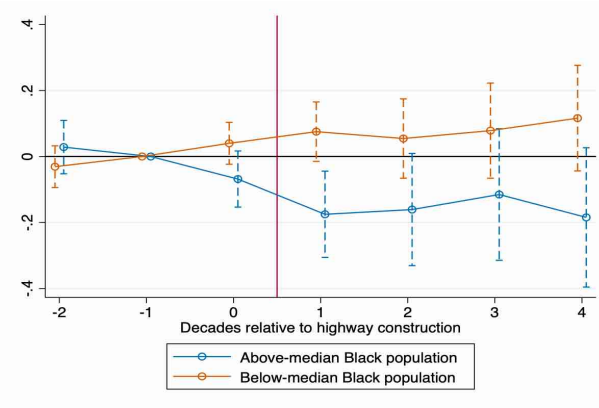
Figure F.4: Above- and Below-Median Black Population



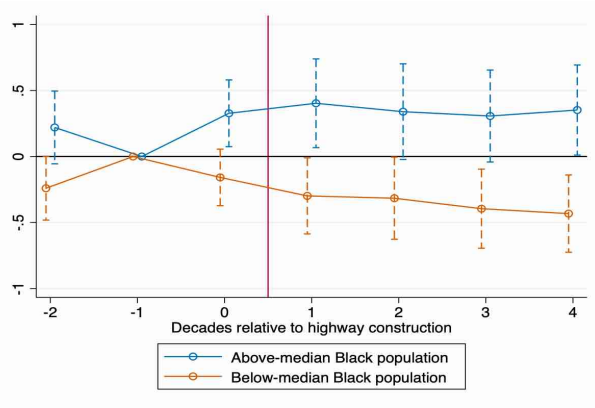
(a) Log Total Population



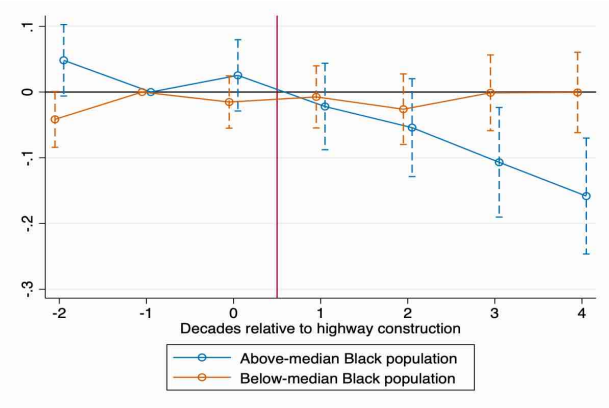
(b) Log Black Population



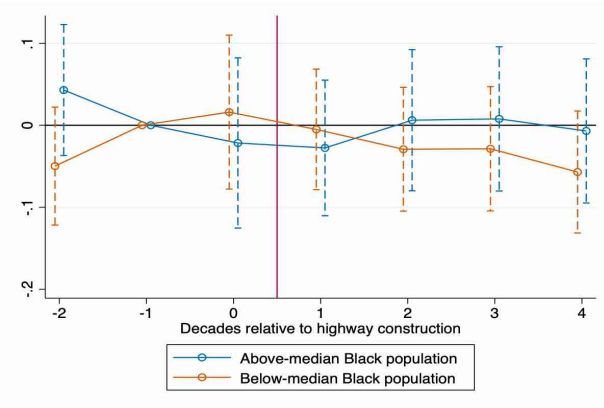
(c) Log White Population



(d) Log Black Share



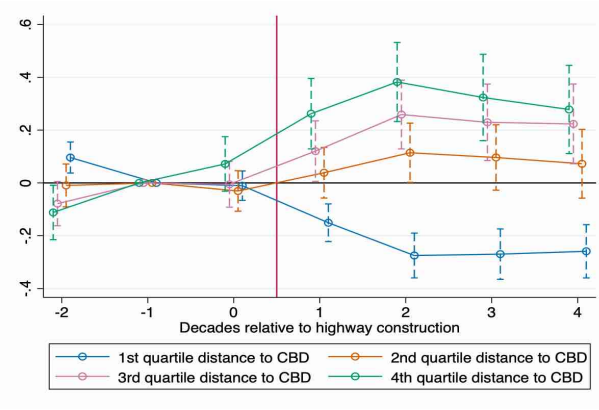
(e) Log Home-ownership Share



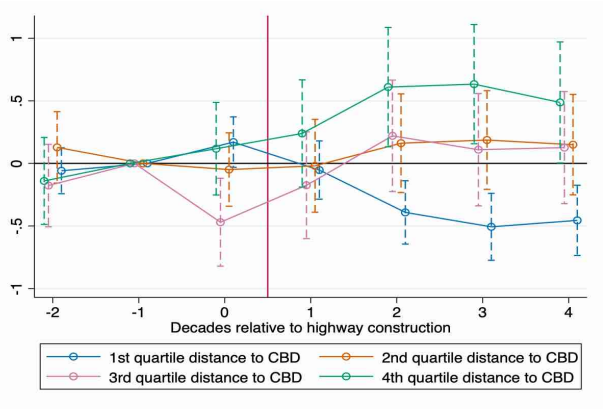
(f) Log Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. Tracts with above-median Black population in the last census before construction are plotted in blue, whereas below-median tracts are plotted in orange. The coefficients at $k = -1$ are normalized to zero. The sample is weighted by the log population of the tract in the decade before highway construction, and standard errors are clustered at the census tract level. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the log total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share of the tract, Panel (e) for the log home-ownership share, and Panel (f) shows the effect on the log median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

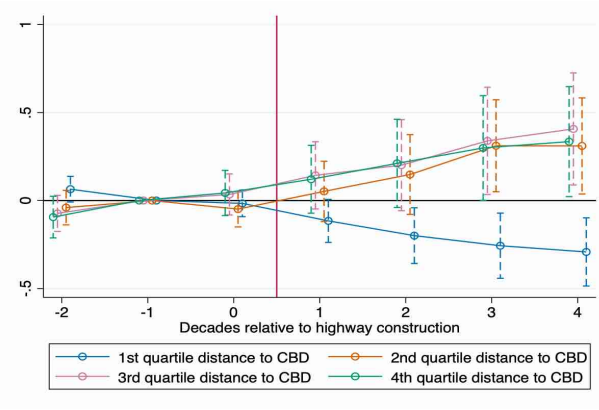
Figure F.5: Quartiles of Distance to the Central Business District



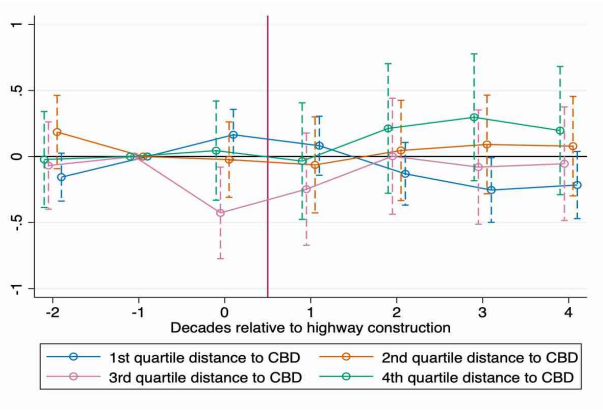
(a) Log Total Population



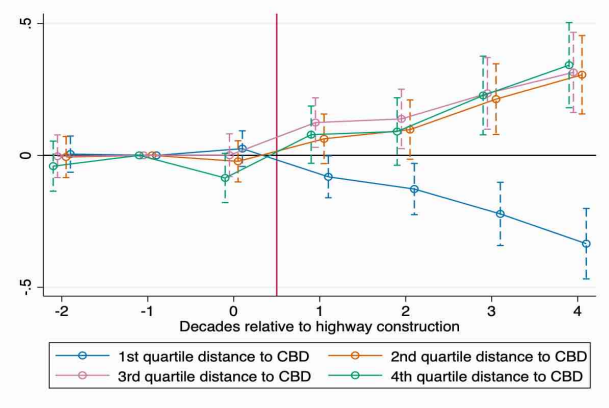
(b) Log Black Population



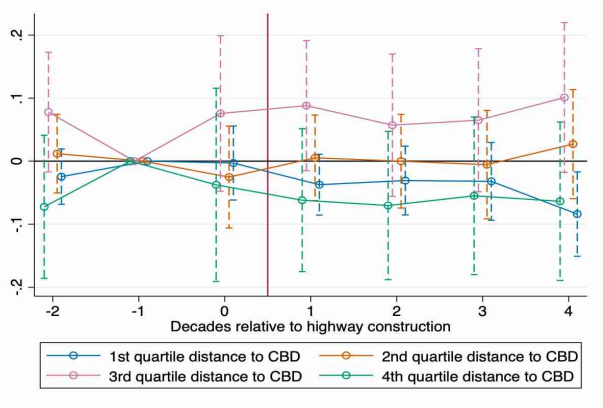
(c) Log White Population



(d) Log Black Share



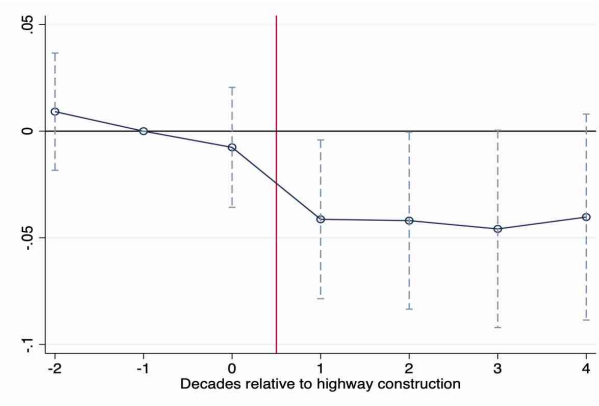
(e) Log Home-ownership Share



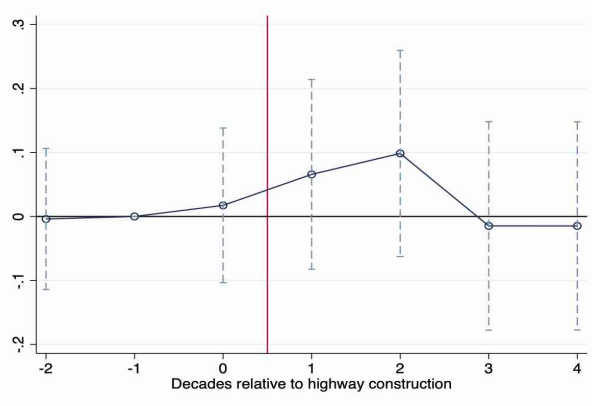
(f) Log Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. The first quartile correspond to all tracts which it's centroid is within 3.3 kilometers of the CBD, the second quartiles is within 3.3 and 6 kilometers, the third quartile between 6 and 11.8 kilometers, and the fourth quartile are those located more than 11.8 kilometers from the CBD. The coefficients at $k = -1$ are normalized to zero. The sample is weighted by the log population of the tract in the decade before highway construction, and standard errors are clustered at the census tract level. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the log total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share of the tract, Panel (e) shows the effect for the log home-ownership share, and Panel (f) shows the effect on the log median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

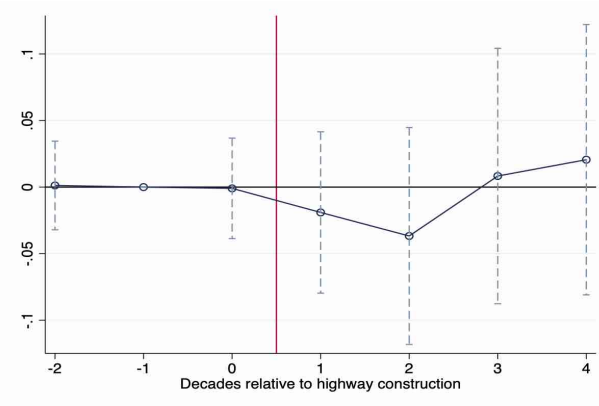
Figure F.6: Spillovers into Adjacent Neighborhoods



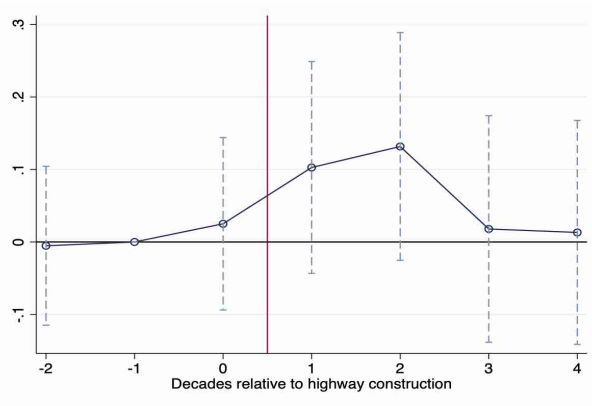
(a) Log Total Population



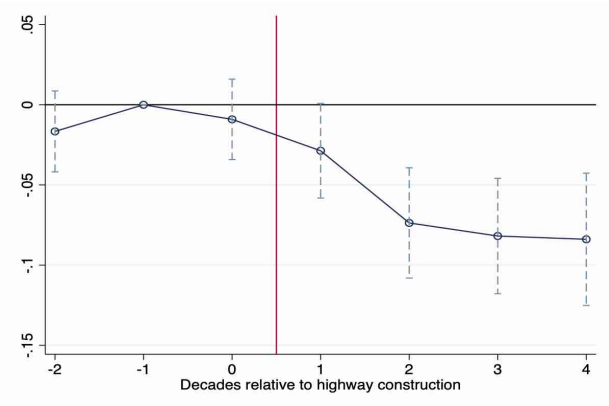
(b) Log Black Population



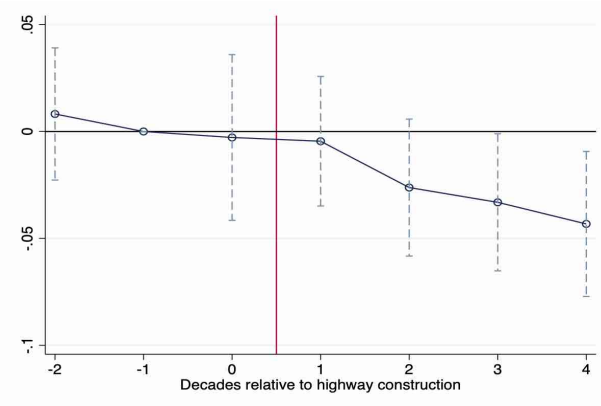
(c) Log White Population



(d) Log Black Share



(e) Log Home-ownership Share



(f) Log Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 2,071/3,364 events. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. The coefficients at $k = -1$ are normalized to zero. Treatment es equal to one when a highway is constructed in an adjacent tract, and zero otherwise. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the log total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share of the tract, Panel (e) shows the effect for the log home-ownership rate, and Panel (f) shows the effect on the log median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening. Standard errors are clustered at the census tract level, and observations are weighted by the log total population before construction.

F.3 Additional Tables

In this section I present descriptive statistics of the tracts in the last decade before highway construction.

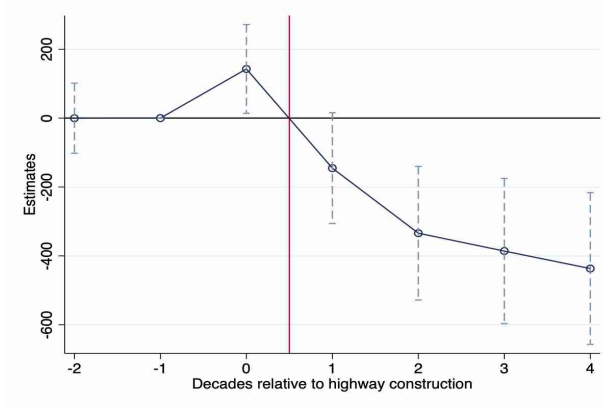
Table F.1: Descriptive Statistics

	Matched Sample (1)	Matched Treated (2)	Matched Control (3)	p-val (4)
(log) Total population	8.28	8.30	8.27	0.236
	(0.66)	(0.68)	(0.63)	
(log) Black population	4.19	4.26	4.12	0.158
	(2.66)	(2.72)	(2.59)	
(log) White population	8.02	8.03	8.02	0.759
	(0.83)	(0.83)	(0.83)	
(log) Other population	2.35	2.31	2.38	0.226
	(1.59)	(1.59)	(1.60)	
Black share	12.73	13.53	11.93	0.062
	(23.89)	(24.56)	(23.18)	
(log) Median rent	5.87	5.88	5.86	0.362
	(0.61)	(0.57)	(0.64)	
(log) Median home value	11.04	11.00	11.08	0.071
	(1.13)	(1.15)	(1.11)	
Home-ownership (%)	44.73	45.79	43.68	0.022
	(25.71)	(25.08)	(26.28)	
Distance to CBD	9.00	8.97	9.02	0.878
	(8.81)	(8.88)	(8.73)	
Observations	3,124	1,562	1,562	

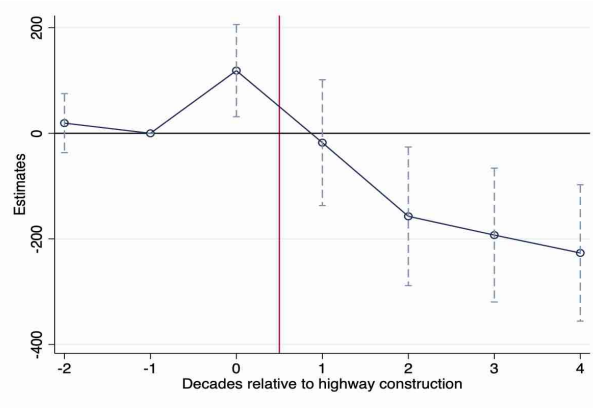
Note: An observation is a census tract in the last decade prior to highway construction. Treated tracts are matched to out-of-city potential control tracts. All statistics are calculated across tract-year observations in the decade before highway construction. Column (1) reports statistics on the matched sample, and columns (2) and (3) limit the sample to treated and control tracts, respectively. Column (4) reports the p-value associated with the null hypothesis that the difference in means between treated and control tracts is equal to zero.

F.4 Robustness Checks

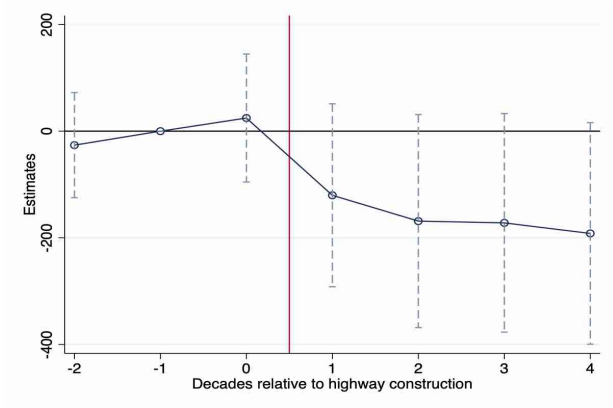
Figure F.7: Dependent Variable in Levels



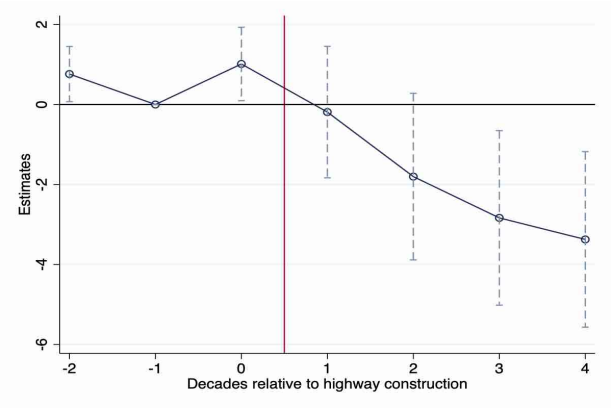
(a) Total Population



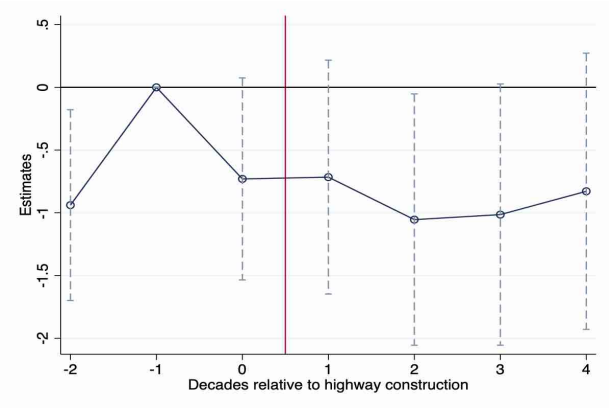
(b) Black Population



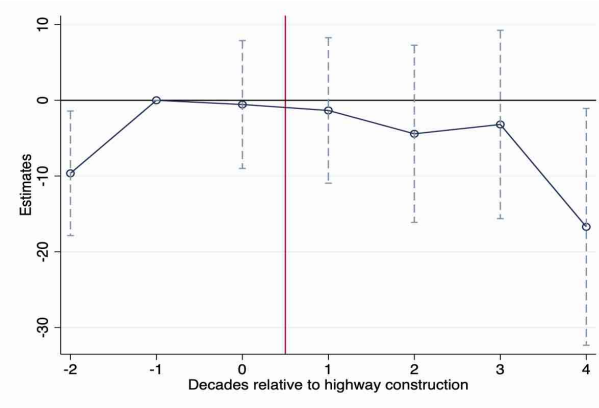
(c) White Population



(d) Black Share



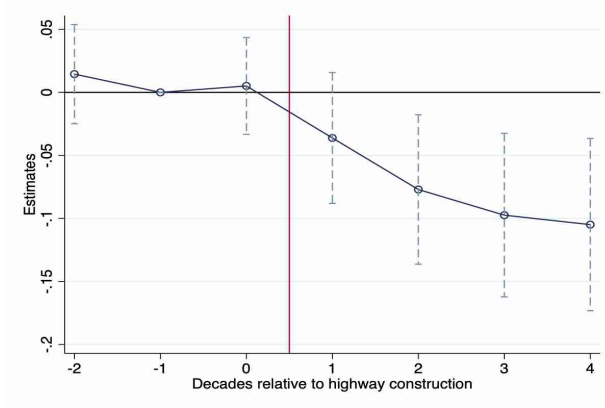
(e) Home-ownership Share



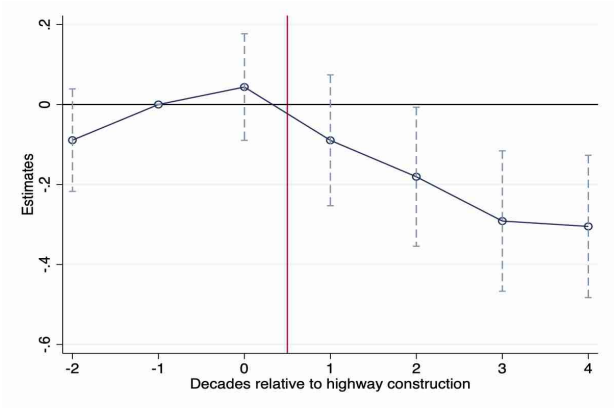
(f) Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. The coefficients at $k = -1$ are normalized to zero. The sample is weighted by the log population of the tract in the decade before highway construction, and standard errors are clustered at the census tract level. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share, Panel (e) on the home-ownership share, and Panel (f) shows the effect on the median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

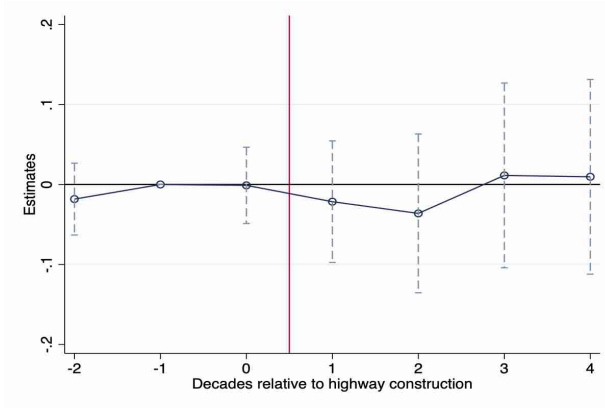
Figure F.8: No Population Weights



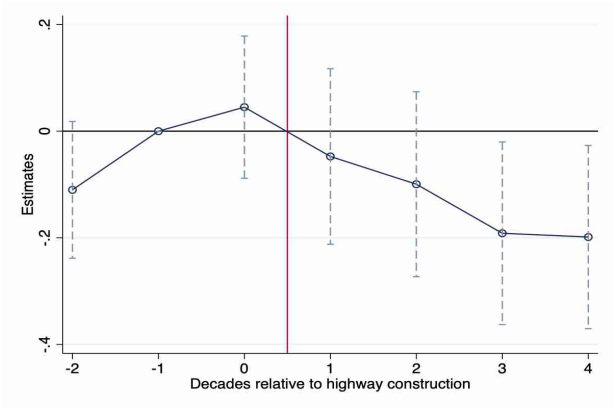
(a) Log Total Population



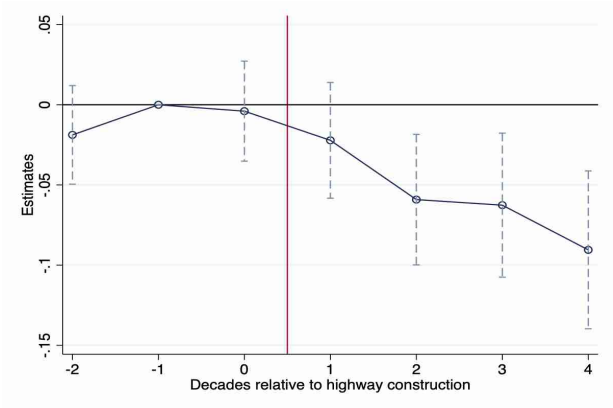
(b) Log Black Population



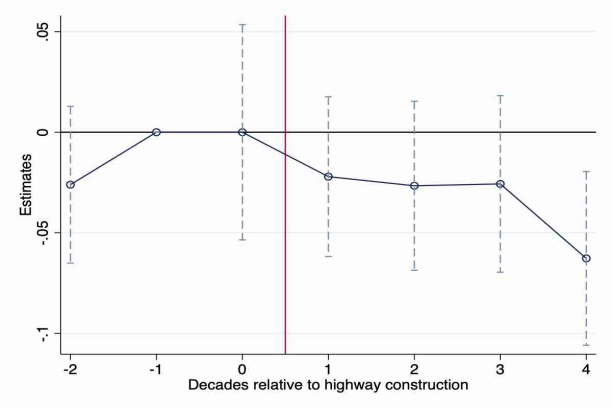
(c) Log White Population



(d) Log Black Share



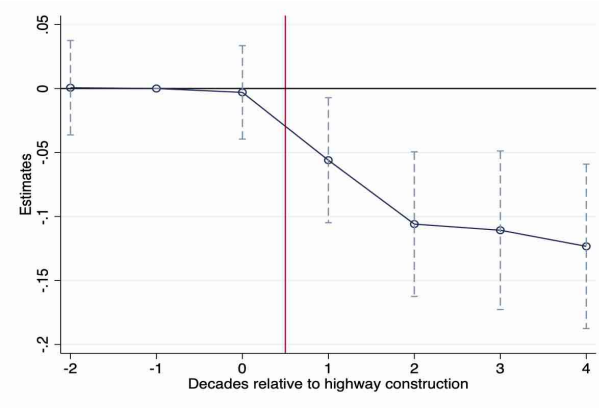
(e) Log Home-ownership Share



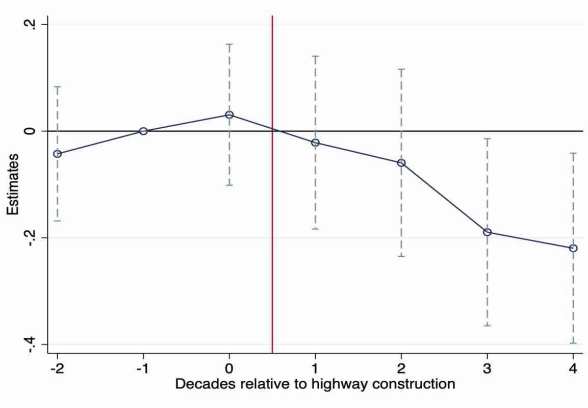
(f) Log Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. The coefficients at $k = -1$ are normalized to zero. The standard errors are clustered at the census tract level. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the log total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share of the tract, Panel (e) for the home-ownership share, and Panel (f) shows the effect on the log median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

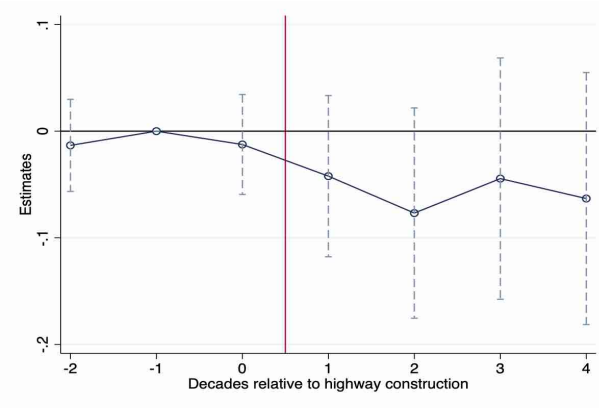
Figure F.9: Including Tracts Planned to Receive a Highway



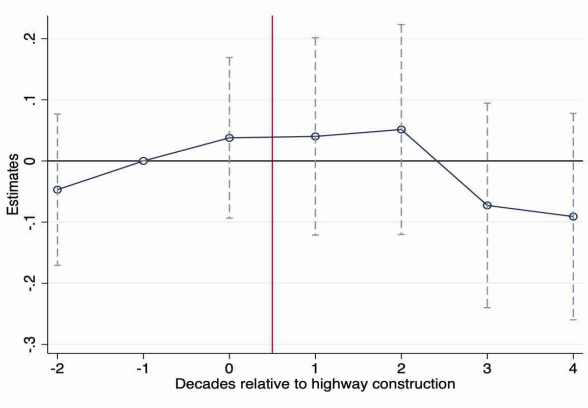
(a) Log Total Population



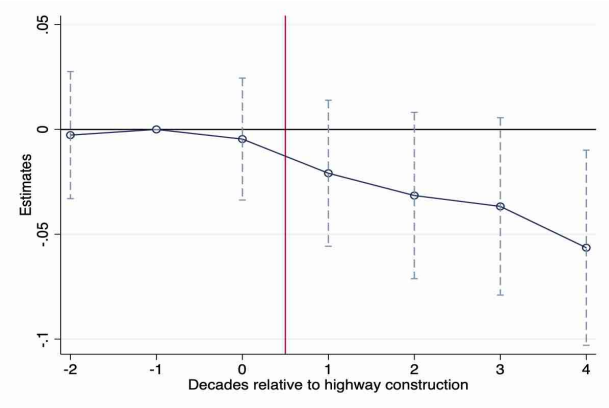
(b) Log Black Population



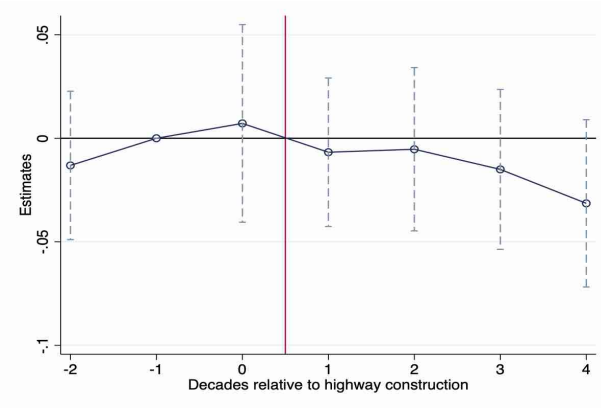
(c) Log White Population



(d) Log Black Share



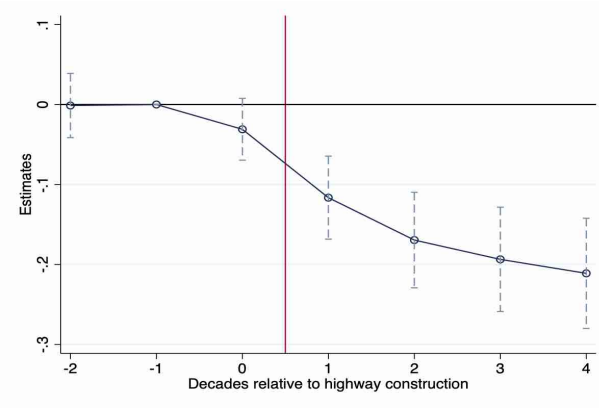
(e) Log Home-ownership Share



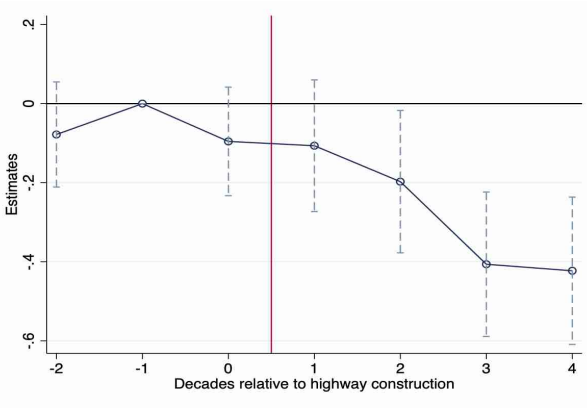
(f) Log Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. Potential control tracts are all the out-of-city tracts that did not receive a highway outside, including those which were planned to receive a highway. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. The coefficients at $k = -1$ are normalized to zero. The sample is weighted by the log population of the tract in the decade before highway construction, and standard errors are clustered at the census tract level. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the log total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share of the tract, Panel (e) for the log home-ownership share, and Panel (f) shows the effect on the log median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

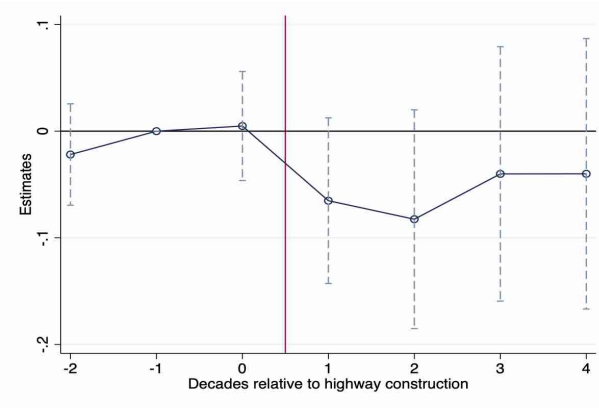
Figure F.10: Potential Controls 3 Kilometers from Highways



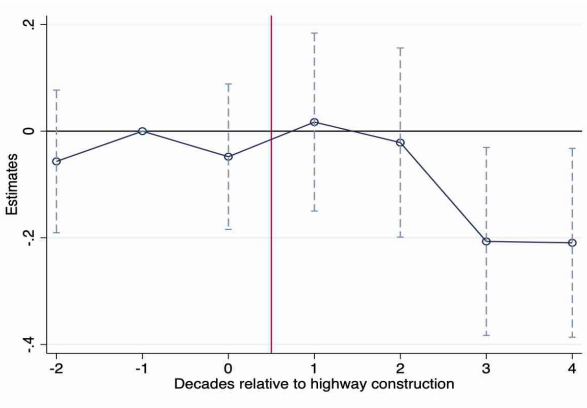
(a) Log Total Population



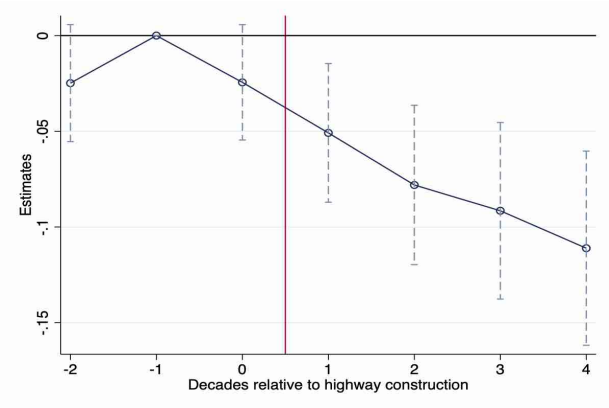
(b) Log Black Population



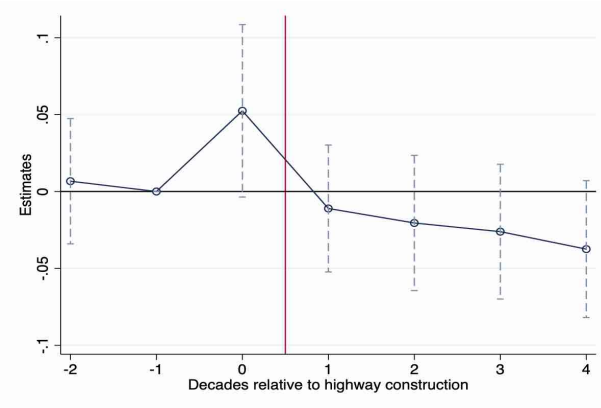
(c) Log White Population



(d) Log Black Share



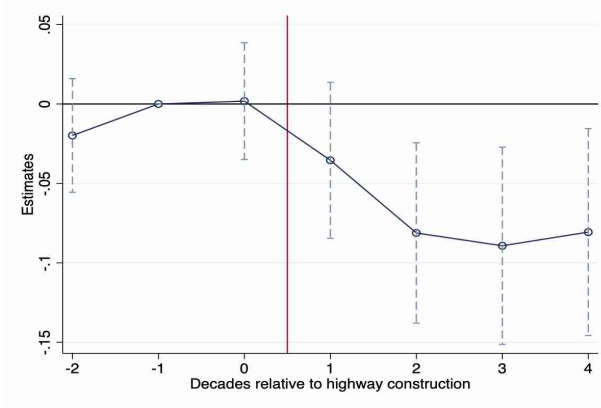
(e) Log Home-ownership Share



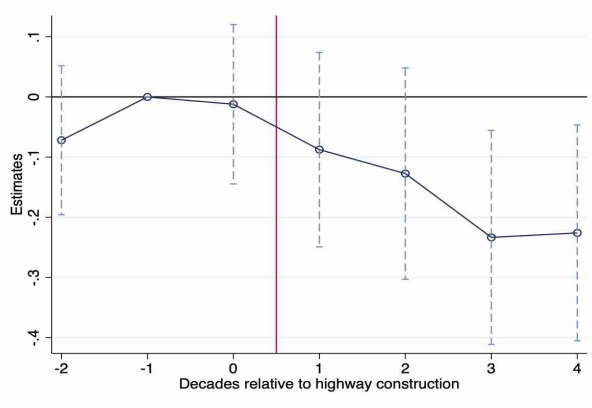
(f) Log Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. The distance between the potential controls' centroid and the closest highway is at least three kilometers. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. The coefficients at $k = -1$ are normalized to zero. The sample is weighted by the log population of the tract in the decade before highway construction, and standard errors are clustered at the census tract level. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the log total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share of the tract, Panel (e) for the log home-ownership share, and Panel (f) shows the effect on the log median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

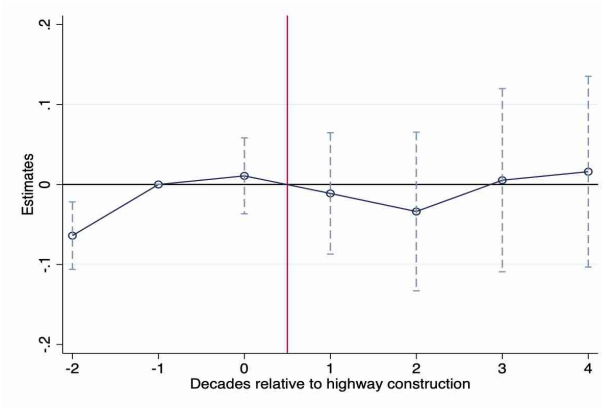
Figure F.11: All Cities



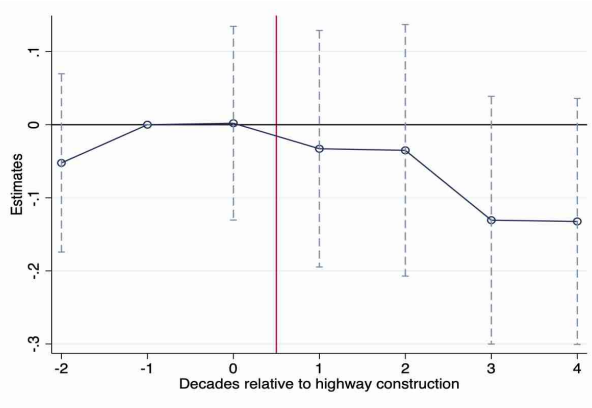
(a) Log Total Population



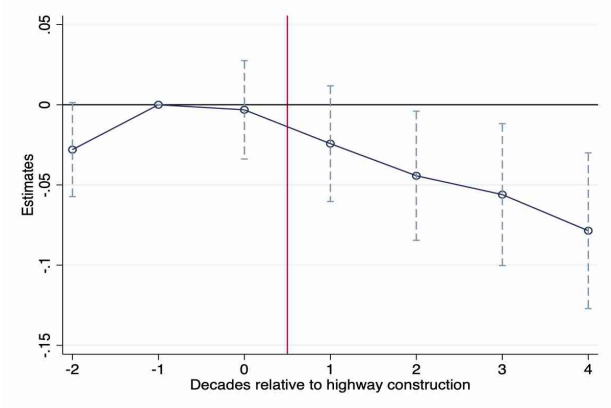
(b) Log Black Population



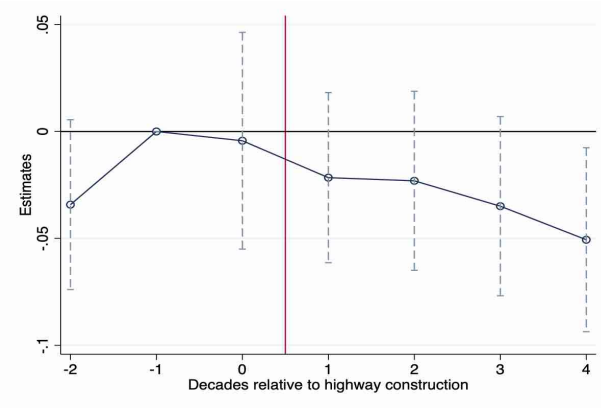
(c) Log White Population



(d) Log Black Share



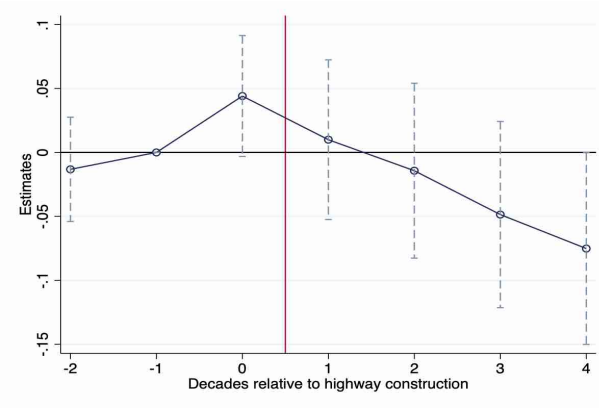
(e) Log Home-ownership



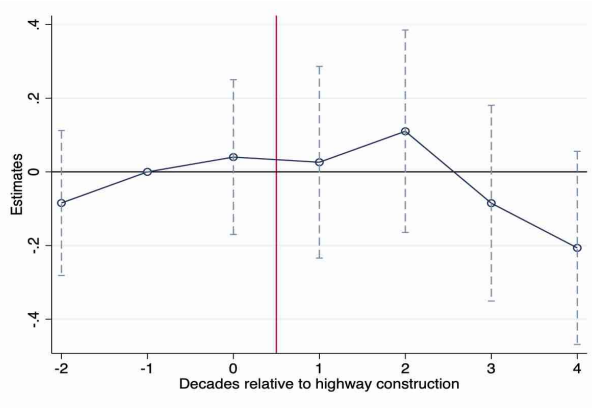
(f) Log Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 1,562/1,562 events. Potential control tracts are located in any city. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. The coefficients at $k = -1$ are normalized to zero. The sample is weighted by the log population of the tract in the decade before highway construction, and standard errors are clustered at the census tract level. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the log total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share of the tract, Panel (e) for the log home-ownership share, and Panel (f) shows the effect on the log median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

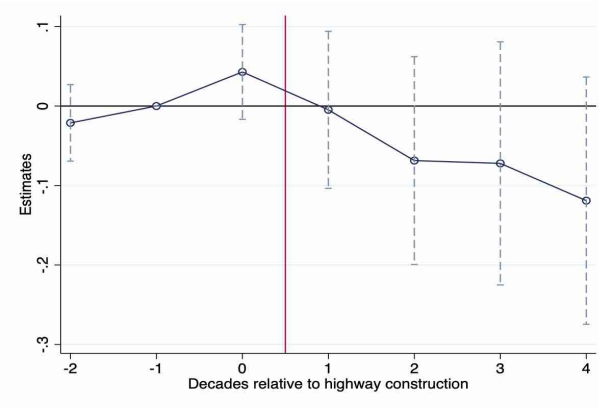
Figure F.12: Potential Controls in the Same city



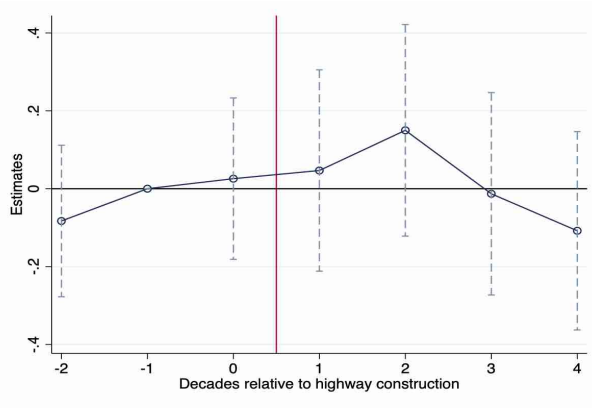
(a) Log Total Population



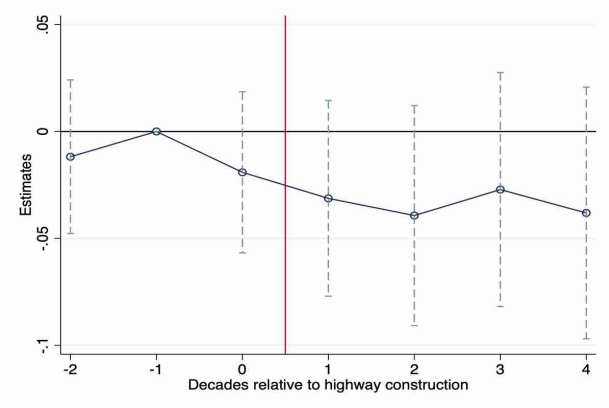
(b) Log Black Population



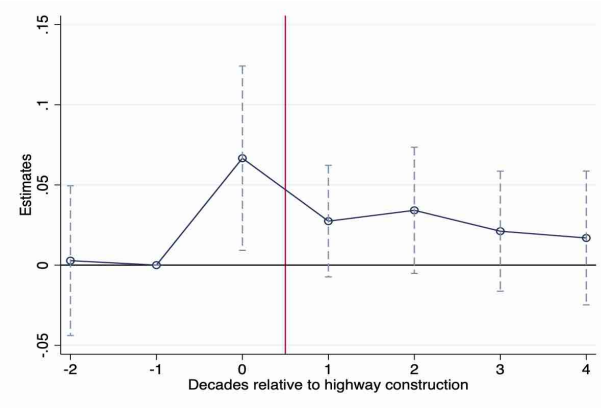
(c) Log White Population



(d) Log Black Share



(e) Log Home-ownership Share



(f) Log Median Rent

Note: Matched tracts sample, consistent boundary census tracts from 1930 to 2020. The matching algorithm managed to match 772/1,562 events. Potential control tracts are located in the same city. All panels display the coefficients and the associated 95% confidence intervals for the difference between trated and control tracts. The coefficients at $k = -1$ are normalized to zero. The sample is weighted by the log population of the tract in the decade before highway construction, and standard errors are clustered at the census tract level. All regressions include tract, decade, decades relative to treatment, and city-by-decade fixed effects. Panel (a) shows the effect of highway construction on the log total population, Panel (b) and Panel (c) show the effects for Black and White population. Panel (d) shows the effect on the log Black share of the tract, Panel (e) on the log home-ownership share, and Panel (f) shows the effect on the log median rent. The x-axis indexes event time. An event time equals to zero is the last decade before the highway opening.

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