Unequal Access: Racial Segregation and the Distributional Impacts of Interstate Highways in Cities

Laura Weiwu*

Stanford University

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Abstract

This paper investigates the impact of the largest infrastructure project in American history—the Interstate highway system—on inequality and the role of institutional segregation in its disparate incidence. To evaluate the distributional impacts, I develop a general equilibrium spatial framework that incorporates empirical estimates from disaggregated Census microdata in 1960 and 1970 for 25 cities. Highways generated substantial costs from local harms on adjacent areas as well as benefits from reductions in commute times. In the urban core, costs outweigh benefits as proximity to highways is greater and commute connectivity improves predominantly in remote suburbs. I find residential constraints account for much of the initial concentration of the Black population in central areas and their low mobility away, which contribute to racial rather than class gaps in impacts from the Interstate highway system. When barriers are eliminated and Black households are granted access beyond central neighborhoods, the gap in highway impacts is reduced while all groups experience large gains from interstate development. These results highlight how institutions shape inequality in the incidence of place-based shocks.

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1 Introduction

The Interstate highway system is a defining infrastructure project of American history and dramatically transformed cities nationwide. Immense sums of public investment have been channeled into Interstate development to achieve benefits from facilitating commuting between locations. But along with these benefits, highways were deeply destructive and produced substantial costs through local environmental pollution, noise near routes, and the splitting of existing communities (Mohl, 2004).[1]

I investigate the distributional consequences of the Interstate system, which conventional wisdom suggests promoted aggregate American economic growth—yet, a few crucial facts allude to highly heterogeneous impacts. Coinciding with construction in the 1960s, segregation reached extraordinary levels as pervasive legal and extralegal institutions excluded Black Americans from predominantly White neighborhoods (Cutler et al., 1999). As political advocacy by lower-income neighborhoods was often ineffectual in averting construction, disadvantaged groups in central areas where Interstate roads intersected disproportionately bore the costs (Brinkman and Lin, 2022). Commuting improvements further appeared largely in suburban areas with few minority families. Given differential car usage, the commute benefits of highways then accrued unequally by race.

A long history of analysis has examined how the Interstate system acutely increased inequality in cities, e.g. Caro (1974), Jackson (1985), and Rose (1990). However, considerable challenges have stood in the way of a systematic assessment, which this paper overcomes by collecting spatially granular commuting statistics for the entire U.S. using restricted Census microdata and newly digitized road maps. These unique historical data enter a quantitative spatial framework that richly captures the reallocation of households and the equilibrium evolution of neighborhoods and workplaces. I propose a novel mechanism for why, in particular, racial disparities emerged: Black households were constrained by *exclusionary institutions*, which interacted with the Interstate system to create stark inequality in impacts. To quantify this mechanism, I concurrently address how to distinguish institutional forces of segregation from competing *economic forces* through housing affordability and *social forces* through preferences for same-race neighbors.

Taken together, I find via the model framework that the Black population faced losses from Interstate highways while the White population garnered gains. Within race, dispar-

[1] The Interstate Highway System originally cost \$114 billion, around \$500 billion in 2020 dollars, and is to date the most expensive infrastructure project in U.S. history. Investment in highways has continued with the Infrastructure Investment and Jobs Act of 2021 providing \$550 billion to fund infrastructure. To address the local costs of highways, \$1 billion is set aside to reconnect communities divided by the Interstate highway system. An additional \$21 billion is allotted to environmental remediation with a focus on environmental justice (Department of Transportation, 2021).

ities by class are minimal. Institutions are a key determinant of segregation and inequality in impacts—absent neighborhood barriers, Black households would have resided farther from the central business district and benefited more from Interstate highways, reducing the gap in impacts. While White families migrated outwards in reaction to the positive and negative consequences of highways, enlarging their gains, Black families were initially concentrated and remained in the urban interior.

To reach these conclusions, the paper is organized in three parts. The first characterizes the empirical variation provided by two natural experiments. Using quasi-exogenous features affecting the placement of highways, I measure population responses across neighborhoods, which feeds into estimation of parameters for the costs and benefits of highways and a subset of the forces of segregation. I then exploit spatial discontinuities in where spatial barriers prevailed and sharply establish that institutions are an important determinant of segregation. In the second part, I develop the model features and discipline the magnitude of the channels in the spatial equilibrium framework using the two sources of variation. Lastly, I employ the framework to conduct distributional analyses across race and class and quantify the role of institutions for inequality in impacts.

Following that order, I show first empirically that the Interstate system introduced substantial costs and benefits to cities. I leverage restricted microdata from the 1960 and 1970 Decennial Censuses, which include the previously under-studied Journey to Work survey, to construct the first historical measures of commute flows in 25 cities. As commuting time surveys with broad coverage were never administered for this period, I generate commute time matrices at high spatial resolution across 49 million bilateral pairs using road maps I digitized from Shell Atlases for 71 cities and a database on when each Interstate segment was built to focus on the 1960 to 1970 period (Baum-Snow, 2007).

In long differences between 1960 and 1970, I document declines in population, rental prices, and racial composition (percentage White) by highways, which are informative of the local costs and equilibrium responses for neighborhoods. The population shifts are driven by White migration as the Black population response is statistically insignificant, and the differential migration by race contributes to the changes in racial composition.

Non-random placement of Interstate routes, often in disadvantaged areas, conflates selection on trends with highway costs. To attain sharper identification, in the Shell Atlases, I separately categorize major roads as candidates for Interstate construction. Not all were converted, and these untouched historical roads serve as natural control groups. The location of historical railroads, ports, canals, rivers, and the central business district are used as features to compare neighborhoods with similar propensity of receiving an interstate road. As two separate instruments, I digitize planned engineering maps for 100 metropolitan areas that were less subject to political influences and construct a Euclidean ray network to intersect cities where neighborhoods coincidentally located between cities are treated (Chandra and Thompson, 2000). With this empirical strategy, I find declines by highways can be interpreted as causal.

I next show the population grew in suburban areas where connectivity increased due to the commute benefits of highways. Because peripheral growth was already underway and was not solely from Interstate construction,[2] I control for distance from the central business district and exploit variation within the suburbs relative to the comparison roads using the same identification strategy from above (Borusyak and Hull, 2023). Commuter Market Access (CMA), a model-implied aggregator of commute costs, summarizes the commuting impacts of highways (Donaldson and Hornbeck, 2016; Tsivanidis, 2022). Consistent with the population response to highway costs, the response to benefits is differential by race with substantial White migration and near zero Black migration.

Why do Black households not respond to the costs or benefits of Interstate highways? Spatial frictions from institutions may be a central force. As a proxy for formal and informal institutional barriers, I use redlining maps from the Home Owners' Loan Corporation (HOLC) which evaluated the credit risk of neighborhoods and traced longstanding racial and economic divisions (Nelson et al., 2020). The lowest grades were issued to racially diverse neighborhoods, deeming them "redlined." Non-redlined areas were homogeneous White neighborhoods created by private actors, real estate agents, and government officials through practices such as refusal to sell or rent housing and restrictive covenants.

In line with prior evidence, I find the maps are highly effective at conveying where Black households were permitted and that racial composition discontinuously shifts across the redlining borders (Fishback et al., 2020; Aaronson et al., 2021). Including redlining fixed effects and measuring Black responsiveness to CMA within redlined areas, population responses are no longer zero and are in fact significantly positive. These results, while suggestive, indicate the limited response by the Black population stems from barriers that inhibit free movement across neighborhoods.

The reduced form facts, though transparent, are nevertheless unable to separate feedback between the equilibrium responses and lack the structure needed to assess welfare. In the second part of the paper, I extend Ahlfeldt et al. (2015) and Tsivanidis (2022) to develop a within-city model of neighborhoods that has a novel focus on the role of institutional constraints for heterogeneous impacts by race.

[2]Increasing crime in the central city, desegregation of school districts, the Great Migration, and subsidies for suburban development were parallel contributors to suburbanization (Jackson, 1985; Cullen and Levitt, 1999; Boustan, 2010; Baum-Snow and Lutz, 2011; Boustan, 2012).

By design, the model incorporates the empirical facts of household reallocation across locations and the endogenous evolution of housing prices, racial composition, and wages. Sorting is captured via residential elasticities for spatial mobility by race, differential price sensitivity through housing consumption shares, and endogenous amenities through preferences for racial composition. Institutional barriers are present via capacity constraints, price wedges, and amenity wedges that differentially lead Black households to live less in certain areas; these barriers I show are isomorphic for the allocation of households. Direct impacts of highways appear through commute time reductions between bilateral pairs and the decline of amenities that decay over distance from routes. In equilibrium, housing prices change elastically, and wages adjust at firms as employment reallocates.

Importantly, the model's expressions for residential choice govern how segregation arises *in levels* and *in changes* in response to shocks. One set of parameters determines both why the Black population was initially concentrated and how the Interstate system affects sorting with feedback mechanisms for welfare. Yet, a challenge that looms large is disentangling institutional barriers from economic and social forces.

The Interstate shock provides variation for estimating some parameters: residential elasticities and racial preferences. In line with the evidence on differential mobility by race to CMA improvements, estimated residential elasticities are larger for White households, which further informs the creation of instruments to estimate racial preferences (Davis et al., 2019). Given high White mobility and low Black mobility to the highway shock, I simulate model-predicted declines in percent White in the urban core to use as shifters and find White households strongly prefer White neighbors while Black preferences are also homophilic but less so. These preferences do not conflate institutional barriers as estimation uses variation within redlined areas where institutions only weakly bind, nor do they represent preferences for class as a rich set of controls accounts for socioeconomic factors. Housing price sensitivity is then calibrated to the Consumer Expenditure Surveys.

In the third part of the paper, I employ the structure of the model and key parameters to evaluate the effects of the Interstates on inequality. In a general equilibrium counterfactual, highway construction lowers welfare by -1.04% for Black households and raises welfare by 2.9% for White households. In a calculation of direct impacts where location choices are fixed, Black losses are now -1.6% and White gains are 1.7%. As Black families resided near Interstate routes and commuted with cars at a lower rate, both direct effects push for increases in inequality. Including equilibrium effects only slightly raises Black welfare but greatly increases White welfare, a result of the lower reallocation of Black households, who remained in central areas where costs outweigh benefits. General equilibrium outcome adjustments play a smaller role and are somewhat offsetting for welfare.

Finally, I show that institutional segregation is a primary mechanism behind disparities in impacts. Racial composition sharply shifts over borders of redlining maps, but not all of the discontinuity is due to institutions. Housing prices vary, and racial preferences can reinforce any differences along the border. In a border discontinuity design and with the estimated parameters, I find 65% of the tremendous 140 log point increase in the Black population entering redlined neighborhoods is unaccounted for by prices, racial preferences, or socioeconomic variables and thus represents residual spatial institutions. For White households, the 50 log point decrease in population is mostly explained by their racial preferences; no residual discontinuity remains, and the identification assumption of fundamental characteristics being continuous over the border is satisfied.[3]

I simulate removing institutions at the border, and in this new environment, constructing Interstate highways leads to less unequal impacts: Black households are more spatially dispersed and consequently are harmed less by Interstate development. However, the racial gap for highway impacts does not close substantially. While the border discontinuity design has the advantage of allowing for a testable identification assumption, the change in racial composition at the border, while sizable, fails to capture the stark degree of segregation more broadly. Outlying suburbs far from bordering neighborhoods are more fortified from contact with minority households.

With this insight, I extrapolate to examine barriers writ large. I make the stronger assumption that any residual location characteristics should not be valued differentially by race *for all neighborhoods* and thus provide Black households the same access to neighborhoods that White households possess, a hypothetical upper bound on how far exclusionary barriers can be eliminated. Under this arrangement, I find that the Black population gains by 1% from Interstate highways, and the racial gap in welfare impacts closes by a striking 54%. Notably, all groups benefit from highway development, and gains for the White population remain the same, so raising welfare for Black households does not lead to a zero-sum game for aggregate highway impacts.

Related Literature – This paper builds on a literature in quantitative spatial economics that proceeds from an earlier body of work on urban models (Rosen, 1979; Roback, 1982; Redding and Rossi-Hansberg, 2017). Most closely, it extends the frameworks of Ahlfeldt et al. (2015) and Tsivanidis (2022) and applies these powerful tools to carefully disentangle the sources of segregation. Sorting via endogenous amenities has been studied recently

[3]I probe this assumption in several tests. I remove physical barriers of large roads, railroads, and highways from the sample to only measure social barriers. I further drop areas near school district borders that may fall along the borders of redlining maps. After gathering several datasets on natural amenities, I find that land cover types of open water and wetlands are continuous along the border, supporting the identification assumption of no change in fundamental amenities.

by Kuminoff et al. (2013), Diamond (2016), and Almagro and Dominguez-Iino (2020). The methodological departure of this paper is to incorporate institutions into the theoretical framework and elucidate how they are a central determinant of spatial inequality by race.

This paper also contributes to a rich literature on the impacts of transportation infrastructure. Duranton and Turner (2012), Duranton et al. (2014), Allen and Arkolakis (2014), Donaldson and Hornbeck (2016), and Donaldson (2018) examine the benefits of transportation improvements through their reduction of travel or trade frictions. Directly related to the setting of this paper are several studies on the Interstate highway system (Baum-Snow, 2007; Michaels, 2008; Baum-Snow, 2020; Brinkman and Lin, 2022). Recent work by Miller (2023), Mahajan (2023), and Bagagli (2024) provides reduced form evidence on heterogeneous racial responses. This paper is the first to quantify the distributional impacts in a comprehensive general equilibrium framework, made possible with novel disaggregated data and granular archival maps that span the entire country.[4]

The final related literature is an interdisciplinary one on racial inequality and *de jure* segregation influencing the economic access of Black Americans (Kain, 1968; Wilson, 1987; Massey and Denton, 1993). I find highways increased segregation, as with railroads in Ananat (2011), with effects shaped by pre-existing divides. Methodologically similar, Bayer et al. (2007) employs the border design to study preferences for neighbors. I apply the same design to test for institutional exclusion. I find discrimination entails welfare costs, in line with experimental research by Christensen and Timmins (2021, 2022) but I do so in an *observational* setting. I thus uncover larger magnitudes for their importance and go one step further—I examine how barriers *interact* with highway infrastructure. This interplay between institutions and policy extends to place-based policies beyond transportation infrastructure and animates the profoundly disparate impacts by race.

2 Historical Context and Data on the Interstates and Inequality

2.1 The Interstate Highway System

The Federal-Aid Highway Act of 1956 initiated the monumental construction of 42,800 miles of Interstate freeways, which became the largest and one of the most advanced road networks in the world. While the Interstate system would be used for defense if necessary, its primary purpose was to support automobile traffic and stimulate economic growth. Post World War II, several federal programs spurred the population to flee the urban

[4] In other social science disciplines that follow empirical or qualitative approaches, there is evidence of unequal impacts by Hirsch (1983), Rose and Mohl (2012), Avila (2014), Connolly (2014), Rothstein (2017), Nall (2018), Nall and O'Keeffe (2019), and Trounstine (2018).

core and heighten road congestion. The GI Bill promoted homeownership for millions of veterans, and the Federal Housing Act of 1949 expanded mortgage insurance for newly developed suburbs while simultaneously funding renewal of downtown areas. Interstate roads were one factor among many catering to the new social order of cities (Rose, 1990).

The harms and inequities of highways were however soon apparent. Urban commentators Lewis Mumford, Jane Jacobs, and Patrick Moynihan criticized how roads displaced neighborhoods and polluted the nearby environment. Freeway revolts successfully shifted the course of many routes and at times terminated their construction.[5] Yet, revolts were only effective for some, as without the support of influential actors, disadvantaged populations were regularly disregarded (Rose and Mohl, 2012). City planners likewise targeted roads towards low-income housing for urban renewal, and displacement triggered racial turnover in adjoining working-class neighborhoods (Hirsch, 1983).

Decennial Censuses by Race and Education – To measure disparities in Interstate incidence, I collect residences and workplaces separately by race and education from Decennial Censuses in 1960 and 1970. Crucially, this decade covers 51% of network construction. Residential units are census tracts, and workplace units are Place of Work Zones, newly assembled as the intersection of county and municipality codes from the 1960 Census Journey to Work questionnaire. The sample is limited to 25 of the largest cities, listed in G.29, as some have few Place of Work zones. Later, I expand the set of cities using tract-level aggregates from IPUMS-NHGIS for the longer panel of 1940 to 1990 (Manson et al., 2017). Race is split into White and Non-White since finer cuts leave too few counts, where Non-White is treated equivalent to Black (which comprised almost all of the Non-White population in 1960).[6] Education is split into high school graduates and those without a high school degree. Attached to groups and geographies are wages and quality-adjusted housing prices. Appendix G contains more details.

Commuting Networks – Commute cost reductions are a central impact of highways, but commuting time surveys were conducted sparsely.[7] I build commute time matrixes using digitized Shell Atlases in 1951 and 1956 for 71 cities and categorize roads into superhigh-

[5] A prominent example is the Lower Manhattan Expressway (I-78) which was shut down after advocacy by Jane Jacobs against metropolitan planner Robert Moses.

[6] In 1960, 11.4 percent of the population was Non-White and 10.5 percent of the population was Black (Census Bureau, 1961). Only 3.5% of the population was Hispanic (with Spanish origin surname) in 1960 and were enumerated under the White category as the Census did not ask respondents about ethnicity until 1980. Black households thus comprise almost all of the Non-White population.

[7] Brinkman and Lin (2022) use travel surveys for Chicago and Detroit in 1953 and 1956, respectively. However, these surveys only report aggregated flows and are not suitable for evaluating distributional impacts. They are also for years when few segments of Interstate highways were completed.

ways and other major roads, assigned different speeds following travel surveys (Gibbons and Proctor, 1954; Walters, 1961; Rumsey, 2020). The Interstate network is set to each segment's speed limit (between 55-65 mph), and to only examine routes built between 1960 and 1970, I employ the PR-511 database from Baum-Snow (2007). Commute times are generated in ArcGIS Network Analyst by overlaying the Interstate and historical road networks. To assess commuting via public transit and other transport modes, I retrieve reported times by mode from the 1980 Decennial Census, the first census to survey travel time, and non-parametrically estimate times and mode shares (in 1960 and 1970) over bins of bilateral distance and distance from the central business district (CBD).

Summary Statistics on Racial Inequality – With these novel datasets, in Table 1, I calculate statistics in 1960 which indicate large differences by race *conditional on education*. 49% of Black higher-educated workers commute by car compared to 66% for White higher-educated workers, so upgrades in road speed benefit the White population more. Among the higher educated, Black workers are located 3.6 miles closer to the CBD, where commuting improvements are muted. They also reside 0.8-0.9 miles closer to a highway within education, which can be due to political influences leading to unequal route placement, as previously described. In Table 2, Columns 1–3 show highways were built further from more-educated, higher-income, and White areas at baseline in 1950, driven partially by highways being designed to intersect the central city (see Columns 5–6).

Are the racial differences in location explained by economic characteristics? As shown in Table 1, wages, rents, and home values of Black higher-educated workers are comparable to White less-educated workers. Yet, the two groups still experience vast differences in location relative to highways and the central city. Prices alone thus do not appear to be the major determinant of segregation, confirming past findings (Bayer et al., 2021).

2.2 Institutional Segregation

What mechanisms underlie the striking differences in where Black and White families live? Prior to and during the era of highway construction, various obstacles limited the residential choices of Black families. Although some were dismantled before the Interstate system, others endured.[8] Between 1960 and 1970, segregation reached its peak as Black

[8] In the 1968 Kerner Commission Report to President Lyndon B. Johnson, commission members write "What white Americans have never fully understood — but what the Negro can never forget — is that white society is deeply implicated in the ghetto. White institutions created it, white institutions maintain it, and white society condones it." Policies such as racial zoning established White-only districts through local ordinances, and restrictive covenants placed language in property deeds to prevent the sale of homes to anyone outside of the Caucasian race. Racial zoning was outlawed in the Supreme Court case Buchanan

Americans migrated from the rural South into crowded, racially-mixed neighborhoods of the urban North (Cutler et al., 1999; Boustan, 2010). Segregation began to decline with the Civil Rights of 1968 authorizing provisions to combat housing discrimination, leading to its colloquial title: the Fair Housing Act. Yet enforcement was uneven, and only through decades of advocacy by fair housing organizations did segregation lessen to the lower levels of today. Institutions that imposed the geographic separation of the races encompass both state law and individual behavior that can be inextricably linked, and this paper uses federal maps to proxy for this complex mix of government and private exclusion.

HOLC Redlining Maps – The Home Owners' Loan Corporation (HOLC) was a federal agency formed in 1933 after the Great Depression to appraise the risk of neighborhoods for mortgage refinancing and purchase. Created in consultation with local lenders, its maps reflected existing racial and economic characteristics, with high-risk neighborhoods deemed "redlined" (Harriss, 1951). Concurrently with the HOLC as part of the New Deal, the Federal Housing Administration (FHA) also engaged in redlining by denying mortgage insurance to Black families, majority-Black neighborhoods, and socially or racially mixed areas (Hillier, 2003). While the HOLC maps are not the same as those by the FHA, some evidence suggests a correlation exists between the maps for Chicago (Aaronson et al., 2021).[9] Additionally, Faber (2020) and Aaronson et al. (2021) posit the FHA directly increased segregation. The agency often encouraged real estate agents to preserve racially homogeneous neighborhoods, e.g. with restrictive covenants in property deeds that prevented sales to non-White households (Jones-Correa, 2000). However, recent work argues not all of the segregation associated with the maps can be placed on policies by the FHA or HOLC and was present before the 1930s (Fishback et al., 2020). For this paper's purposes, the HOLC borders delineate institutional segregation from both federal redlining and private behaviors such as refusal to sell homes to Black families.[10]

Summary Statistics on Segregation – In spite of some limitations, I provide descriptive evidence that the HOLC maps are highly informative for where the Black population lived and suggest where institutions prohibited them. Figure B.1 shows Black households

v. Warley in 1917, and restrictive covenants were ruled unenforceable in Shelley v. Kraemer in 1948.

[9]FHA maps for most cities have unfortunately been lost. Fishback et al. (2022) finds additional maps for Baltimore City, Maryland; Peoria, Illinois; and Greensboro, North Carolina.

[10]While the qualitative literature provides cases of discriminatory pricing preventing Black households from living in White neighborhoods as in Taylor (2019), I do not find Black families faced substantially higher prices in non-redlined neighborhoods for similar quality housing. In Appendix Table A.1, after including neighborhood fixed effects and housing quality controls, Black households face 3% higher rents in non-redlined areas and 8% higher rents in redlined areas. As the race differential is not greater in non-redlined areas, the concentration of Black households there can not be explained by lower price discrimination in redlined areas. However, the existence of a positive race differential suggests some discrimination.

are far more clustered near the CBD compared to White households. Redlined neighborhoods are located close to the center in a pattern strikingly similar to the distribution of the Black population. These two facts are consistent with the heavy concentration of the Black population in redlined areas. Table A.2 lists that in 1950, 93% of the Black population in Chicago lived in redlined areas compared to 32% for the White population. After 1950, these neighborhoods continued to be the residences of most Black families as Figure B.2 shows the racial composition of the median non-redlined tract remained close to 100% White until 1970. However, redlined areas were not wholly Black, and most were racially integrated as depicted in Table A.3. These simple tabulations notably reveal an asymmetry where while White households were located across all neighborhoods, Black households lived in a reduced set often concentrated in older downtown areas.

Although these statistics are highly suggestive, they do not rule out economic differences or social preferences of homophily as contributors to segregation. This paper aims to provide compelling evidence that institutions are indeed a dominant force, which then interact with Interstate highways to widen racial inequality. Next, I provide evidence on the geographic distribution of costs and benefits of highways, which informs the distributional consequences given that the Black population was centrally concentrated.

3 Motivating Evidence on Neighborhood Changes in Cities

I present several empirical facts to illustrate how Interstate highways impacted cities through their localized costs, commuting benefits, and subsequent equilibrium responses in neighborhood characteristics. These results motivate the key mechanisms of the quantitative model and the sources of quasi-experimental variation for parameter estimation.

3.1 Population and Equilibrium Responses to Highway Impacts

With a long differences specification, I measure changes in population at the tract-level, denoted by i, which revealed preference logic implies is correlated with the impacts of highways, and equilibrium changes in neighborhood rents and racial composition.

$$\Delta Y_i = \beta_1 \log DistHW_i + \beta_2 \log DistCBD_i + \beta_3 Redlined_i + \mathbf{X}_i \eta + \gamma_{m(i)} + \epsilon_i \qquad (1)$$

Changes are over 1960 to 1970 (and occasionally 1950 to 1960 for cities with earlier construction, stacked together) using the expanded set of cities in the public-use dataset.[11] I

[11] Tracts in cities where less than 10% of the mileage of Interstate highways was built in 1960 are in the 1960 to 1970 sample. Tracts in cities where less than 10% of the mileage of Interstate highways was built in 1950 (occasionally some cities began construction on Interstate highways before the Federal Highway Act

examine differences over distance from highways $DistHW_i$ as representing the costs and over distance from the central business district $DistCBD_i$ as representing the benefits. A redlined indicator captures heterogeneity in redlined versus non-redlined areas and leads the empirical variation to come from within the two types of neighborhoods. Results are presented in Table 3 Panel A where no controls are yet specified ($\mathbf{X}_i$ is empty).[12] In later specifications, I discuss which controls are fruitful to incorporate for identification. City fixed effects $\gamma_{m(i)}$ for each city m lead the variation to be within-city. Standard errors adjust for spatial correlation following Conley (1999) within a radius of 1 kilometer.

I find relative declines by highways in population, rental prices, and percentage White for racial composition, displayed as elasticities in Columns 1–3, suggestive of the harms of highways reducing the desirability of adjacent areas. Additionally, I document growth in population, rental prices, and percentage White in suburban areas connected by the Interstate highway system, although I do not yet make any claims on causality. The shifts in racial composition stem largely from White households leaving areas by highways and the central city, as shown in Columns 4 and 5. Black households did not appear to move away from highways as the coefficient is not significant, and while they migrated slightly into the suburbs, they did so at a far lower rate.[13] Comparing magnitudes of outcomes, the changes in rents and racial composition are smaller than the White population response, so for highway impacts, the large reallocation of White households may be more meaningful for their gains than adjustments in these two characteristics.

Feedback channels link the three characteristics. As income is correlated with race, a positive relationship between changing rents and racial composition may be due to differential responsiveness to price changes i.e. non-homotheticity in consumption. Preferences for racial composition further reinforce sorting. For example, when an area becomes less White after a direct shock, the feedback effect of homophilic preferences precipitates more out-migration of White households. These population responses then transmit into housing price changes. The equilibrium system should thus aim to characterize how the channels are determined simultaneously and measure the importance of each.

Heterogeneity by Redlining – I find in the bottom row of Table 3 Panel A that redlined areas experienced substantial inflows of Black households and outflows of White house-

of 1956) but more than 10% was built by 1960 are in the 1950 to 1960 sample. Cities here are Core Based Statistical Areas and include both Metropolitan Statistical Areas and Micropolitan Statistical Areas.

[12]One control included in all specifications is the gradient = $DistCBD_i/DistHW_i$ to account for how $DistHW_i$ is mechanically lower near the city center. This is also addressed by including $DistCBD_i$ in the estimating equation.

[13]I examine the additional outcome of home values in Appendix Table A.4 and find no significant changes by highways, so they are not considered to be a central impact of Interstate highways.

holds, leading to a drop in the percentage White of redlined neighborhoods. Although not directly related to the Interstate system, this result shows Black households moved predominantly into redlined neighborhoods. In addition to large changes over time in the racial composition of redlined areas, there exist sizable cross-sectional differences between redlined and non-redlined neighborhoods. In Figure 1, percentage White sharply shifts over the border of the HOLC maps with around a 20 percentage point decline crossing into redlined neighborhoods. The Black population, in flows and in levels, appears strongly concentrated in redlined areas in the center of cities.

Historical Comparison Areas – Non-random placement of Interstate routes can lead changes by highways to be contaminated by selection on trends. To obtain cleaner identification, I create comparison areas likely to have received an Interstate highway.

Guidance from the 1944 report, *Interregional Highways*, recommended engineers: (1) build along existing roads with heavy traffic since a primary goal was to combat congestion, and (2) account for topographic features and other transportation methods.[14] I thus consider super-roads from the digitized Shell Atlases as Interstate candidates, where those not converted to highways are counterfactual control routes to be compared against. This strategy addresses Borusyak and Hull (2023)'s concern that transportation infrastructure tends to non-randomly impact areas depending on its location relative to existing markets, which can be alleviated if counterfactual networks are specified. In Figure 2a, I overlay the Interstate system on the historical network for the Boston area and illustrate that the two are closely aligned; yet several historical roads were never re-built as Interstate highways, and these serve as the control routes. Additionally, maps on historical railroads, canals, steam-boat navigable rivers for the late 19th century, and features such as bodies of water, shores, and ports are retrieved from Atack (2015, 2016, 2017) and Lee and Lin (2017) as geographic characteristics that influenced highway placement.

Using these various maps, in Table 3 Panel B, I include log distance from the super-roads, railroads, canals, rivers, etc. as controls $\mathbf{X}_i$ in Equation 1. The estimating equation thus compares tracts near areas with historically higher levels of traffic to areas that ultimately received Interstates. While in previous research, historical routes have often been employed as instruments, past infrastructure influences subsequent economic development, leading to a violation of the exclusion restriction (Donaldson and Hornbeck, 2016). This paper aims to instead purge these historical influences by including them as controls.

[14]The introduction to *Interregional Highways* states that the "recommended system follows in general the routes of existing Federal-aid highways" and Interstate development would occur through "the improvement of a limited mileage of the most heavily traveled highways." The section Principles of Route Selection in Cities in *Interregional Highways* states there should be "desirable coordination of highway transportation with rail, water, and air transportation."

I find that relative to Panel A, the results are essentially unchanged—declines by highways in population, rents, and racial composition are of the same magnitude as without geographic controls, so selection does not appear to play a huge role. While somewhat surprising, note that distance from the CBD and redlining fixed effects were previously included, so some of the non-exogenous placement was already partially absorbed.

Planned Maps as Instrumental Variables – Conditional on geographic features, the final placement of highway routes may continue to be biased due to local political factors, e.g. protests in high-income areas. To address this bias, transportation plans can be used as instruments since they were designed before external influences occurred and because engineers were often indifferent to local socioeconomic conditions (Rose and Mohl, 2012). I digitize plans created by state engineers for 100 metro areas in the 1955 *General Location of National System of Interstate Highways* (informally called the "Yellow Book") (Brinkman and Lin, 2022). These maps are consolidated with a 1947 plan from Baum-Snow (2007) I re-digitized at finer spatial scales to create a regional and metropolitan planned network.

Still, transportation planners may not have been fully neutral in their route choices. In a second strategy, I construct an Euclidean ray network that connects cities in the planned maps with straight lines, similar to the "inconsequential units" approach where neighborhoods coincidentally between cities are treated by Interstate highways (Chandra and Thompson, 2000; Faber, 2014; Morten and Oliveira, 2018). This variation from the Euclidean ray network is thus likely to be more quasi-random than from the plans.

Figure 2b-2d plots the two instruments next to the Interstate network for Boston and shows they are often adjacent. I test for instrument validity at baseline and in pre-trends as well as the strength of the first-stage, described in Appendix C.1. In Table 3 Panels C and D, I instrument distance from highways with distance from the planned routes and Euclidean rays. On the whole, the IV results concur with those measured with OLS as magnitudes are similar for all the outcomes of population (including separately by race), rental prices, and percentage White. Although coefficients are slightly larger with the ray instruments, the estimates do not differ greatly qualitatively. As the results are consistent across OLS, with controls, and with instruments, declines by highways can be interpreted as causal and a consequence of the local harms of Interstate highways.

In Appendix Figures B.3 and B.4, I present results similar to the long-differences specification but in non-parametric bins over distance from highways and by distance from the CBD. These figures depict the curvature of the decline near roads, and given that OLS is comparable to IV, they can also be interpreted as representing the costs of highways.

3.2 Population Elasticities to Commuter Market Access

In the preceding section, I documented considerable population growth in suburban areas. However, this growth cannot be attributed to only the Interstate highway system as ongoing factors pushed for outmigration to the periphery e.g. school desegregation and rising crime as well as government policies aforementioned (Cullen and Levitt, 1999; Boustan, 2010). To pinpoint highway impacts, I analyze population responses to a specific measure of connectivity that will be microfounded by the spatial model presented later.

Commuter Market Access (CMA) summarizes commute frictions with heterogeneity by race $r \in \{B, W\}$, for Black and White, and education $g \in \{L, H\}$, for less-educated and high-educated. Residences i are connected to workplaces j paying group-specific wages ω_{jgr} with commute costs d_{ijgr} that can be differentially affected by road infrastructure.

$$CMA_{igr} = \left(\sum_j \omega_{jgr} / {d_{ijgr}}^{\phi} \right)^{\frac{1}{\phi}}$$

CMA_{igr} aggregates over workplaces, accounting for wages and commute costs with substitution elasticity ϕ, and increases when commute costs are reduced or wages are raised.

In the Decennial microdata, I measure how population L_{igr} responds to improvements in CMA from 1960 to 1970 separately by race through elasticity β_r. Within CMA, the parameter ϕ is set to 3 in the middle of estimates from the literature (Ahlfeldt et al., 2015; Morten and Oliveira, 2018; Severen, 2021). [15]

$$\Delta \log L_{igr} = \beta_r \, \Delta \log CMA_{igr} + \mathbf{X}_i \mu_r + \psi_{m(i)} + v_{igr}$$

Importantly, I control for *distance from the CBD* to exploit variation in concentric rings around cities, i.e. within the suburbs, and eliminate the correlation stemming from preexisting suburbanization (as CMA increases the most in the suburbs). This variation is also relative to the comparison roads as following Borusyak and Hull (2023), I take a control function approach and construct CMA where the possible counterfactual shocks of large historical roads are converted into Interstate highways (shown in Figure B.5). Borusyak and Hull (2023) argues this re-centering addresses non-exogenous exposure where areas connected by highways are systematically different in the existing spatial

[15] $\Delta \log CMA_{igr} = \frac{1}{\phi} \left(\log \sum_j \omega_{jgr,1970} / {d_{ijgr,1970}}^{\phi} - \log \sum_j \omega_{jgr,1960} / {d_{ijgr,1960}}^{\phi} \right)$. In this observed CMA measure, I use wage changes from 1960 to 1970 as well as commute cost changes. Since commute times are all computer generated, the change in commute costs comes from the addition of the segments of the Interstate highway system built between 1960 and 1970 as well as changes in mode of transport weights by race and education between 1960 and 1970 (all groups increase their car usage). The functional form for d_{ijgr} is detailed in the model section. $\omega_{jgr} = T_{jgr} (w_{jgr})^{\phi}$ is scaled wages as explained in the model section.

network. Further included in the specification are the geographic controls of railroads, canals, etc. (plus distance to the CBD), all interacted with race, and city fixed effects.

Results are reported in Table 4 with standard errors clustered at the tract level and Conley (1999) standard errors in brackets. Population elasticities are in the range of 1.2–1.4 for the White population across Columns 1–3 where Column 1 includes only the geographic controls, Column 2 adds city fixed effects, and Column 3 includes the control variable of CMA where historical large roads are built as highways. Because the estimates do not vary greatly, non-exogenous exposure to the highway shock does not drive the findings. Elasticities for the Black population are in the range of 0.1–0.4 and are much lower than for White households; including city fixed effects in Column 2 leads the coefficient to no longer be significant. Consistent with the previous results, Black households do not respond to the benefits of highways, nor do they respond to the costs.

Instruments for Estimation – However, CMA changes not only from commute costs but also from wages. Employing only commuting variation from the highway shock, I define the instrument $\mathbb{Z}_{igr}^{HW} = \frac{1}{\phi}\left(\log \sum_j \omega_{jgr,1960}/{d_{ijgr,1970}^{HW}}^{\phi}\right) - \frac{1}{\phi}\left(\log \sum_j \omega_{jgr,1960}/{d_{ijgr,1960}}^{\phi}\right)$ where I fix wages to 1960 levels and exploit the panel nature of when Interstate segments were built with $d_{ijgr,1970}^{HW}$ containing the segments built by 1970. Furthermore, I build two additional instruments where the change in commute costs comes from the plans or the Euclidean rays by replacing $d_{ijgr,1970}^{HW}$ with d_{ijgr}^{Plans} and d_{ijgr}^{Rays}.

I report IV estimates in Columns 7–9 and find the Kleibergen-Paap rk Wald and Cragg-Donald Wald F-statistics are all far above 10, with details in Appendix C.2. Compared to the Interstate instrument, elasticities with the planned and ray instruments for the White population are larger in magnitude, possibly because of the negative selection of routes. Coefficients are smaller than with OLS, so the previous estimates may include responses to endogenous wage changes rather than solely the Interstate shock. Black population responses are imprecisely estimated as standard errors are large. Yet overall, the population responses to CMA appear to result from causal treatment effects of Interstate highways.

Institutions as Mechanism – The previous descriptive evidence suggested that institutional barriers could be driving the varying responses by race, especially for the low mobility response of the Black population. I explore heterogeneity in how the population elasticities are shaped by this factor by including redlining by race fixed effects in Columns 4–6, which repeat Columns 1–3 and add the fixed effects. With variation within types of neighborhoods, population elasticities for White households are reduced in size to around 1, so some of their earlier estimated response to CMA improvements was across types e.g. by moving from redlined to non-redlined neighborhoods in the suburbs.

For Black households, elasticities are now in the range of 0.3–0.6 and statistically significant across all specifications (though still lower than for White households). Their dampened overall elasticities mask how Black households respond to commuter access changes within redlined areas and highlight how institutions create spatial frictions that inhibit the Black population from leaving centrally located, redlined neighborhoods for suburban, non-redlined neighborhoods. Importantly, outlying neighborhoods are where highway benefits are the largest and simultaneously, where costs are more muted.

Additional Results on changes in equilibrium outcomes of rents and racial composition and robustness checks on controls and heterogeneity are presented in Appendix C.3.

3.3 Discussion

While the reduced form evidence is informative for some of highway impacts, it captures both direct and indirect effects through endogenous reallocation and equilibrium outcome adjustments. For example, the low reallocation of the Black population can stem from the declining prices and changing composition of central neighborhoods, rather than spatial barriers. In the next section, I lay out a quantitative urban model rich enough to encompass all channels and carefully consider the forces at play. This model guides the derivation of estimating equations to measure commuting benefits and localized costs and to disentangle the sources of segregation that shape the population responses and welfare impacts. These specifications are reminiscent of the reduced form equations, and accordingly, parameter estimation captures the key empirical facts of differential mobility and changes in rents and racial composition influencing location decisions.

Notably, the model's expressions for residential choice are instructive for why segregation arises both cross-sectionally and in response to shocks. The former application is especially important for understanding the role of institutional barriers in the clustering of the Black population in central neighborhoods.

4 A Quantitative Model of Cities

The general equilibrium framework extends previous advances in Allen and Arkolakis (2014), Ahlfeldt et al. (2015), and Tsivanidis (2022) by translating the forces of segregation to components of classic urban models and augmenting these models to incorporate spatial barriers in residential choice. It enables the evaluation of distributional impacts where group-specific location barriers shape welfare inequality. With neighborhoods linked via commuting networks, transportation infrastructure lowers the costs of travel which feeds into the rest of the spatial economy. In the quantitative analysis later, I employ Decennial microdata for 25 cities to investigate within-city impacts in a closed city set-up.

4.1 Model Features

Workers are differentiated by education $g \in \{L, H\}$ for less-educated and higher-educated groups and by race $r \in \{W, B\}$ for White and Black groups. Each city consists of neighborhoods indexed by $i = 1, \ldots, S$ and contains fixed population levels $\mathbb{L}_{gr}$ by education and race. Under the closed city assumption, no migration occurs across cities.

Workers – As in the standard spatial model, individuals choose where to live (i) and work (j) depending on idiosyncratic shocks and location characteristics. Each worker o has Cobb-Douglas preferences over consumption $c_{ij}(o)$ and residential floorspace $l_i(o)$. Differential sensitivity to housing prices Q_i appears through non-homothetic preferences where the β_{gr} share of consumption varies by education and race, a tractable approach in the literature to study sorting (Davis and Ortalo-Magné, 2011; Balboni et al., 2020; Diamond and Gaubert, 2021).[16] Incorporating homeownership, the budget constraint includes income from redistributed rents in φ_{gr} based on the ratio of home values owned by each group. Group-specific amenities B_{igr} further contribute to heterogeneous choices.

Spatial barriers can arise in several forms. A group-specific amenity wedge $\tau^b_{igr} \geq 0$ affects whether individuals desire to live in a location, e.g. due to discrimination or racial animus. A group-specific price wedge $\tau^Q_{igr} \geq 0$ leads groups to experience different effective housing prices even when the nominal price is the same, e.g. through barriers in credit access. Lastly, capacity constraints limit residential populations where $\bar{c}_{igr}$ is the maximum number of individuals of a group in location i.

Concretely, individual utility is specified as

$$\max_{c_{ij}(o), l_i(o)} \quad \frac{z_i(o)\epsilon_j(o)(1-\tau^b_{igr})B_{igr}}{d_{ijgr}} \left(\frac{c_{ij}(o)}{\beta_{gr}}\right)^{\beta_{gr}} \left(\frac{l_i(o)}{1-\beta_{gr}}\right)^{1-\beta_{gr}}$$

$$\text{s.t.} \quad c_{ij}(o) + (1+\tau^Q_{igr})Q_i l_i(o) = w_{jgr}\varphi_{gr}$$

and after utility maximization, indirect utility is expressed following

$$u_{ijgr}(o) = \frac{z_i(o)\epsilon_j(o)(1-\tau^b_{igr})B_{igr}\left((1+\tau^Q_{igr})Q_i\right)^{\beta_{gr}-1} w_{jgr}\varphi_{gr}}{d_{ijgr}}$$

[16]Cobb-Douglas with varying shares β_{gr} allows for price changes to generate sorting but does not accommodate income changes leading to sorting compared to Stone-Geary. In Appendix D.1.1, I provide an extension with Stone-Geary preferences.

At workplaces, workers in location j receive wage w_{jgr} set by firms in equilibrium. Traveling from i to j entails commute costs d_{ijgr} that reduce utility with the functional form $d_{ijgr} = (t_{ijgr})^{\kappa_{gr}}$ adopted from Heblich et al. (2020). Parameter κ_{gr} translates times t_{ijgr} into costs, which depend on public transit/other transport usage by each group.

Beyond group-level factors, workers additionally have idiosyncratic preferences for residences $z_i(o)$ drawn from a Frechet distribution $F(z_i(o)) = \exp(-z_i(o)^{-\theta_r})$ and for workplaces $\epsilon_j(o)$ from $F(\epsilon_j(o)) = \exp(-T_{jgr}\epsilon_j(o)^{-\phi})$ where T_{jgr} is a scale parameter for each workplace, e.g. representing amenities beyond wages. θ_r is a shape parameter for the dispersion of shocks and responsiveness to changes in the attractiveness of residences, i.e. a substitution elasticity for mobility across neighborhoods. Following the evidence that Black and White households respond differently to CMA improvements, θ_r is heterogeneous by race.[17] Likewise, ϕ is a workplace elasticity governing the responsiveness of choices to workplace changes.[18]

With the model features for worker choice defined, population levels at locations are derived using the Frechet properties of $\epsilon_j(o)$. Conditional on living in i, the probability a worker works in j is

$$\pi_{j|igr} = \frac{T_{jgr}(w_{jgr}/d_{ijgr})^{\phi}}{\sum_s T_{sgr}(w_{sgr}/d_{isgr})^{\phi}} = \frac{T_{jgr}(w_{jgr}/d_{ijgr})^{\phi}}{\Phi_{igr}} \tag{2}$$

With commute costs scaled by elasticity ϕ, the commuting elasticity ν_{gr} combines the workplace elasticity ϕ with the commute cost parameter κ_{gr} such that $(d_{ijgr})^{\phi} = (t_{ijgr})^{\kappa_{gr}\phi} = (t_{ijgr})^{\nu_{gr}}$. The denominator Φ_{igr} is a transformation of the commuter market access (CMA) measure introduced earlier following $CMA_{igr} = \Phi_{igr}^{1/\phi}$. Labor supply L_{Fjgr} aggregates over all residences and the probability each residence sends workers to j

$$L_{Fjgr} = \sum_i \pi_{j|igr} L_{igr} \tag{3}$$

where L_{igr} is the population of group gr workers at residence i.[19] The probability a worker

[17] In Appendix D.1.2, I include an extension with a Nested Frechet structure to explicitly incorporate spatial frictions across types of neighborhoods for Black households. To allow for a more parsimonious framework, this feature is not included in the main model.

[18] Departing from the canonical Ahlfeldt et al. (2015) model, I allow for separate residence and workplace shocks as the earlier reduced form residential elasticities are much smaller in magnitude compared to estimates of ϕ found in the literature (Monte et al., 2018; Severen, 2021). See Appendix D.2 for an expanded discussion of this choice.

[19] Expected income at location i can be computed by weighting wages with the probability of commuting to workplace j. $\bar{w}_{igr} = E[w_{jgr}|i] = \sum_j \pi_{j|igr} w_{jgr} = \sum_j \frac{T_{jgr}(w_{jgr}/d_{ijgr})^{\phi}}{\sum_s T_{sgr}(w_{sgr}/d_{isgr})^{\phi}} w_{jgr}$.

lives in i is of a similar form using the Frechet properties of the residential shocks.

$$\pi_{igr} = \frac{\left((1-\tau^b_{igr})B_{igr}CMA_{igr}\left((1+\tau^Q_{igr})Q_i\right)^{\beta_{gr}-1}\right)^{\theta_r}}{\sum_t\left((1-\tau^b_{igr})B_{tgr}CMA_{tgr}\left((1+\tau^Q_{igr})Q_t\right)^{\beta_{gr}-1}\right)^{\theta_r}} \tag{4}$$

Residential population combines the probability above with the total city population of a group $\mathbb{L}_{gr}$. Importantly, this expression is the key equation for determining segregation.

$$L_{igr} = \pi_{igr}\mathbb{L}_{gr} \tag{5}$$

Sources of Segregation – With the factors characterizing residential choice, sorting by race and education arises from (1) group-specific commuter market access, (2) differing substitution elasticities, (3) housing prices which, while not group-specific, are valued differentially by race and education,[20] (4) group-specific amenities, and (5) spatial barriers through wedges or capacity constraints. I expand on a few components below.

Preferences in Endogenous Amenities – Amenities are partially endogenous in racial composition L_{iW}/L_i which evolves with migration and partially fundamental in b_{igr}.

$$B_{igr} = b_{igr}\underbrace{(L_{iW}/L_i)}_{\text{Pct White}}^{\rho_r} \tag{6}$$

Parameter ρ_r represents the social forces of segregation where preferences for composition may stem from retail amenities or public goods available such as school quality (Diamond, 2016; Almagro and Dominguez-Iino, 2020). Prejudice or biases, often considered to be homophilic, can create taste-based reasons (Becker, 1971; Bobo et al., 2012). Fundamental amenities are often considered natural amenities such as persistent geography.

Spatial Barriers – Exclusionary practices that segregated Black households to certain neighborhoods appear as wedges or constraints that are invariant to highway policy.[21] There is limited evidence exclusion occurred along class divisions within race or was experienced by White households, so I consider only that institutions affected Black residential choice.

[20] Balboni et al. (2020) have a segmented housing construction sector where prices are group-specific. In this setting, prices are not sufficiently different by race after accounting for quality controls and neighborhood fixed effects to merit segmented housing. See Table A.1.

[21] Institutions may be a function of the proportion of the neighborhood that is White i.e. through endogenous institutions, but other institutions are codified into law and persistently invariant to the racial composition of the neighborhood. Aaronson et al. (2021) find a border discontinuity in racial composition at redlining borders even as non-redlined areas became more racially diverse over time. Zoning is an endogenous exclusionary barrier that arises as neighborhood racial composition changes, as studied in Lee (2022), Song (2022), and Krimmel (2022).

In the estimation to follow, I sharply test for the magnitude of these barriers along the borders of the redlining maps. However, institutions are difficult to separate from racial preferences as any desire to self-segregate by Black households translates into higher utility for redlined neighborhoods, which is equivalent to smaller institutional wedges. A central aim of estimation is then disentangling these distinct forces.

Within the set of barriers, further disambiguating them is challenging as all prevailed during this time. Violence and hostility against minority families may produce preference (amenity) wedges, while the unavailability of low-interest mortgages to Black households can create price wedges that fall along the same spatial divides (Rothstein, 2017). Strict capacity constraints may fail to capture subtler forms of housing discrimination. Given this ambiguity and the lack of granular data on home loans or discriminatory practices, I next show how all forms of institutions can lead to the segregation observed in the data.

Isomorphisms Between Barriers – I begin with only capacity constraints where a limited number of Black households can locate in areas that enact barriers. Given the idiosyncratic shocks to residential choice, suppose entry is only allowed for those in the upper tail of the distribution. We can interpret $z_i(0)$ as either especially high idiosyncratic preferences to move into predominantly White neighborhoods, which are often higher-opportunity, or alternatively, as idiosyncratic capability to overcome spatial barriers.

Proposition 1. *With capacity constraint $\bar{c}_{igr}$ and no price or amenity wedges ($\tau^b_{igr} = \tau^Q_{igr} = 0$), the average idiosyncratic shock of residents in neighborhood i follows*

$$\bar{z}_{igr} = \Gamma\left(1 - \frac{1}{\theta_r}\right)\pi_{igr}^{1/\theta_r} = \Gamma\left(1 - \frac{1}{\theta_r}\right)(\bar{c}_{igr}/\mathbb{L}_{gr})^{1/\theta_r}$$
$$= \Gamma\left(1 - \frac{1}{\theta_r}\right)\left(\frac{\sum_{t\neq i}\left(B_{tgr}CMA_{tgr}Q_t^{\beta_{gr}-1}\right)^{\theta_r} + \mathbf{k}_{igr}\left(B_{tgr}CMA_{tgr}Q_t^{\beta_{gr}-1}\right)^{\theta_r}}{\mathbf{k}_{igr}\left(B_{tgr}CMA_{tgr}Q_t^{\beta_{gr}-1}\right)^{\theta_r}}\right)^{1/\theta_r}$$

where $\mathbf{k}_{igr}$ is defined as

$$\mathbf{k}_{igr} = \frac{\bar{c}_{igr}/\mathbb{L}_{gr}\sum_{t\neq i}\left(B_{tgr}CMA_{tgr}Q_t^{\beta_{gr}-1}\right)^{\theta_r}}{(1 - \bar{c}_{igr}/\mathbb{L}_{gr})\left(B_{igr}CMA_{igr}Q_i^{\beta_{gr}-1}\right)^{\theta_r}}$$

This same allocation can arise when instead of constraint $\bar{c}_{igr}$, price or amenity wedges follow

$$\tau^b_{igr} = 1 - \mathbf{k}_{igr}^{1/\theta_r}$$
$$\tau^Q_{igr} = \mathbf{k}_{igr}^{1/(\theta_r(\beta_{gr}-1))} - 1$$

Proof. See Appendix D.3. □

Notice that as $\bar{c}_{igr}$ binds more tightly, the average idiosyncratic shock rises. To generate the same allocation created by the capacity constraint, intuitively either the amenity or the price wedge must sufficiently increase to reduce the number of Black households in a location. Amenity wedges in indirect utility easily map into price wedges with the Cobb-Douglas form. However, price wedges have different equilibrium welfare implications since they also impact the housing market. No existing dataset enables measuring the price wedges directly, so I proceed with the amenity wedge going forward.

Firms and Housing – As worker mobility across locations reacts to reductions in commute costs, firms alter wages in equilibrium and housing supply responds to affect prices. These adjustments are not as central to the paper as residential choices, so I relegate these features to Appendix D.4. They are necessary to close the model and conduct a comprehensive assessment. In the counterfactual exercises, I probe their importance for welfare.

To summarize, firms are perfectly competitive using Cobb-Douglas technology over labor and housing. Labor is a Nested CES aggregate over education and race types, and productivity by group differs across locations. Agglomeration in density alters firm productivity. The housing construction sector responds to changes in demand following a constant elasticity structure with an arbitrage condition over residential versus commercial uses. Homeownership is akin to holding a portfolio of homes across neighborhoods, where rents are re-distributed based on the share of home values owned by each group.

Welfare – Finally, welfare up to a normalization constant, U_{gr}, aggregates over all residential locations accounting for amenities, commuter access, prices, and homeownership.

$$U_{gr} = \left(\sum_i \left((1-\tau^b_{igr}) B_{igr} \underbrace{\left(\sum_j T_{jgr} (w_{jgr}/d_{ijgr})^{\phi} \right)^{\frac{1}{\phi}}}_{CMA_{igr}} Q_i^{\beta_{gr}-1} \varphi_{gr} \right)^{\theta_r} \right)^{1/\theta_r} \tag{7}$$

4.2 Impacts of the Interstate Highway System

Commuting benefits of highways lead to declines in bilateral times t_{ijgr} in the commute cost function $d_{ijgr} = t_{ijgr}^{\kappa_{gr}}$. These reductions improve commuter access differentially across locations depending on which bilateral pairs are connected and wages at workplaces.

Localized costs of highways scale fundamental amenities b_{igr} and decay over distance $DistHW_i$ at the rate η (Brinkman and Lin, 2022). At $DistHW_i = 0$, fundamental amenities are discounted by $1 - b^{HW}$, and remaining amenities are contained in $\bar{b}_{igr}$.

$$b_{igr} = \bar{b}_{igr}(1 - b^{HW}\exp(-\eta DistHW_i)) \tag{8}$$

Residential Choice Expression – In summary, the Interstate system generates changes in *fundamentals* of commute times between places and amenities by highways which through the general equilibrium system of equations lead to adjustments in the *equilibrium objects* of endogenous amenities, housing prices, and wages.

Residential choice, expanded below, evolves with the direct impacts of Interstate highways as well as with equilibrium adjustments across residences and workplaces.

$$L_{igr} = \Bigg(\bar{b}_{igr}\underbrace{(1-\tau^{b}_{igr})}_{\text{Institutions}}\underbrace{(1 - b^{HW}\exp(-\eta DistHW_i))}_{\text{Local Costs}}\underbrace{(L_{iW}/L_i)^{\rho_r}}_{\text{Pct White}} \\ \times \Big(\sum_j T_{jgr}(\underbrace{w_{jgr}}_{\text{Wages}})^{\phi} * (\underbrace{t_{ijgr}}_{\text{Commute Times}})^{-\kappa_{gr}\phi}\Big)^{\frac{1}{\phi}} \times \underbrace{Q_i}_{\text{Prices}}{}^{\beta_{gr}-1}\Bigg)^{\theta_r}\mathbb{L}_{gr}U_{gr}^{-\theta_r} \tag{9}$$

Note that if much of the cross-sectional variation in where Black households live appears in time-invariant wedges, only large shocks can alter the degree of segregation. Although Interstate highways impacted cities immensely, they may not be sufficiently large to affect Black residential locations, in line with the observed low Black mobility.

Impacts to Welfare in Equilibrium – Welfare changes are tightly tied to the population responses and can be expressed in exact-hat algebra form $\hat{x} = x'/x$ to show the dependence on initial allocations. The change in welfare $\hat{U}_{gr} = U'_{gr}/U_{gr}$ follows

$$\hat{U}_{gr} = \Bigg(\sum_i \pi_{igr}\Big(\underbrace{\hat{b}_{igr}}_{\text{Fund Amen}} \times \underbrace{(\hat{L}_{iW}/\hat{L}_i)^{\rho_r}}_{\text{Pct White}}\Big(\sum_j \pi_{j|igr}(\underbrace{\hat{w}_{jgr}}_{\text{Wages}})^{\phi} \times (\underbrace{\hat{t}_{ijgr}}_{\text{Commute Times}})^{-\kappa_{gr}\phi}\Big)^{\frac{1}{\phi}}\underbrace{\hat{Q}_i}_{\text{Prices}}{}^{\beta_{gr}-1}\underbrace{\hat{\varphi}_{gr}}_{\text{Homeown}}\Big)^{\theta_r}\Bigg)^{1/\theta_r} \tag{10}$$

and is determined by the (1) initial distribution of groups across locations in π_{igr} and $\pi_{j|igr}$, (2) changes in *fundamentals* and in *equilibrium outcomes*, and (3) elasticities to residential and workplace shocks. Given $\theta_B << \theta_W$, Black households respond less to any residential changes with subsequent impacts on welfare. Furthermore, their lower residential elasticities imply that their initial residential locations, which may be determined heavily by time-invariant wedges, are especially important for the incidence of highway impacts. As is evident, the initial allocation, equivalent across types of barriers, is the only necessary information at baseline for understanding changes in welfare inequality.

4.3 General Equilibrium and Uniqueness

Definition 1. Given the model's parameters, city populations by education and race, and location characteristics, the general equilibrium is represented by a vector of endogenous objects including $\{L_{igr}, L_{Fjgr}, Q_i, w_{jgr}, B_{igr}, U_{gr}\}$ determined by the set of equations governing residential demand, labor supply, housing demand from residents and firms, housing supply, zero profit and profit maximization by firms, and the closed-city assumption. More details are in Appendix D.5.

The equilibrium defined has many sources of spillovers, most immediately via endogenous amenities and agglomeration externalities, and thus the possibility of non-uniqueness.

Proposition 2. *There exists a unique equilibrium when model parameters satisfy the condition $\rho(A) < 1$ where A is a matrix of elasticity bounds on the economic interactions across endogenous equilibrium outcomes and $\rho(A)$ is the spectral radius.*

Proof. See Appendix F.4 □

I follow Allen et al. (2022) where I rewrite the equilibrium conditions as a set of H types of interactions conducted by the set of N heterogeneous agents and then construct the $H \times H$ matrix of the uniform bounds of the elasticities. With these conditions on model parameters, I derive theory-consistent equations to estimate parameter values next.

5 Parameter Estimation and Model Inversion

The steps for estimation and inversion are intertwined, so I summarize the overarching goals before presenting the estimating equations.

5.1 Estimation and Inversion Overview

Parameter Estimation – The focus of estimation is on two main strands of parameters: (1) direct impacts of Interstate highways through commuting connectivity and local harms near routes, and (2) the sources of segregation.

To measure commuting benefits, a key initial step is estimating the "gravity" equation for how commute flows relate to commute times by race and education. I obtain commuting elasticities $\nu_{gr} = \kappa_{gr}\phi$, which combine the commute cost parameter κ_{gr} with the workplace substitution elasticity ϕ, and ν_{gr} enters into the CMA measures to determine residential location decisions. Within the commuting elasticity, the workplace elasticity is assigned from the literature to $\phi = 3$ following studies with settings similar to this paper.[22] The commute cost parameter is then $\kappa_{gr} = \nu_{gr}/\phi$.

Commuting elasticities on hand, I construct several instruments to estimate some of the sources of segregation, residential elasticity θ_r and racial preferences ρ_r, by exploiting quasi-random variation from the highway shock. Building on the reduced form empirical equations, CMA improvements directly affect residential attractiveness, providing variation for θ_r. They indirectly alter racial composition as the population responds in race-specific ways to CMA, providing variation for ρ_r. Lastly, housing price sensitivity β_{gr} is calibrated using the Consumer Expenditure Surveys (CEX).

With the set of parameters, I invert the model to retrieve fundamental amenities (including the amenity wedge) as the residual component of population choices unexplained by characteristics such as prices, racial composition, or commuting access. This residual is then projected over distance from routes to measure local costs in non-parametric bins.

In Section 7, I return to the composite amenity term to investigate the role of institutional barriers as an amenity wedge. This residual component removes the sources of segregation that arise from rents or social preferences and represents other factors that drive location choice. As a time-invariant term, however, it is not necessary for measuring highway welfare impacts.

Model Inversion – In tandem with parameter estimation described above, model inversion occurs in the background to acquire components that enter estimation. Inversion uses the set of parameters (partially estimated, partially from the literature as described in later sections) to map observed data on residential and workplace populations, commute times, housing prices, and wages to productivity and residential amenities i.e. B_{igr}. During this process, several location characteristics such as T_{jgr} are also inferred.

Using the commuting equation for labor supply in Equation (3) and following the iterative procedure of Allen and Arkolakis (2014), I invert for workplace factors $\omega_{jgr} = T_{jgr}(w_{jgr})^{\phi}$ which combines observed wages with the scale parameter T_{jgr}.[23] Aggregating the workplace factors into the CMA measure and combining CMA with rents, racial com-

[22] The elasticity ϕ has been estimated in various contexts and ranges from 6.8 in Ahlfeldt et al. (2015) during the division of Berlin, 1.9 in Morten and Oliveira (2018) with highway expansion in Brazil, 3.3 in Monte et al. (2018) with commuting data in the U.S, and 2.18 in Severen (2021) with development of the Los Angeles Metro Rail.

[23] This process is isomorphic to taking the workplace fixed effect from the "gravity" equation estimated later. Unlike Ahlfeldt et al. (2015) which lacks wage data, making inversion a necessity to infer determinants of workplace choice, I observe wages by race and education at employment locations. Confirming evidence from Severen (2021) and Kreindler and Miyauchi (2022), wages do not fully determine workplace location decisions. The scale parameter T_{jgr} is another determinant and captures variation in the size of the POW Zone units. T_{jgr} can also be affected by workplace amenities that are differential by race and education across locations e.g. through discrimination beyond wages.

position and the estimated parameters θ_r and β_{gr}, I infer amenities up to a scaling factor with the mapping provided by the residential share in Equation (4).

Not central to the paper but necessary for the general equilibrium system, I calibrate parameters in the production function using the Nested CES structure for labor demand, wages by race and education, and elasticities of substitution by race and education. Productivity is determined by the zero profit condition. As the workplace data is at the POW Zone unit, I assume that the distribution of economic activity across tracts is uniform within the POW Zone. Housing supply, land used in housing production, and the allocation across residential and commercial uses are recovered from the conditions for residential and commercial demand. Details are provided in Appendix E.1.

Summary – The key parameters estimated in the subsequent sections pertain to the *direct benefits and costs of highways*: commuting elasticities (ν_{gr}), local costs (b^{HW} in amenities and η for the rate of decay over distance) and the *sources of segregation*: residential elasticity (θ_r), racial preferences (ρ_r), and price sensitivity (β_{gr}). Secondary parameters for the equilibrium framework are calibrated or taken from the literature.

5.2 Gravity Equation for Commuting Elasticity

Using the commute shares in Equation (2) and the functional form of commute costs as $d_{ijgr} = t_{ijgr}^{\kappa_{gr}}$, I estimate the following gravity equation for commuting elasticities.

$$\log \pi_{j|igr,t} = \underbrace{\gamma_{jgr,t}}_{\log \omega_{jgr}} + \underbrace{\gamma_{igr,t}}_{\log \Phi_{igr}} - \underbrace{\nu_{gr}}_{\kappa_{gr}\phi} \log t_{ijgr,t} + \epsilon_{ijgr,t}$$

Location by year fixed effects $\gamma_{jgr,t}$ and $\gamma_{igr,t}$ account for factors that are workplace-specific (scaled wages ω_{jgr}) and residence-specific (transformed commuter access Φ_{igr}) in each year. The error term $\epsilon_{ijgr,t}$ captures remaining factors outside of the model or mismeasurement in commute times. Commute flows from the 1960 and 1970 Censuses are pooled together, and commute times are computer-generated. Bilateral variation in commute times then identifies the elasticity.

Splitting by race and education leads to some zero-count bilateral pairs, which happens often for the Black population (11 percent of the sample). To reduce sparsity, I aggregate residential tracts up to the Place of Work Zone, so estimation is for POW Zone by POW Zone by year with standard errors clustered for POW Zone by POW Zone.

In Table 5 Panel A, I find that less-educated groups, both White and Black, tend to have higher elasticities compared to the higher-educated, in line with findings from Tsivanidis (2022) in the context of Bogota. Parameter values for Black workers are lower than values for White workers, suggesting that Black households consider commute times less in their commuting decisions. These values are similar to those in Heblich et al. (2020) of -4.90, estimated with commuting data from 19th-century London. Instrumenting times with the planned routes and rays for 1970 in Panels B and C, respectively, does not greatly alter the results (first stages are reported in Appendix Table A.11), and the estimates from Panel C are the preferred values used for counterfactual analysis later on.

Additional Results – In Appendix E.2.2, I address sparsity with the Poisson Pseudo Maximum Likelihood (PPML) estimator following Silva and Tenreyro (2006). I additionally use an alternative instrument of Euclidean distance that is estimated via PPML through a control function approach (Wooldridge, 2015). Results do not change substantially.

5.3 Residential Elasticity and Preferences as Endogenous Amenities

I now estimate the residential elasticity θ_r and racial preferences ρ_r following the equation below which relates population flows to changes in CMA and racial composition.

$$\Delta \log L_{igr} = \theta_r \Delta \log CMA_{igr} + \underbrace{\tilde{\rho}_r}_{\theta_r \rho_r} \Delta \log \underbrace{\left(L_{iW} / L_i \right)}_{\text{Pct White}} + \mathbf{X}_i \beta_{gr} + \underbrace{\gamma_{m(i)gr}}_{\Delta \log(\mathbf{L}_{gr} / U_{gr}^{\theta_r})} + \alpha_{red(i)} + \underbrace{\epsilon_{igr}}_{\theta_r \Delta \log b_{igr}} \tag{11}$$

The first difference is between 1960 and 1970 using the Census microdata. Similarly to the reduced form elasticities, this specification measures population responses to CMA improvements where CMA contains the inverted values for scaled wages ω_{jgr} and the commuting elasticities ν_{gr}. Controls in $\mathbf{X}_i$ are interacted with race and education. City by group fixed effects and redlining fixed effects are also included.

This equation is theory-consistent with the appropriate set of controls. Combining the residential share expression (4), endogenous amenities in (6), and localized highway costs in (8) yields the above specification when $\mathbf{X}_i$ accordingly contains changes in rental prices and bins in distance from routes for the localized costs (all interacted with race and education). Rents and highway costs are controlled for as they are related to changing residential choice, commuter access improvements, and changing demographics.[24]

Unlike past studies that focus on one city, this paper analyzes multiple cities pooled together. I include city by group fixed effects to capture factors such as average welfare

[24] As commuter access increases closer to highways, it is correlated with the localized costs of highways and it may not be immediately clear there are enough sources of variation for identification. By controlling for the distance bins, identification of the effects of commuter access comes from comparing neighborhoods by highways that experience minimal commuter access changes, e.g. closer to the central city, to neighborhoods by highways that experience large commuter access changes, e.g. in the suburbs.

U_{gr} and aggregate population $\mathbf{L}_{gr}$, absorbing migration across cities and leading the variation to come from within cities. Importantly, this equation also contains redlining fixed effects to compare within neighborhood types (redlined vs. non-redlined) as in the previous empirical evidence, I found that Black households faced spatial frictions across types. The coefficient on racial composition thus more closely represents racial preferences since within redlined areas, institutional frictions are less relevant.

To obtain cleaner variation in commuter access changes, I augment the model-informed controls with all the previous geographic controls as well as the Borusyak and Hull (2023)-proposed control for CMA. I additionally incorporate socioeconomic status controls for average income, home values, percentage of residents who are high school graduates, bottom income quintile, and top income quintile. Consequently, the racial preferences parameter omits preferences for socioeconomic status.

Main Results – In Table 6 Column 1 are OLS results with the geographic controls and the base set of model-informed controls on rents and local costs. Standard errors are clustered at the tract-level with Conley (1999) standard errors in brackets. Estimates of the residential elasticity are 0.802 (0.183) for White households and 0.119 (0.172) for Black households. In line with the descriptive evidence, Black households are far less responsive to highway commuting impacts.

White households have strong preferences for living in more White neighborhoods with an estimated value of $\tilde{\rho}_W = 1.049$ (0.024) while Black households have weaker preferences against living in more White neighborhoods with $\tilde{\rho}_W = -0.364$ (0.055), consistent with Bayer et al. (2004) although with larger magnitudes for White families. Adding demographic controls in Column 2 lowers how much Black households care about racial composition, implying that some of the earlier estimate was driven by the correlation between race and socioeconomic characteristics. However, the preference elasticity estimate for White households is unchanged, so their preferences are strongly related to race rather than other status variables. The above specification includes redlined fixed effects, using variation within type of neighborhoods. These results continue to hold when limiting the sample to only redlined neighborhoods, as shown in Table A.13.

Instruments for Estimation – Bias in the above estimates can arise from the error term corresponding to structural residuals of fundamental amenities, i.e. $\epsilon_{igr} = \theta_r \Delta \log b_{igr}$. Practices targeted to particular populations affect residential locations and are correlated with changing racial composition. Historically, speculative realtors steered Black families into transitioning areas, and groups such as the Southtown Planning Association in Chicago barred Black households from prospering White neighborhoods (Hirsch, 1983).

These events do not fit neatly into the model framework and thus appear in the residual.

To exogenously shift racial composition (percent White), I construct three sets of instruments. The first uses Hausman (1996) or Berry et al. (1995) style instruments from the industrial organization literature where changes in other markets (i.e. other neighborhoods) shift local demand. CMA improvements and rental price changes in neighborhoods 3-5, 5-10, and 10-15 miles away are such shifters.

As price changes may not be fully exogenous, the second set of instruments only uses variation from the highway shock following the 3-step approach of Davis et al. (2019). In an initial step, I estimate a simpler version of Equation (11) that represents the model without endogenous amenities. I then solve the pared-down model with the estimated residential elasticities, which I find are heterogeneous by race, to predict shifts in racial composition from the highway shock. Central areas that White families migrate from are those with the largest predicted changes in percent White, and in the final step, I use the predictions for racial composition as instruments (while keeping the Hausman instruments from CMA improvements).

Lastly, following the same intuition of race-specific responses to CMA changes, the group-specific CMA measures are a third set of instruments. To address the non-exogenous placement of Interstate routes, changes in commute times assume the planned maps or Euclidean rays are built rather than the Interstate network. Concretely, $\mathbb{Z}_{igr}^{Plans}$ is the planned CMA instrument previously presented in Section 3.2, and $\mathbb{Z}_{igr}^{Rays}$ is the corresponding measure for the Euclidean rays. More details are provided in Appendix E.2.3.

The two variables of interest are $\{\Delta \log CMA_{igr}, \Delta \log(L_{iW}/L_i)\}$ where the first variable of CMA changes uses $\mathbb{Z}_{igr}^{Plans}, \mathbb{Z}_{igr}^{Rays}$ as instruments. The second variable of racial composition changes uses the above three sets of instruments. Consistent estimation relies on an orthogonality condition, where $\mathbf{Z}_{igr}$ contains all of the instruments.

$$\mathbf{E}[\epsilon_{igr} \times \mathbf{W}_{igr}] = \mathbf{E}[f(\theta, \rho_r) \times \mathbf{W}_{igr}] = 0$$

The matrix $\mathbf{W}_{igr}$ includes the city by group fixed effects, redlining fixed effects, controls $\mathbf{X}_i$, and excluded instruments $\mathbf{Z}_{igr}$.

In Table 6 Columns 3–8, I report IV estimates across the three sets of instruments. Residential elasticities for White households are in the range of 0.420 (0.185) to 0.918 (0.161) and are higher than for Black households, except when using the Davis et al. (2019) instruments. Black residential elasticities are challenging to estimate precisely because of large standard errors and the lower point estimate. The most stable estimate across all specifications is racial preferences for White households, which ranges from 1.016 (0.154) to 1.239 (0.066) and is highly statistically significant. Interestingly, I now find that Black racial preferences are fairly weak with point estimates in the range of -0.0418 (0.137) to -0.0973 (0.048), many not statistically significant. These results suggest the previous findings on Black preferences stem from correlations with changing unobserved characteristics.

At the bottom of Table 6, Sanderson-Windmeijer multivariate F statistics for weak instruments with multiple endogenous regressors are reported and are consistently above 10 for parameters estimated for White households. For Black households, the F statistics can reach lower values, leading IV to be more biased towards OLS.

5.4 Localized Costs

With the estimated parameters, I invert the model to recover fundamental amenities b_{igr} and estimate how the Interstate highway system affected nearby neighborhoods' amenities following $b_{igr} = 1 - b^{HW} \exp(-\eta DistHW_i)$.

$$\Delta \log b_{igr} = \sum_{k=1}^{5} \beta_k \mathbf{1}\{DistHW_i = k\} + \mathbf{X_i}\eta_{gr} + \gamma_{m(i)gr} + \alpha_{red(i)} + \epsilon_{igr}$$

The exponential decay is approximated with non-parametric mile-wide bins up to 5 miles from Interstate segments built between 1960 and 1970. The equation controls for distance from the CBD and geographic features in $\mathbf{X_i}$ interacted with group, city by group fixed effects, and redlining fixed effects. Standard errors are clustered at the tract level.

In Column 1 of Table 7 with no controls, there is a large drop in fundamental amenities where at 1 mile from the constructed network, $\Delta \log B_{igr} = -0.453$ (0.0501). However, much of the decline by highways is due to selection in route placement as including geographic controls in Column 2 reduces the estimate to -0.119 (0.0516). To gain precision, I further report results for 0.5 mile-wide bins in Column 3 where $\Delta \log b_{igr} = -0.191$ (0.0581) in the first 0.5 mile. These estimates are comparable in size to findings in Brinkman and Lin (2022) using cross-sectional variation from Chicago. To assign parameter values for b^{HW} and η, I match the functional form of $b_{igr} = 1 - b^{HW} \exp(-\eta DistHW_i)$ to two of the estimated bins in Column 3 at $k = 0.5, 1.5$.[25]

Additional Results – In Appendix E.2.4, I conduct additional tests of how much of the change in amenities is endogenous in addition to fundamental. I examine changes near the large candidate roads that were not rebuilt as interstates in a placebo test and find no decline. Lastly, I measure how modern-day pollution is related to proximity to highways.

[25]Parameters are set to solve two equations: $1 - b^{HW} \exp(-\eta 0.5) = \exp(-0.191), 1 - b^{HW} \exp(-\eta 1.5) = \exp(-0.0994)$.

5.5 Parameters from External Sources

For the economic forces of segregation, price sensitivity i.e. the consumption share of housing $1 - \beta_{gr}$ is predicted using the Consumer Expenditure Surveys (CEX) microdata in 1980, the earliest year available, using average income levels by race and education (see Appendix E.2.5). Finally, I close the model with additional parameters on the production function and housing supply construction sector, which are described in Appendix E.2.6.

5.6 Validation Exercises

I conduct several tests to validate that the model predictions match the empirical moments. Figure B.6 Panel A displays the linear fit and binned scatter plot for log predicted vs observed commute flows in 1960 and 1970.[26] Panel B plots the CDF of flows over time. Predictions tightly fit the data, with the R-squared of the weighted linear fit around 0.9 in Table A.19. Moreover, model predicted changes in non-targeted moments align with the empirical relationships. In Table A.20, predicted and observed rent prices, racial sorting, and income over changes in CMA exhibit similar qualitative and quantitative patterns.

I also examine how model-recovered productivity is related to changes from the Interstate highway system and workplace characteristics to validate the modeling assumptions. In Table A.21, changes in log productivity are uncorrelated with distance from Interstate segments constructed between 1960 and 1970, so highway construction does not appear to contribute to agglomeration or reallocation of economic activity near Interstate routes. This result also rules out highway impacts on trade costs as an important channel for the location of firms because the productivity term contains any effects unrelated to the commuting channel of labor supply to workplaces. In the cross-section, firm productivity is unrelated to redlining in either 1960 or 1970 as shown in Table A.22. Interestingly, productivity is not substantially higher in the central city despite previous evidence that dense areas tend to be more productive (Combes et al., 2012; Baum-Snow, 2020).[27]

6 Counterfactuals and Welfare

Having estimated the set of key model parameters, I undertake several counterfactual analyses to investigate the impacts of Interstate highways on inequality. In Section 7, I return to the role of institutions as a primary mechanism for racial disparities. However for

[26]The gravity equation was estimated from POW Zone by POW Zone bilateral counts in the observed data, so I aggregate predicted commute flows for residential tracts to the POW Zone level.

[27]However, given the larger spatial scale of the workplace geographic units, finer correlations between workplace characteristics and productivity may be present but challenging to detect.

the moment, because institutions are assumed to be within fundamentals and invariant to highway policy, I take the constraints on Black residential locations as given and proceed with the welfare assessment of the Interstate system.

6.1 The Impacts of the Interstates

What are the essential forces that drive inequality in highway policy? Returning to the welfare impacts expression in Equation (10), the Interstate system affects *fundamentals* of local costs by highways and commute times between bilateral pairs, which lead to adjustments in *equilibrium outcomes* of prices, racial composition, and wages. Both changes in fundamentals and equilibrium outcomes are weighted by *initial shares* in the cross-sectional distribution and are aggregated using *substitution elasticities* across locations.

As residential elasticities of the Black population are extremely low, the pattern of their initial shares being heavily concentrated in the urban core strongly suggests that shocks there come close to fully determining highway impacts for welfare. To illustrate this hypothesis more definitively, I next focus on specific channels in the equilibrium framework and explore how welfare changes when different parts are allowed to adjust.

Solving for Equilibrium Counterfactual Outcomes – For each city, I study the counterfactual world where highways enter into the 1960 observed equilibrium with the reduction in commute times and the addition of localized costs along routes built between 1960 to 1970.[28] Across the 25 cities in the analysis, I calculate a weighted average with city-level population weights and report these averages as the main counterfactual numbers.

The general equilibrium framework through the system of equations provided in Appendix F.3 governs how reallocation affects housing prices, endogenous amenities, and wages. Solving for equilibria follows the iterative procedure described by Allen and Arkolakis (2014), and model parameters are listed in Table 8. Residential elasticities are obtained from Table 6 where the elasticity for Black households is set to $\theta_N = 0.35$, lower than the elasticity for White households of $\theta_W = 0.8$. Preference parameter $\rho_B = 0$ because estimates of racial preferences were often insignificant for Black households, and

[28] To conduct the simulation, I set the commuting time matrix to t_{ijgr}^{HW} where the Interstate highways are overlayed on the historical urban road network with the mode of transport weights for each race and education group set at their 1960 weights. The counterfactual therefore does not allow for changes in the mode of transport as a margin of adjustment. It is unlikely that accounting for this margin would change the ordering of the welfare impacts because Black households continue to commute with private automobiles at a lower rate than White households, even in the modern day (Bunten et al., 2022). I modify the exogenous amenity parameters $b_{igr,1960}$ to include the localized costs from the highway such that $b_{igr}^{HW} = b_{igr,1960}(1 - b^{HW}\exp(-\eta DistHW_i))$ with full decay at 5 miles.

for White households, $\rho_W = 1$ at the low range of the confidence intervals.[29] As empirically home values did not change substantially, in the baseline counterfactual $\varphi_{gr} = 0$, and I incorporate homeownership in an additional exercise to measure its importance.

To obtain the new equilibrium, I take the "covariates based approach" characterized by Dingel and Tintelnot (2023). Rather than the "exact-hat algebra" approach of predicting counterfactual changes from initial observed flows as in Dekle et al. (2008), I infer counterfactual changes with predicted flows generated using the estimated commuting elasticities. This approach avoids overfitting to the considerable sparsity of the data, especially for Black households, while largely conveying patterns of commuting behavior. The predicted flows are also used to recover fundamentals in levels.

General Equilibrium Impacts – In Table 9 Panel A, I present the GE welfare impacts separately for the four groups and pooled by race and by education to evaluate which demographic dimension exhibits larger disparities. Welfare changes are the lowest for less-educated Black households at −1.45% and the highest for higher-educated White households at 3.01%. Pooled by race, there continue to be losses for Black households of −1.04% and sizable gains for White households of 2.86%. Disparities by education are minimal with welfare gains of 2.07% and 2.79% for the less-educated and higher-educated, respectively. Consequently, I focus mainly on racial disparities.

Channels Behind Impacts – To show how general equilibrium effects alter the welfare results, I break down the impacts further with additional counterfactual exercises.

Direct Impacts – Returning to welfare equation (7), with a derivation provided in Appendix F.1, the direct change in welfare ignoring location responses is a transparent weighted average that depends on the initial shares in each residence and workplace and the changes in commute times and fundamental amenities from the Interstate system.

$$d \log U_{gr} = -\kappa_{gr} \sum_{i,j} \pi_{igr} \pi_{j|igr} \underbrace{\Delta t_{ijgr} / t_{ijgr}}_{\text{Commute Times}} - \sum_{i} \pi_{igr} \underbrace{b^{HW} \exp(-\eta DistHW_i)}_{\text{Local Costs}}$$

These direct impacts are visualized in Figure 3 for the city of Boston where the spatial distribution of the Black population is also provided for comparison. Given the disparate placement of highways across neighborhoods, it is unsurprising that in Table 9 Panel A, the direct changes in local costs are unequal; losses are −8.03% and −6.18% for Black and

[29] Larger values tend to create convergence issues. With these parameters, solving for counterfactuals with the iterative procedure leads to uniform convergence. Given the magnitude of these parameters, the sufficient conditions for uniqueness are no longer satisfied. See Appendix F.4. However, the conditions are not necessary for uniqueness, and I do not encounter multiple equilibria with the smaller preference parameters.

White populations, respectively. As Black car usage is lower and commute time reductions are muted in the central city, where the Black population lives, gains from commute benefits for Black households are 6.47% compared to 7.9% for White households. Both effects lean in the direction of increasing racial inequality so that on net, the direct impacts are -1.56% for the Black population and 1.72% for the White population.

Homeownership – Incorporating homeownership increases inequality across race groups but does not greatly affect inequality across education groups. Welfare for the Black population declines further relative to the general equilibrium counterfactual from -1.04% to -1.32% while White welfare increases from 2.86% to 3.11%. Because rents increase in more affluent areas that White households reside in and decrease in integrated neighborhoods, re-distributing rents to homeowners enlarges the racial gap in welfare.

Reallocation Only – To understand how spatial mobility impacts welfare, I allow for household reallocation across locations, but no equilibrium outcome adjustments. The only forces at play are the changes in fundamentals as well as the elasticities for residential and workplace choice. This exercise is operationalized by setting the hat $\hat{x} = x'/x$ of equilibrium outcomes to one in Equation (10). I find that welfare losses are -0.98% for the Black population and welfare gains are 2.96% for the White population.

Compared to the direct impacts, the reallocation-only impacts are much more positive for White households. As they migrate both towards positive and away from negative aspects of the highway shock, they enlarge their gains relative to the Black population and widen racial inequality. Compared to the general equilibrium impacts, the reallocation-only values are similar, suggesting that equilibrium outcome adjustments play a small role in welfare. The minimal difference can be due to offsetting adjustments, e.g. White households who reallocate to suburbs pay higher housing prices (lowering utility) but also live in more segregated neighborhoods (raising utility), canceling out overall.

Partial Equilibrium and No Spillovers – As most of the empirical evidence was related to residential changes, I shut down adjustments on the firm side in a partial equilibrium counterfactual where any changes in labor supply do not affect wages paid to workers or housing demand from firms. The system of equations is provided in Appendix F.2. I find that the welfare results look broadly similar to the general equilibrium results in Table 9.

In a last counterfactual, I shut down spillovers from endogenous amenities and agglomeration, and again, welfare impacts are similar. These findings highlight how changes in equilibrium outcomes are of lesser importance compared to the mobility of groups.

Changes in Equilibrium Objects – The differential welfare effects are apparent in the changes in equilibrium outcomes, shown in Appendix Table A.23. Black households experience large drops in amenities, which are central to their welfare losses, although mobility responses somewhat reduce their incidence to highway costs. Their wages are slightly lower, and they move marginally further into the periphery of cities and outside of redlined areas. With the commuting benefits, Black workers reduce their commute times overall even though they also substantially increase their commute distance in response.

White households experience smaller drops in amenities, and they move substantially farther from the central city and from redlined areas. They respond more to the commute benefits by increasing their commute distances more than Black households. All of these equilibrium adjustments, differential by race, suggest how disparities emerge.

Additional Counterfactual Results – I probe the sensitivity of welfare to slight modifications in key parameters in Appendix Table A.24. Researchers may hesitate to allow racial composition to affect welfare directly, so I set spillovers from racial preferences to zero and find welfare for White households does not change substantially relative to baseline.

Alternatively, I allow for positive racial preferences for Black households by setting $\rho_N = -0.2$,[30] and with this change, Black households experience smaller welfare losses from the Interstate highway system of -0.62%. Because White households migrated out of the central city, the neighborhoods that Black households lived in experienced large shifts in racial composition. The model predicts homophilic preferences contribute to some Black welfare gains, but they do not fully compensate for the overall losses from Interstate highways. Given the detrimental consequences of urban decline from the suburbanization of advantaged families, I report the results with positive racial spillovers for Black households as only a robustness check rather than as a main finding.[31]

Policy Implications – Lastly, I conduct counterfactual exercises on policy directions for transportation infrastructure. In Appendix Table A.24, I find that welfare changes when Interstates are built according to the planned routes are similar to the original impacts. Gains are larger with the ray network as Interstates, which removes beltways that contribute less to commute time reductions but substantially increase costs. Yet, all routes lead to disparities by race because Interstate highways were required to intersect central cities, further highlighting the importance of residential constraints, and because of differences in car usage. Mitigating costs increases welfare, especially for Black households, shown at the bottom of Panel C in Table 9, which suggests that an effective policy would

[30] This value comes from the elasticity estimate of -0.07 from Table 6 divided by the residential elasticity of $\theta_N = 0.35$.

[31] Research across a variety of disciplines finds greater spatial separation by race leads to worse economic outcomes (Jackson, 1985; Massey and Denton, 1993; Bullard, 1993).

be reducing highway harms. Indeed, construction costs have greatly risen over time, partially in order to limit negative highway consequences (Brooks and Liscow, 2020).

An alternative path to reducing disparities is increasing spatial mobility, e.g. by lowering information frictions (Ferreira and Wong, 2020). Setting the Black residential elasticity to the greater value of White households raises Black welfare, and setting both Black and White elasticities to three times the original value of White households leads the Black population to experience positive changes from the Interstate system. Spatial frictions (from institutions or other factors) affecting mobility thus also limit welfare gains.[32]

7 The Role of Institutional Segregation in Welfare Impacts

In this section, I explore the factors behind the spatial concentration of Black households in central areas and how segregation interacts with the Interstate highway system to produce unequal policy impacts. The focus is on institutional wedges in fundamentals, given that Black racial preferences are more muted and economic differences do not appear to determine much of Black residential isolation (recall the summary statistics from Section 2.1). Fundamentals that affect the cross-sectional spatial distribution then translate into inequality in highway impacts since initial shares are a key determinant of welfare.

I begin with differences in racial composition around the borders of redlining maps where an identification strategy permits clean tests of the presence of institutional barriers. I then discuss the takeaways from this strategy and consequently examine barriers away from the border to study institutional segregation more broadly.

7.1 Institutional Segregation in Border Discontinuity

Past research has measured how racial composition sharply shifts across the grades of HOLC maps (Hillier, 2003; Faber, 2014; Aaronson et al., 2021). In Figure 1, percent White drops by a sizable 18 percentage points upon crossing into redlined neighborhoods. Most similarly to Aaronson et al. (2021), I employ a border discontinuity design to analyze segregation along the HOLC maps. Yet instead of solely studying empirical changes in racial composition, I take a revealed preference approach and infer the *sources* of segregation. In equilibrium, rental prices are lower in redlined areas and endogenous amenities reinforce sorting, so the differences Aaronson et al. (2021) find are not due entirely to institutions.

[32] Interestingly, raising Black mobility leads to smaller gains for White households, who may then face more competition in response.

The border discontinuity design is estimated separately by race following

$$Y_{igr} = \alpha_{gr} + \psi_r D_i^{red} + \mathbf{F}_r(DistRED_i) + D_i^{red} \times \mathbf{G}_r(DistRED_i) + \lambda_{ilr} + \xi_{igr}$$

where α_{gr} are education by race fixed effects, D_i^{red} is an indicator for i being a redlined neighborhood, and λ_{ilr} are fixed effects for if the nearest border is border l. $DistRED_i$ is the distance to the nearest border separating redlined neighborhoods from other neighborhoods, and a positive value represents being in a redlined neighborhood. $\mathbf{F}_r$ and $\mathbf{G}_r$ are non-linear functions of distance. Estimation uses the 1960 Census microdata.

Y_{igr} corresponds to several outcomes for the factors behind residential choice. Redlined neighborhoods may be more racially diverse either because Black households live there relatively more or because White households live there relatively less, so as the first outcome, log population $\log L_{igr}$ is informative of how each race group is distributed across the border. Then, with the estimated parameters and the model-implied relationship in Equation (9) for the cross-section, I decompose how residential choices are related to prices, commuter access, and amenities (endogenous and fundamental). Fundamental amenities, capturing the discriminatory wedge $(1 - \tau_{igr}^b)$, are the central outcome of interest where the identification assumption is that fundamentals should not be changing along the border except through institutional factors.[33]

I follow the local polynomial approach of Calonico et al. (2014) and use the corresponding optimal bandwidth for each outcome. When inverting for amenities, I take the highest estimates for racial preferences for both White and Black households to obtain the most conservative value for the institutional component as well as the highest residential elasticity for White households and assign it to Black households. Parameters used are listed at the bottom of Table 10. Additionally, to avoid confounding the effect of social institutions with physical barriers or changes in school districts, I remove neighborhoods immediately by railroads, large roads, highways, and school district borders (which come from the National Center for Education Statistics).[34]

Main Results – In Table 10 Column 1, I find that the combination of Black households living more and White households living less in redlined neighborhoods leads to the drop in percentage White. In Panel A for Black households, I estimate a striking 1.425 (0.226)

[33]This identification assumption is distinct from that of Aaronson et al. (2021) who search for borders where there were no pre-existing racial divisions before the maps were drawn in 1932, as they aim to measure the treatment effects of the HOLC maps. Consequently, the discontinuity estimates of this paper capture institutions prior to the HOLC while those of Aaronson et al. (2021) do not.

[34]The sample is limited to tracts at least 0.1 miles away from historical large urban roads, constructed highways in 1960, or historical railroads and also at least 0.1 miles away from a school district boundary where school districts come from the 1989-1990 school year, the earliest year with district maps from NCES.

increase in log population, in line with historical evidence that Black households were heavily concentrated in redlined areas. For White households in Panel B, there is a sizable -0.546 (0.122) decline in log population entering into redlined neighborhoods.

When amenities B_{igr} are the outcome and the price and CMA components are removed from residential choice in Column 2, I find the discontinuity is only slightly reduced for Black households to 1.370 (0.238). For White households, the estimate of -0.603 (0.112) is more negative as they also prefer lower prices. Accordingly, cheaper rents cannot explain why White households live less in redlined areas nor much of the change in Black and White populations over the border.

With fundamental amenities as the outcome in Column 3, the discontinuity remains large for Black households at 1.266 (0.209) and disappears for White households to 0.0031 (0.097). Racial preferences fully account for why the White population does not live in redlined areas, indicating institutions play *no role in White residential locations*. Moreover, because of these preferences, barriers likely benefit White households by preventing racial integration. Yet, preferences only explain a portion of the rise in the Black population, leaving a large residual to be attributed to institutions.

Adding socioeconomic controls in Column 4 does not change the results for White households and lowers the discontinuity for Black households to a still sizable value of 0.914 (0.181). This estimate is the preferred value, and I set parameter τ^b_{ngB} following that $\psi_B = 0.914 = \theta_r[\log b_{mB} - \log b_{nB}] = \theta_r \log(1 - \tau^b_{ngB})$ for $m \in \mathbf{R}, n \notin \mathbf{R}$ where $\mathbf{R}$ is the set of redlined tracts. As the discontinuity estimate in fundamental amenities is essentially zero for White households, neighborhoods at the border do not appear to be substantially different in their characteristics, and importantly, the identification assumption is satisfied. For Black households, 65% of the population rise entering redlined areas is in residual fundamental amenities and thus a result of institutional barriers.

Additional Results – In Appendix Table A.25, I assess if natural amenities of land cover types and tree cover change discontinuously along the border. I find amenities that are less manipulable, i.e. open water and wetlands, are smooth across the border, which bolsters the identification assumption.[35] In Appendix E.2.7, I conduct additional robustness checks. I decompose the sources of segregation using controls to reduce the reliance on the estimated parameters. I also examine estimates in the discontinuity over time, for different sample definitions, and for additional variables.

[35] Data on land types such as open water, wetlands, and deciduous forests come from the National Land Cover Database (NLCD), and tree cover canopy comes from the U.S. Forest Service. Interestingly, features such as tree cover and deciduous forest, which may be considered *endogenous* amenities, do differ across the border.

Welfare Impacts – To understand how institutions influence the impact of the Interstate highway system, I conduct a counterfactual exercise where (1) institutional barriers from the border discontinuity are removed and then (2) Interstate highways are constructed in this new environment. To do so, I adjust the fundamental amenity term for Black households in non-redlined neighborhoods by removing the wedge $(1 - \tau^{b}_{ngB})$ for $n \notin \mathbf{R}$, thereby expanding access to non-redlined areas.

I re-compute the general equilibrium counterfactual for Interstate impacts to measure the interaction between barriers by the border and infrastructure policy. Welfare results are displayed in Table 9 Panel C where losses for Black households are reduced from -1.04% to -0.64%. Notably, White households regardless of education experience essentially the same welfare effects. Reducing institutional barriers limits inequality in highway impacts because absent exclusionary barriers, the Black population is able to live farther from the central business district by 11% (see Table A.27). They bear less of the costs of Interstate highways (as shown through a smaller drop in amenities in Table A.23) and are able to gain more from commute benefits rising in suburban areas.

In the intermediate step for the welfare calculation when institutions are relaxed, higher-educated White households experience a -0.5% drop in welfare as shown in Table 9 Panel C; this result motivates why exclusionary barriers were upheld and why there were tenacious efforts to preserve the status quo (Massey and Denton, 1993). Because of homophilic preferences, racial integration lowers the welfare of White households, and in Table A.27, I find that amenities for higher-educated White households are 0.8% lower as they face more competition in their choice of neighborhoods. Reducing barriers by the border allows Black households to live 27.5% less in redlined areas and in neighborhoods that are 8.4% more White.

7.2 Institutional Segregation Writ Large

Nonetheless, removing institutions by the border only somewhat improves Black welfare gains and does not greatly close the welfare gap, which decreases by a modest 10%. The discontinuity estimate is likely an underestimate of the extent to which Black households are excluded from broad sections of cities as the change in racial composition at the border pales in comparison to the stark segregation during this era. In Figure B.7, I plot the spatial distribution of the Black and White population over the racial composition of census tracts in 1960. Visible in this figure is how most White families lived in racially homogeneous neighborhoods—70% of census tracts in this sample are more than 99% White. Near the border, non-redlined areas tend to be more racially integrated than the average White neighborhood while redlined areas tend to be less racially diverse than the average Black neighborhood. The discontinuity estimate is then a local average treatment effect that overlooks heterogeneity in institutional factors further away.

These findings illustrate a perennial tradeoff in economics between proper identification and the potential scope of the question. While the border design allows for a testable identification assumption, it limits the paper to examining a narrow set of neighborhoods. However, useful conceptual lessons are gleaned from the border design. Specifically, institutional barriers appear to be a large determinant of Black residential choices and the relative Black-White difference in fundamentals.

Welfare Results – With this insight, I examine how institutional segregation *writ large* impacts inequality from Interstate highways. I make the stronger assumption that fundamental amenities, generally representing natural amenities such as ocean views or green hills, should not be valued differentially by race *across all neighborhoods*. For example, forested suburbs should receive a high valuation from Black families but do not because of discrimination. I subsequently set the fundamentals of Black households equal to those of White households, who have free rein in choosing where to live, and open up residential access for the Black population. This scenario represents an upper bound on the extent to which erasing discrimination can reduce segregation as there may be true racial differences in fundamentals, e.g. from social networks or information frictions.

In this new environment, I display the changes to welfare from Interstate development in Panel C of Table 9. The racial gap in the general equilibrium impacts from highways is greatly diminished by 54%, and thus institutional barriers determine the majority of inequality from the Interstate system. Black households now receive welfare gains from highways 1.04%, versus previously they were facing losses of -1%. This result follows from the major reduction in the spatial concentration of Black families, who now live 93% farther from the CBD. White households experience similar gains to before of 2.8% so relaxing residential discrimination does not greatly alter their benefits from Interstate development. The remaining gap by race can be attributed to differences in commuting, mode of transport, and general equilibrium outcome adjustments, although this latter channel is likely less important given previous evidence. Segregation, specifically through forces that cannot be accounted for by economic or social factors, plays a crucial role in determining inequality in highway impacts.

Lastly, in the intermediate step when fundamental amenities are assigned to be equivalent across race, there are substantial welfare losses for White households of -1.8%. With further racial integration and increased competition in the housing market, White families fare far worse. Amenities of higher-educated White households are -5.64% lower, and their neighborhoods become 6% less White, providing further justification for why barriers were instituted.

8 Conclusion

This paper develops a theoretical framework and constructs several rich historical datasets to measure the impacts of Interstate highways on inequality. To comprehend why there are profoundly disparate effects, I find that institutions are a primary determinant of the spatial concentration of Black families and interact with highway policy to produce vast disparities. The geographic separation of demographic groups and the selective placement of the Interstate network lead the benefits and costs to be shared unequally, with the most disadvantaged bearing more of the costs while garnering fewer of the benefits. Institutional segregation further generates spatial frictions that limit the spatial mobility of Black households and how much they are able to gain from the Interstate system.

While it may seem that Interstate highways and institutional segregation are things of the past, road infrastructure expansions in the modern day encounter the same equity concerns as they have historically.[36] The persistence of segregation along racial and economic lines and the political disempowerment of groups of color leads the harms of critical infrastructure, such as industrial facilities, to be borne by the most marginalized populations (Currie et al., 2022). Discrimination in housing continues, thereby restricting residential choice for Black families and how much they respond to any placed-based shocks (Bayer et al., 2021). Moreover, the radical and permanent transformation of cities brought about by the Interstate highway system can continually endure through intergenerational consequences, as studied in a companion paper. Future research can aim to understand which neighborhood interventions improve spatial mobility and increase access to economic opportunity for the most disadvantaged families.

Laura Weiwu
Stanford University

[36] A $9 billion highway widening project in Houston, Texas was paused by the Federal Highway Administration in 2021 after local groups opposed the expansion. The re-routing of parts of I-45 would displace predominantly Black and Latino neighborhoods as well as the original Chinatown of downtown Houston.

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9 Tables

Table 1: Summary Statistics by Race and Education in 1960

Variables	(1) Black <HS	(2) Black HS Grad	(3) White <HS	(4) White HS Grad
Economic Variables – Mean (SD)				
Weekly Wages (2010$)	402.3	495.2	569.4	726.7
	(115.6)	(131.6)	(97.6)	(159.1)
Rent (2010$)	382.9	464.6	444.9	607.7
	(124.6)	(136.0)	(140.8)	(194.8)
Home Value (2010$)	65900	92200	93700	130000
	(29850)	(35740)	(32050)	(40200)
Home Ownership Rate	0.334	0.379	0.599	0.626
	(0.238)	(0.273)	(0.266)	(0.280)
Neighborhood Variables – Mean (SD)				
Pct White	0.397	0.418	0.943	0.959
	(0.325)	(0.336)	(0.130)	(0.104)
Pct HS Grad	0.347	0.410	0.474	0.569
	(0.133)	(0.144)	(0.146)	(0.148)
Pct HOLC D	0.661	0.554	0.303	0.189
	(0.405)	(0.436)	(0.409)	(0.342)
Pct HOLC D (w/ missing)	0.509	0.442	0.187	0.110
	(0.451)	(0.448)	(0.353)	(0.278)
Dist Highway (mi)	1.779	1.643	2.578	2.565
	(4.072)	(3.753)	(4.891)	(4.781)
Dist CBD (mi)	6.187	6.337	9.743	9.892
	(7.703)	(6.888)	(9.485)	(9.086)
Commuting Variables – Mean (SD)				
Commute Time (min)	26.86	26.76	26.65	27.74
	(11.07)	(10.75)	(12.03)	(12.42)
Commute Dist (mi)	9.30	9.36	9.22	10.11
	(7.38)	(7.03)	(7.20)	(7.25)
Pct Auto	0.392	0.488	0.561	0.663
	(0.324)	(0.361)	(0.315)	(0.293)
Commute Time (min), Auto	28.56	28.27	28.02	28.31
	(14.89)	(13.97)	(14.66)	(13.93)
Commute Dist (mi), Auto	11.07	10.84	10.56	10.68
	(7.56)	(7.34)	(7.38)	(7.19)
Rounded Count	2,834,000	1,334,000	16,190,000	18,240,000

Notes: Data comes from the 1960 Census restricted microdata. Weekly wages are calculated for employed workers and CPI-adjusted to 2010 dollars from 1960 dollars. Rents are monthly and CPI-adjusted to 2010 dollars from 1960 dollars. Home values are CPI-adjusted to 2010 dollars from 1960 dollars and rounded to four significant digits to meet Census disclosure rules. Pct HOLC D is calculated on tracts where redlining maps exist while Pct HOLC D (w/ missing) includes tracts without redlining maps. Distance from highways is calculated using 1960 residential location and constructed highways. Percentage automobile is the percentage of employed workers whose main mode of transport is private automobile which includes truck and van drivers. Commute time and distance in the bottom rows are shown for workers whose mode of transport is private automobile. Counts of each race by education group are rounded to four significant digits to meet Census disclosure rules. Sample standard deviations are included in parentheses.

Table 2: Placement of Highway Routes for 1950 Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Log Distance from Highway Routes							Plans	Rays
Pct White	0.754***				0.156	0.104	0.125	0.251	0.0645
	(0.0800)				(0.120)	(0.115)	(0.104)	(0.158)	(0.162)
Pct HS Grad		1.015***			0.538***	0.507***	0.428**	0.0343	-0.0327
		(0.181)			(0.204)	(0.193)	(0.171)	(0.284)	(0.343)
Log Median Income			0.0987***		0.0196	0.0247	0.0386*	0.0125	0.0231
			(0.0271)		(0.0221)	(0.0217)	(0.0197)	(0.0205)	(0.0216)
Pct HOLC D				-0.546***	-0.381***	-0.257***	-0.189***	-0.0646	-0.0918
				(0.0576)	(0.0730)	(0.0584)	(0.0533)	(0.0715)	(0.0694)
Pct Bottom Quintile					-0.0584	0.288	0.169	0.429	0.558
					(0.421)	(0.421)	(0.355)	(0.395)	(0.379)
Pct Top Quintile					0.0281	0.234	0.189	0.437	0.623
					(0.293)	(0.293)	(0.297)	(0.401)	(0.386)
Log Rent					-0.0341***	-0.0173*	-0.0147	0.00162	-0.0142
					(0.0113)	(0.0103)	(0.00962)	(0.0133)	(0.0136)
Log Home Value					0.0257*	0.00439	0.00104	0.0233*	0.0215
					(0.0143)	(0.0123)	(0.0111)	(0.0122)	(0.0142)
Log Dist CBD						0.225***	0.207***	0.287***	0.408***
						(0.0411)	(0.0376)	(0.0509)	(0.0660)
R-squared	0.050	0.064	0.040	0.073	0.085	0.106	0.165	0.141	0.170
CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	14,235	14,235	14,235	14,235	14,235	14,235	14,235	14,235	14,235
No. Counties	165	165	165	165	165	165	165	165	165

Notes: Unit of observation is census tract. Data comes from 1950 tract-level aggregates retrieved from IPUMS NHGIS. Tracts are limited to those within 5 miles of the nearest highway route. Fixed effects are at the CBSA (Core-based statistical area) level. Standard errors are cluster-robust with clusters at the county level. The geographic controls are log distance from the central business district (included in all specifications), log distance from rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Changes Over Distance from Central Business District and Distance from Highway (1950-1960, 1960-1970)

	(1)	(2)	(3)	(4)	(5)
	Δ Log Pop	Δ Log Rent	Δ Pct White	Δ Log White Pop	Δ Log Black Pop
Variables			*Panel A* – OLS		
Log Dist Highway	0.0724***	0.0360***	0.0169**	0.110***	0.00703
	(0.0155)	(0.0119)	(0.00674)	(0.0184)	(0.0357)
Log Dist CBD	0.622***	0.165***	0.0629***	0.691***	0.246***
	(0.0267)	(0.0169)	(0.00943)	(0.0303)	(0.0440)
Redlined	0.0102	-0.0408*	-0.159***	-0.154***	0.237***
	(0.0383)	(0.0245)	(0.0211)	(0.0480)	(0.0906)
R-squared	0.143	0.089	0.091	0.155	0.063
			Panel B – OLS + Geo Controls		
Log Dist Highway	0.0594***	0.0348***	0.0249***	0.108***	-0.0298
	(0.0164)	(0.0123)	(0.00742)	(0.0197)	(0.0370)
Log Dist CBD	0.596***	0.102***	0.0742***	0.692***	0.270***
	(0.0311)	(0.0159)	(0.00905)	(0.0346)	(0.0486)
Redlined	0.0626*	-0.00340	-0.165***	-0.110**	0.247***
	(0.0373)	(0.0255)	(0.0210)	(0.0460)	(0.0905)
R-squared	0.153	0.099	0.104	0.173	0.066
			Panel C – IV Log Dist Plans for Log Dist Highway [KP F-Stat = 613.2]		
Log Dist Highway	0.0504	0.0222	0.0266	0.0947**	-0.0160
	(0.0332)	(0.0273)	(0.0188)	(0.0398)	(0.0861)
Log Dist CBD	0.598***	0.105***	0.0738***	0.695***	0.267***
	(0.0318)	(0.0173)	(0.00929)	(0.0353)	(0.0516)
Redlined	0.0607	-0.00600	-0.165***	-0.113**	0.250***
	(0.0380)	(0.0263)	(0.0212)	(0.0468)	(0.0921)
R-squared	0.153	0.099	0.104	0.173	0.066
			Panel D – IV Log Dist Rays for Log Dist Highway [KP F-Stat = 466.7]		
Log Dist Highway	0.121**	0.116***	0.0630***	0.191***	-0.00400
	(0.0475)	(0.0350)	(0.0232)	(0.0539)	(0.116)
Log Dist CBD	0.581***	0.0832***	0.0654***	0.673***	0.264***
	(0.0330)	(0.0177)	(0.00981)	(0.0360)	(0.0550)
Redlined	0.0752**	0.0132	-0.158***	-0.0928**	0.252***
	(0.0383)	(0.0261)	(0.0216)	(0.0472)	(0.0932)
R-squared	0.151	0.095	0.099	0.171	0.066
Dep. Var Mean (1960)	3403	555 (2010$)	0.880	2874	488
CBSA FE	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes
Observations	11,923	11,923	11,923	11,923	11,923

Notes: Unit of observation is census tract. Data comes from 1950, 1960, and 1970 tract-level aggregates retrieved from IPUMS NHGIS. The first difference is either over 1950 to 1960 or 1960 to 1970 depending on when highway construction started in the CBSA and stacked into one panel. Tracts are limited to those within 5 miles of the nearest constructed route and 30 miles from the central business district. Fixed effects are at the CBSA (Core-based statistical area) level. Conley standard errors for spatial correlation within a 1km radius are reported. Panels B-D have as controls log distance from rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads. All specifications include the gradient (Dist CBD/Dist Highway) as a control. Redlined tracts are those where more than 80% of the area is redlined. Kleibergen-Paap rk Wald F statistics are reported for the first-stage. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Elasticity of Population to Commuter Access by Race

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\Delta \log L_{igr}$ (Δ Log Population 1960-1970)								
	OLS			OLS + Redlining FE			IV		
Variables	Geo Cont	+ CBSA FE	+ BH (2023)	Geo Cont	+ CBSA FE	+ BH (2023)	HW	Plans	Rays
$\Delta \log CMA_{igr}$									
Black	0.416***	0.0907	0.0941	0.596***	0.273***	0.273***	-2.026***	-1.757	-3.062*
	(0.101)	(0.0968)	(0.0968)	(0.105)	(0.100)	(0.100)	(0.469)	(1.276)	(1.564)
	[0.114]	[0.110]	[0.110]	[0.119]	[0.116]	[0.116]	[0.564]	[1.490]	[1.838]
White	1.207***	1.401***	1.410***	0.958***	1.069***	1.083***	0.166	0.648**	0.719**
	(0.109)	(0.115)	(0.115)	(0.119)	(0.125)	(0.125)	(0.143)	(0.323)	(0.340)
	[0.126]	[0.142]	[0.143]	[0.137]	[0.157]	[0.157]	[0.190]	[0.456]	[0.458]
R-squared	0.088	0.113	0.113	0.094	0.117	0.118	0.0923	0.099	0.072
CBSA FE		Yes	Yes		Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rounded Obs	60500	60500	60500	60500	60500	60500	60500	60500	60500
C-D F-Stat							1543	203	139
K-P F-stat							520	35	25

Notes: Unit of observation is census tract by race and education. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Fixed effects are at the CBSA (Core-based statistical area) level. Standard errors are cluster-robust with clusters at the tract-level. Conley standard errors for spatial correlation within a 1km radius are reported in brackets. The geographic controls are log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads, all interacted with race. In Column 3, the Borusyak and Hull (2023) control for CMA in large roads is interacted with race. Redlining fixed effects are interacted with race. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. IV specifications include the Borusyak and Hull (2023) control for CMA in large roads interacted with race and CBSA fixed effects. Kleibergen-Paap rk Wald and Cragg-Donald Wald F statistics for weak instruments are reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Commuting Gravity Equation

	(1)	(2)	(3)	(4)
Race x Educ	Black <HS	Black HS Grad	White <HS	White HS Grad
$\nu_{gr} = \kappa_{gr}\phi$	*Panel A* – Log Commuting Share			
Log Commute Time	-4.201***	-3.609***	-4.664***	-4.134***
	(0.119)	(0.120)	(0.0640)	(0.0496)
R-squared	0.692	0.623	0.574	0.579
	Panel B – Log Commuting Share – IV Plans			
Log Commute Time	-4.206***	-3.671***	-4.707***	-4.168***
	(0.126)	(0.120)	(0.0673)	(0.0505)
R-squared	0.232	0.182	0.377	0.367
	Panel C – Log Commuting Share – IV Rays			
Log Commute Time	-4.197***	-3.645***	-4.708***	-4.154***
	(0.127)	(0.122)	(0.0674)	(0.0503)
R-squared	0.232	0.182	0.377	0.367
Rounded Obs	7000	8000	21500	25000
	Panel D – Poisson Pseudo Maximum Likelihood			
Log Commute Time	-4.703***	-3.929***	-3.877***	-3.247***
	(0.0819)	(0.0599)	(0.0471)	(0.0359)
Rounded Obs	20500	21000	26000	27000
POR X Year FE	Yes	Yes	Yes	Yes
POW X Year FE	Yes	Yes	Yes	Yes

Notes: Unit of observation is Place of Work Zone by Place of Work Zone pair by year where commuting flows from residential tracts are aggregated up to the Place of Work Zone geography. Data comes from the restricted Census microdata in 1960 and 1970. Fixed effects are for POR (Place of Residence) by year at the Place of Work Zone scale although it does not represent workplace but rather residential location. POW by year fixed effects are for workplace at the Place of Work Zone level. The conditional commuting share is the share from a residential location that commutes to a workplace. The observation counts are lower for the Black population as some residences and workplaces have zero Black population (while PPML addresses zeros in bilateral flows, it does not address zeros in entire rows or columns). Standard errors are cluster-robust with clusters at the Place of Work Zone by Place of Work Zone level. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Residential Elasticity and Racial Preferences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log L_{igr}$ (Δ Log Population 1960-1970)							
	OLS		IV Hausman		IV Davis		IV CMA	
Variables	Base & Geo Cont	+ SES Cont	Plans	Rays	Plans	Rays	Plans	Rays
θ_r: $\Delta \log CMA_{igr}$								
Black	0.119	0.224	0.353	0.362	1.281***	1.284***	0.00593	0.412
	(0.172)	(0.171)	(0.324)	(0.291)	(0.374)	(0.324)	(0.378)	(0.290)
	[0.196]	[0.196]	[0.579]	[0.563]	[0.626]	[0.585]	[0.672]	[0.494]
White	0.802***	0.802***	0.420**	0.777***	0.576***	0.918***	0.228	0.493**
	(0.183)	(0.183)	(0.185)	(0.190)	(0.167)	(0.161)	(0.244)	(0.203)
	[0.213]	[0.214]	[0.247]	[0.270]	[0.225]	[0.237]	[0.282]	[0.253]
$\tilde{\rho}_r = \theta_r \rho_r$: Δ log Pct White								
Black	-0.364***	-0.283***	-0.0650	-0.0973**	-0.0616	-0.0766	-0.0737	-0.0418
	(0.0546)	(0.0523)	(0.0532)	(0.0481)	(0.111)	(0.0894)	(0.151)	(0.137)
	[0.0722]	[0.0720]	[0.0968]	[0.0919]	[0.176]	[0.147]	[0.238]	[0.214]
White	1.049***	1.066***	1.239***	1.234***	1.202***	1.173***	1.170***	1.016***
	(0.0244)	(0.0246)	(0.0664)	(0.0671)	(0.0556)	(0.0526)	(0.181)	(0.154)
	[0.0436]	[0.0434]	[0.0963]	[0.0943]	[0.0957]	[0.0939]	[0.221]	[0.193]
R-squared	0.190	0.202	0.531	0.528	0.531	0.527	0.565	0.568
CBSA X Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SES Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rounded Obs	56500	56500	56000	56000	56000	56000	38000	38000
S-W F-Stat θ_B			10.66	12.14	6.45	10.09	5.76	14.90
S-W F-Stat θ_W			23.81	23.74	26.26	28.55	11.96	16.98
S-W F-Stat $\tilde{\rho}_B$			7.37	8.41	4.26	5.55	2.68	3.53
S-W F-Stat $\tilde{\rho}_W$			18.45	19.45	17.22	18.61	5.66	6.02

Notes: Unit of observation is census tract by race and education. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Fixed effects are at the CBSA (Core-based statistical area) by race and education group level. Standard errors are cluster-robust with clusters at the tract-level. Conley standard errors for spatial correlation within a 1km radius are reported in brackets. The base controls are change in log rent and 5 binary indicators for distance from highways built between 1960 and 1970 in 1-mile wide bins, all interacted with race and education. Redlining fixed effects are included in all specifications. The socio-economic status (SES) controls are change in log income, change in log percentage high school graduate, change in log percentage bottom income quintile, change in log percentage top income quintile, change in log home values, all interacted with race and education. The geographic controls are log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads, all interacted with race and education. All specifications include the Borusyak and Hull (2023) control for CMA in large roads interacted with race and education. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. Sanderson-Windmeijer multivariate F statistics for weak instruments with multiple endogenous regressors are reported. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Change in Amenities over Distance from Highway

	(1)	(2)	(3)	(4)	(5)
		$\Delta \log b_{igr}$		$\Delta \log B_{igr}$	$\Delta \log b_{igr}$
Variables	OLS	OLS	0.5 mi bins	OLS	Placebo
Dist Highway (mi = 1)	-0.453***	-0.119**		-0.124**	0.00565
	(0.0501)	(0.0516)		(0.0517)	(0.137)
Dist Highway (mi = 2)	-0.379***	-0.0933*		-0.125**	-0.0707
	(0.0499)	(0.0515)		(0.0515)	(0.0997)
Dist Highway (mi = 3)	-0.223***	0.000345		-0.0343	-0.0752
	(0.0531)	(0.0552)		(0.0553)	(0.0910)
Dist Highway (mi = 4)	-0.0795	0.0824		0.0458	0.0307
	(0.0596)	(0.0604)		(0.0606)	(0.0899)
Dist Highway (mi = 5)	0.0369	0.143**		0.140**	0.0437
	(0.0642)	(0.0638)		0.0638)	(0.0793)
Dist Highway (mi = 0.5)			-0.191***		
			(0.0581)		
Dist Highway (mi = 1)			-0.0651		
			(0.0572)		
Dist Highway (mi = 1.5)			-0.0994*		
			(0.0588)		
Dist Highway (mi = 2)			-0.0888		
			(0.0573)		
Dist Highway (mi = 2.5)			0.0116		
			(0.0618)		
Dist Highway (mi = 3)			-0.0153		
			(0.0667)		
Dist Highway (mi = 3.5)			0.0703		
			(0.0738)		
Dist Highway (mi = 4)			0.0955		
			(0.0731)		
Dist Highway (mi = 4.5)			0.140*		
			(0.0808)		
Dist Highway (mi = 5)			0.146*		
			(0.0807)		
R-squared	0.028	0.052	0.052	0.050	0.069
CBSA X Group FE	Yes	Yes	Yes	Yes	Yes
Geo Controls		Yes	Yes	Yes	Yes
Rounded Obs	49500	49500	49500	49500	9000

Notes: Unit of observation is census tract by race and education. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Fixed effects are at the CBSA (Core-based statistical area) by race and education group level. Standard errors are cluster-robust with clusters at the tract-level. There are 5 binary indicators for distance from highways built between 1960 and 1970 in 1-mile wide bins (the value displayed is the upper end of the bin). In Column 3, the bins are split further into 0.5-mile wide bins. The geographic controls are log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads, all interacted with race and education. The sample is limited to tracts within 10 miles of constructed highway routes. For the placebo specification in Column 5, the sample is restricted to not be within 5 miles of a highway and is limited to tracts within 10 miles of historical large urban roads. The geographic control for distance from historical large urban roads is dropped since it is now the endogenous variable. All specifications include redlining fixed effects. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. Parameters used to invert for dependent variables are the same as in Table 10. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Key Model Parameters

Parameters	Source
Labor Supply Elasticity $\phi = 3$	Ahlfeldt et al. (2015), Monte et al. (2018), Morten and Oliveira (2018), Severen (2021)
Commuting Elasticity $\nu_{LB} = 4.20$, $\nu_{HB} = 3.65$, $\nu_{LW} = 4.71$, $\nu_{HW} = 4.15$ $\kappa_{LB} = 1.4$, $\kappa_{HB} = 1.22$, $\kappa_{LW} = 1.57$, $\kappa_{HW} = 1.38$	Estimated in Table 5 Implied with $\phi = 3$
Residential Elasticity $\theta_B = 0.35$, $\theta_W = 0.8$	Estimated in Table 6
Racial Preferences $\rho_B = 0$, $\rho_W = 1$	Estimated in Table 6
Non-Housing Consumption Share $\beta_{LB} = 0.66$, $\beta_{HB} = 0.78$, $\beta_{LW} = 0.70$, $\beta_{HW} = 0.79$	Calibrated to CEX in Appendix E.2.5
Highway Localized Costs $b^{HW} = 0.203$, $\eta = 0.612$	Estimated in Table 7
Institutional Barriers $\tau^b_{ngB} = 0.927$	Estimated in Table 10

Notes: ϕ is set to a value from the literature. Parameters ν_{gr} come from Table 5 Panel C. θ_r come from the midpoint of estimates in Table 6. ρ_N is set to 0 since the estimates from Table 6 are not distinguishable from zero. ρ_W is set to be within the lower range of the confidence intervals from Table 6 and not greater than 1. β_{gr} come from Table A.17. b^{HW} and η come from fitting two values from Table 7 Column 5, and τ^b_{ngB} comes from Table 10 Column 4 where $\tau^b_{ngB} = 1 - \exp(-0.914/\theta_B)$.

Table 9: Welfare Changes (%) by Race and Education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Race	Black	Black	White	White	By Race		By Educ	
x Educ	<HS	HS+	<HS	HS+	Black	White	<HS	HS+
	Panel A – Impacts of the Interstates							
General Equilibrium								
Welfare Change	-1.45	-0.16	2.69	3.01	-1.04	2.86	2.07	2.79
Direct Impacts								
Commuting Benefits	6.21	7.03	8.07	7.75	6.47	7.90	7.79	7.70
Localized Costs	-8.05	-8.00	-6.46	-5.94	-8.03	-6.18	-6.70	-6.08
Welfare Change	-1.84	-0.97	1.61	1.81	-1.56	1.72	1.10	1.62
With Homeownership								
Welfare Change	-1.75	-0.40	2.92	3.28	-1.32	3.11	2.22	2.92
	Panel B – Mechanisms							
Reallocation Only								
Welfare Change	-1.33	-0.25	2.91	3.00	-0.98	2.96	2.28	2.78
Partial Equilibrium								
Welfare Change	-1.17	-0.13	2.85	2.97	-0.84	2.91	2.25	2.76
No Spillovers								
Welfare Change	-1.44	-0.21	2.79	3.00	-1.05	2.90	2.16	2.78
	Panel C – Interaction with Institutional Segregation							
General Eq, No BD								
Welfare Change	-0.99	0.11	2.69	3.01	-0.64	2.86	2.14	2.81
General Eq, Same Fund Amen								
Welfare Change	1.00	1.12	2.64	3.00	1.04	2.83	2.40	2.87

Notes: Welfare calculations are based on data from the restricted Census in 1960. Direct impacts come from the linear approximation in Section F.1. The general equilibrium simulation allows wages to respond in equilibrium. The partial equilibrium simulation keeps wages fixed. No institutions adjusts fundamental amenities for Black households by parameter E in redlined areas. Same fundamental amenities sets fundamental amenities of Black households to those of White households. The general equilibrium simulation with no institutions (same fundamental amenities) adds the highway impacts in the counterfactual world with no institutions (same fundamental amenities). All values are rounded to four significant digits to meet Census disclosure rules. Columns 5–8 are weighted averages of the race by education welfare numbers using population weights from the bottom of Table 1.

Table 10: Border Discontinuity Decomposition

	(1)	(2)	(3)	(4)
	Panel A – Black			
Variables	$\log L_{igr}$	$\theta_r \log B_{igr}$	$\theta_r \log b_{igr}$	+ SES Cont
ψ_B: Border RD	1.425***	1.370***	1.266***	0.914***
	(0.226)	(0.238)	(0.209)	(0.181)
Bandwidth (mi)	0.495	0.447	0.509	0.496
Order of Poly.	1	1	1	1
Education FE	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes
Rounded Obs	13000	13000	13000	13000
	Panel B – White			
Variables	$\log L_{igr}$	$\theta_r \log B_{igr}$	$\theta_r \log b_{igr}$	+ SES Cont
ψ_W: Border RD	-0.546***	-0.603***	0.00305	0.132
	(0.122)	(0.112)	(0.0971)	(0.0937)
Bandwidth (mi)	0.358	0.398	0.297	0.305
Order of Poly.	1	1	1	1
Education FE	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes
Rounded Obs	13500	13500	13500	13500

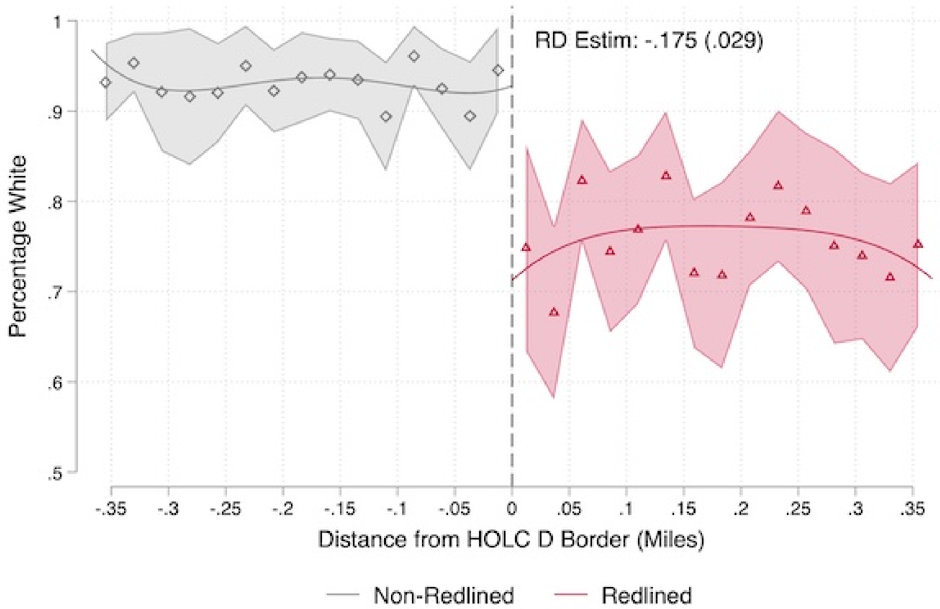
Parameters

$\theta_B = \theta_W = 0.9$
$\theta_B \rho_B = -0.3, \theta_W \rho_W = 1.20$
$\beta_{LB} = 0.66, \beta_{HB} = 0.78, \beta_{LW} = 0.70, \beta_{HW} = 0.79$

Notes: Unit of observation is census tract by border in the redlining maps. Data comes from the 1960 restricted Census microdata. The dependent variable is residualized on fixed effects for education within race and on border fixed effects for all specifications. Controls are log percentage high school grad, log population density, log average income, log percentage top quintile, log percentage bottom quintile, and log home values. Coefficients on controls are estimated with redlining fixed effects. Sample is limited to tracts that are at least 0.1 miles away from possible physical barriers such as historical large urban roads, constructed highways in 1960, or historical railroads and also at least 0.1 miles away from a school district boundary. The bandwidth is chosen optimally following Calonico et al. (2014). Distance from the border is measured in miles. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. Parameters used to invert for dependent variables are displayed at the bottom. *** p<0.01, ** p<0.05, * p<0.1

10 Figures

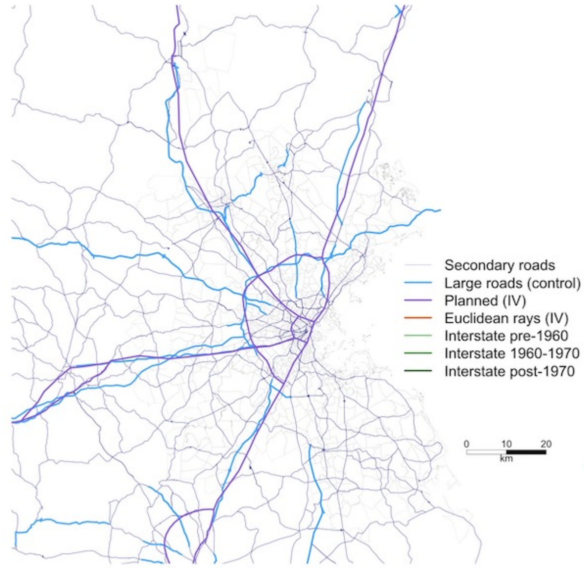
Figure 1: Border Discontinuity for Percentage White in 1960 at HOLC D Border



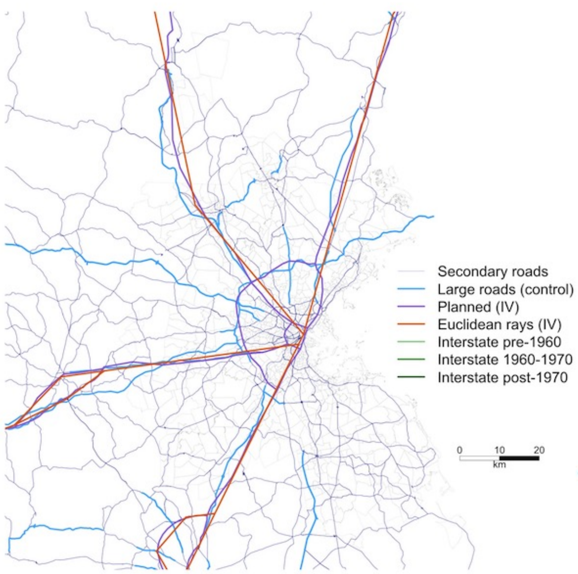
Notes: Unit of observation is census tract by HOLC border pair. Data comes from 1960 tract-level aggregates retrieved from IPUMS NHGIS. The left side of the discontinuity is non-redlined and the right side is redlined. The order of polynomial fit is 4 with optimal bandwith of 0.368 chosen following Calonico et al. (2014), and the kernel is Epanechnikov. Redlined tracts are tracts where more than 80% of the area is redlined. There are 15 bins on the left (N=752) and 15 bins on the right (N=752). The estimated coefficient is from the balanced sample RD shown in Table A.25 Panel A with the order of polynomial set to 1, the same optimal bandwidth of 0.368, and the same number of effective observations (however N=2957 enter into the regression for both sides).

Figure 2: Historical Road Networks and Highway Routes for the Boston Metro Area

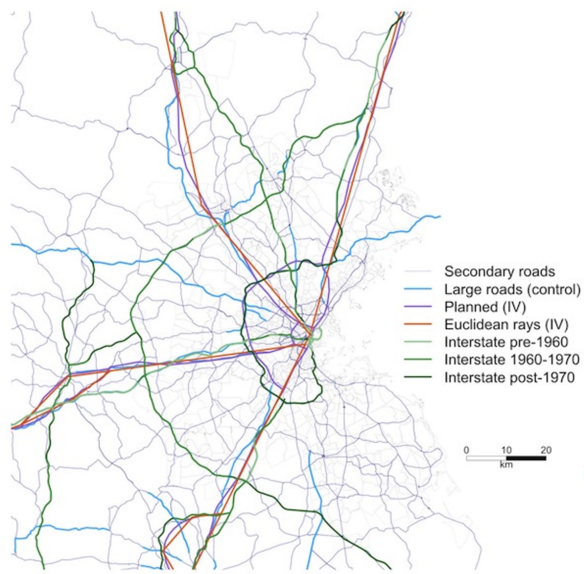
(a) Historical Urban Roads



(b) Planned Routes



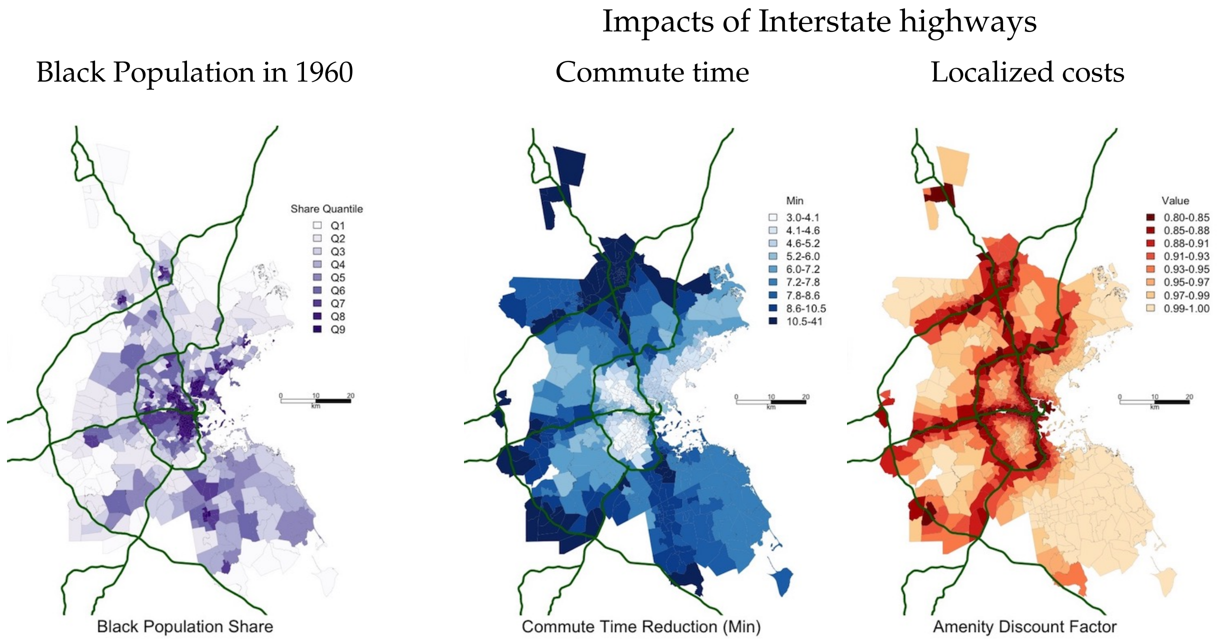
(c) Euclidean Rays



(d) Interstate Highways

Notes: Historical urban roads are split into two categories: smaller roads and large roads (superhighways in the legend of Shell Atlases) with large roads in light blue. These large roads were candidates for Interstate construction, and as is evident in Panel 2a compared to Panel 2d, Interstate routes were often built on top of these large roads. Planned routes are digitized from Yellow Book maps. Euclidean rays connect major cities in the 1947 highway plan. Interstate routes are the constructed Interstate network.

Figure 3: Black Population Relative to Highway Impacts for Boston Metro Area in 1960



Notes: Unit of observation is census tract. Data for the Black population share comes from 1960 tract-level aggregates retrieved from IPUMS NHGIS. Commute time changes come from the author's calculations as the difference between commute times for the historical road network and for the entire Interstate network overlayed on the historical road network. Local costs are calculated by taking the estimate from Table 8 and applying it to census tracts using the distance of the centroid of the tract to the nearest Interstate highway. The sample of tracts is limited to those where population is observed in 1960.

Appendices

A Tables

Table A.1: Housing Price Discrimination in Rents and Home Values in 1960

	(1)	(2)	(3)	(4)
Variables		*Panel A* – Log Rent		
Black	-0.155***	-0.0250***	-0.0295***	0.0260***
	(0.0117)	(0.00719)	(0.00939)	(0.00584)
Redlined	-0.340***		-0.212***	
	(0.0107)		(0.00804)	
Black x Redlined	0.183***	0.0845***	0.0929***	0.0508***
	(0.0174)	(0.0103)	(0.0138)	(0.00873)
Constant	4.272***			
	(0.00514)			
R-squared	0.104	0.433	0.394	0.592
Tract FE		Yes		Yes
Quality Controls			Yes	Yes
Rounded Obs	1729000	1729000	1729000	1729000
Variables		*Panel B* – Log Home Value		
Black	-0.332***	-0.0453***	-0.143***	-0.0146**
	(0.0175)	(0.0112)	(0.0121)	(0.00675)
Redlined	-0.361***		-0.205***	
	(0.0171)		(0.0134)	
Black x Redlined	0.142***	0.0602***	0.0967***	0.0509***
	(0.0319)	(0.0189)	(0.0245)	(0.0123)
Constant	9.625***			
	(0.00567)			
R-squared	0.078	0.522	0.404	0.658
Tract FE		Yes		Yes
Quality Controls			Yes	Yes
Rounded Obs	1562000	1562000	1562000	1562000

Notes: Unit of observation is household. Household level data comes from the 1960 Census microdata. Fixed effects are at the census tract level. Standard errors are cluster-robust with clusters at the tract level. The quality controls include categorical variables for availability of air conditioning, dryer, elevator, freezer, hot water, kitchen, shower, basement, toilet, and the type of heating, type of fuel for cooking, type of fuel for heat, type of fuel for water, source of water, source of water, sewage facilities, number of stories, number of rooms, number of bathrooms, number of bedrooms, and year built. Redlined tracts are tracts where more than 80% of the area is redlined. Observation counts are rounded to nearest 1000 to meet Census disclosure rules. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.2: Percentage of the 1950 Population by Group in HOLC D (Redlined) Areas for the 10 Most Populous Cities (Core-Based Statistical Areas)

Black		White		<HS		HS Grad	
CBSA	% HOLC D	CBSA	% HOLC D	CBSA	% HOLC D	CBSA	% HOLC D
New York	0.85	New York	0.36	New York	0.45	New York	0.28
Chicago	0.93	Chicago	0.32	Chicago	0.44	Los Angeles	0.20
Philadelphia	0.87	Los Angeles	0.25	Los Angeles	0.34	Chicago	0.26
Detroit	0.84	Detroit	0.30	Philadelphia	0.53	Boston	0.20
Baltimore	0.79	Philadelphia	0.40	Detroit	0.44	Detroit	0.25
Los Angeles	0.77	Boston	0.29	Boston	0.36	Philadelphia	0.31
St. Louis	0.78	Cleveland	0.31	St. Louis	0.36	San Francisco	0.28
New Orleans-	0.82	San Francisco	0.33	Cleveland	0.44	Cleveland	0.26
Cleveland	0.90	St. Louis	0.25	Baltimore	0.42	Pittsburgh	0.24
Memphis	0.75	Pittsburgh	0.32	Pittsburgh	0.41	Minneapolis	0.17

Notes: Data comes from 1960 tract-level aggregates retrieved from IPUMS NHGIS. Calculations are limited to tracts with HOLC grades. This encompasses most of the population as 85.3% of the less than high school, 83.1% of the high school graduate or more, 87.2% of the Black, and 83.3% of the White population lived in a tract with a HOLC grade.

Table A.3: Summary Statistics for Redlined vs. Non-Redlined Tracts in 1960

	(1)	(2)	(3)	(4)
	Redlined	Non-Redlined		
Variables	Mean (SD)	Mean (SD)	Difference (SE)	T-Stat
Demographic Variables				
Pct White	72.46	93.91	-21.45***	(-29.29)
	(34.40)	(14.92)	(0.73)	
Pct HS Grad	28.82	47.57	-18.75***	(-64.21)
	(12.76)	(16.00)	(0.29)	
Pct Bottom Quintile	27.47	16.97	10.49***	(34.01)
	(14.25)	(10.08)	(0.31)	
Pct Top Quintile	13.07	22.84	-9.77***	(-46.25)
	(8.92)	(13.56)	(0.21)	
Population	4463.4	2570.3	1893.1***	(30.67)
	(2838.9)	(2166.6)	(61.8)	
Economic Variables				
Rent (2010$)	449.8	556.5	-106.7***	(-37.52)
	(121.2)	(175.4)	(2.8)	
Home Value (2010$)	96236.6	117697.9	-21461.3***	(-23.67)
	(40617.5)	(42236.3)	(907.2)	
Dist CBD (Miles)	6.89	15.87	-8.98***	(-59.35)
	(6.11)	(11.11)	(0.15)	
Commuting Variables				
Pct Auto	0.41	0.69	-0.28***	(-52.06)
	(0.24)	(0.20)	(0.01)	
Pct Pub Trans	0.37	0.16	0.21***	(47.51)
	(0.21)	(0.17)	(0.00)	
Observations	2256	19445	21701	

Notes: Unit of observation is census tract. Data comes from 1960 tract-level aggregates retrieved from IPUMS NHGIS. Rents are monthly and CPI-adjusted to 2010 dollars from 1960 dollars. Home values are CPI-adjusted to 2010 dollars from 1960 dollars. Percentage automobile is the percentage of employed workers whose main mode of transport is private automobile which includes truck and van drivers. Percentage public transport is the percentage of employed workers whose main mode of transport is railroad, subway, elevated, bus, streetcar, or other public means. Sample standard deviations are included in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.4: Change in Home Values over Distance from Central Business District and Distance from Highway (1950-1960, 1960-1970)

	(1)	(2)	(3)
	OLS	IV for Log Dist Highway	
Variables	Δ Log Home Value	Plans	Rays
Log Dist Highway	-0.0159	-0.0994***	-0.0469
	(0.0179)	(0.0373)	(0.0531)
Log Dist CBD	-0.168***	-0.148***	-0.161***
	(0.0389)	(0.0388)	(0.0410)
Redlined	0.284***	0.265***	0.277***
	(0.0648)	(0.0648)	(0.0667)
Dep. Var Mean (1960)	120,572 (2010$)		
R-squared	0.121	0.118	0.121
CBSA FE	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes
Observations	10,395	10,395	10,395
KP F-Stat		678.5	469.7

Notes: Unit of observation is census tract. Data comes from 1950, 1960, and 1970 tract-level aggregates retrieved from IPUMS NHGIS. The first difference is either over 1950 to 1960 or 1960 to 1970 depending on when highway construction started in the CBSA and stacked into one panel. Tracts are limited to those within 5 miles of the nearest constructed route and 30 miles from the central business district. Fixed effects are at the CBSA (Core-based statistical area) level. Conley standard errors for spatial correlation within a 1km radius are reported. All specifications have as controls log distance from rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads, and the gradient (Dist CBD/Dist Highway). Redlined tracts are those where more than 80% of the area is redlined. Kleibergen-Paap rk Wald F statistics are reported for the first-stage. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.5: Pre-Trends for Placement of Highway Routes (1940-1950, 1950-1960)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Log Distance from Highway Routes					Plans	Rays
Δ Pct White	0.931***				1.055***	-0.0153	0.0139
	(0.211)				(0.216)	(0.254)	(0.267)
Δ Pct HS Grad		-0.260			-0.585***	-0.366	-0.413*
		(0.179)			(0.174)	(0.229)	(0.224)
Δ Log Rent			-0.0446***		-0.0221**	-0.0275	-0.0232
			(0.0132)		(0.0110)	(0.0168)	(0.0155)
Δ Log Home Value				-0.0285***	-0.0194**	0.00178	-0.0140
				(0.0110)	(0.00977)	(0.0118)	(0.0136)
Log Dist CBD	0.178***	0.205***	0.195***	0.199***	0.238***	0.314***	0.439***
	(0.0242)	(0.0245)	(0.0241)	(0.0242)	(0.0344)	(0.0386)	(0.0407)
R-squared	0.032	0.026	0.028	0.027	0.163	0.140	0.151
CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,166	7,166	7,166	7,166	7,166	7,166	7,166

Notes: Unit of observation is census tract. Data comes from 1940, 1950 and 1960 tract-level aggregates retrieved from IPUMS NHGIS. The first difference is either over 1940 to 1950 or 1950 to 1960 depending on when highway construction started in the CBSA. Tracts are limited to those within 5 miles of the nearest constructed route. Fixed effects are at the CBSA (Core-based statistical area) level for all specifications. Conley standard errors for spatial correlation within a 1km radius are reported. Median income is missing in 1960 and so is not included in the pre-trends table. Change in percent bottom and top quintile are not shown as they are available only starting in 1950, and very few cities began construction on the Interstate highway system post-1960. All specifications have as controls log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.6: First-Stage for Highway Placement

Variables	(1) Log Dist HW	(2) Log Dist HW	(3) Dist HW = 1 mi	(4) Dist HW = 1 mi
Log Dist Plans	0.325*** (0.0175)			
Log Dist Rays		0.246*** (0.0196)		
Dist Plans = 1 mi			0.426*** (0.0223)	
Dist Rays = 1 mi				0.312*** (0.0292)
Log Dist CBD	0.0863*** (0.0212)	0.0752*** (0.0241)	-0.0379*** (0.00957)	-0.0422*** (0.0101)
F-Stat	342.8	156.5	366.3	113.9
R-squared	0.291	0.224	0.251	0.174
CBSA FE	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Observations	31,627	31,627	31,627	31,627
No. Counties	467	467	467	467

Notes: Unit of observation is census tract. Tracts are limited to those within 5 miles of the nearest constructed route. Fixed effects are at the CBSA (Core-based statistical area) level. Standard errors are cluster-robust with clusters at the county level. All specifications have as controls log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads. The reported F-stat comes from testing a single coefficient on the excluded instrument. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: First-Stage for Commuter Market Access Improvements

Variables	(1) Δ Log CMA	(2) Δ Log CMA	(3) Δ Log CMA	(4) Δ Log CMA HW	(5) Δ Log CMA HW
Δ Log CMA HW	0.639***				
	(0.0127)				
Δ Log CMA Plans		0.107***		0.382***	
		(0.0120)		(0.0088)	
Δ Log CMA Rays			0.0888***		0.336***
			(0.0108)		(0.0079)
F-Stat	2534	79.68	67.14	1884	1797
R-squared	0.313	0.262	0.262	0.505	0.484
CBSA FE	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes
Rounded Obs	60500	60500	60500	60500	60500

Notes: Unit of observation is census tract by race and education. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Fixed effects are at the CBSA (Core-based statistical area) level. Standard errors are cluster-robust with clusters at the tract-level. All specifications have as controls log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads. All specifications include the Borusyak and Hull (2023) control for CMA in large roads. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. The reported F-stat comes from testing a single coefficient on the excluded instrument. *** p<0.01, ** p<0.05, * p<0.1

Table A.8: Elasticity of Rents, Pct White, and Population to Commuter Market Access

	(1)	(2)	(3)	(4)
Variables	Δ Log Rent	Δ Log Pop + Δ Log Rent Cont	Δ Log Pct White	Δ Log Pop + Δ Log Pct White Cont
$\Delta \log CMA_{igr}$	0.0432***		-0.0180	
	(0.00720)		(0.0139)	
$\Delta \log CMA_{igr}$				
Black		0.137		0.141
		(0.0974)		(0.0959)
White		1.267***		1.403***
		(0.118)		(0.114)
R-squared	0.225	0.121	0.071	0.146
CBSA FE	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Rounded Obs	59000	59000	60000	60000

Notes: Unit of observation is census tract by race and education. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Fixed effects are at the CBSA (Core-based statistical area) level. Standard errors are cluster-robust with clusters at the tract-level. The geographic controls are log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads, all interacted with race in Columns 2 and 4 and with race and education in Columns 1 and 3. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. All specifications include the Borusyak and Hull (2023) control for CMA in large roads. Kleibergen-Paap rk Wald and Cragg-Donald Wald F statistics for weak instruments are reported. *** p<0.01, ** p<0.05, * p<0.1

Table A.9: Elasticity of Population to Commuter Market Access – Additional Results

	(1)	(2)	(3)	(4)
	$\Delta \log L_{igr}$ (Δ Log Population 1960-1970)			
Variables	+BH (2023) Plans	+BH (2023) Rays	Unscaled CMA	Race x Educ
$\Delta \log CMA_{igr}$				
Black	0.104	0.107		
	(0.0973)	(0.0970)		
White	1.469***	1.458***		
	(0.121)	(0.121)		
$\Delta \log \Phi_{igr}$				
Black			0.0314	
			(0.0323)	
White			0.470***	
			(0.0385)	
$\Delta \log CMA_{igr}$				
Black <HS				0.218*
				(0.124)
Black HS Grad				-0.712***
				(0.155)
White <HS				0.958***
				(0.127)
White HS Grad				0.946***
				(0.141)
R-squared	0.113	0.113	0.113	0.139
CBSA FE	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Rounded Obs	60500	60500	60500	60500

Notes: Unit of observation is census tract by race and education. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Fixed effects are at the CBSA (Core-based statistical area) level. Standard errors are cluster-robust with clusters at the tract-level. The geographic controls are log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads, all interacted with race for Columns 1–3 and with race and education for Column 4. Column 1 and Column 2 include the Borusyak and Hull (2023) control for CMA interacted with race when the planned network and the Euclidean ray network are built, respectively. Columns 3–4 include the Borusyak and Hull (2023) control for CMA in large roads where in Column 3 it is interacted with race and in Column 4 it is interacted with race and education. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

Table A.10: Elasticity of Population to Commuter Market Access for Instruments

	(1)	(2)
	$\Delta \log L_{igr}$ (Δ Log Pop)	
Variables	Plans	Rays
$\Delta \log CMA_{igr}$		
Black	0.665*	0.624*
	(0.365)	(0.333)
	[0.587]	[0.550]
White	0.430**	0.745***
	(0.174)	(0.172)
	[0.578]	[0.628]
R-squared	0.517	0.513
CBSA X Group FE	Yes	Yes
Base Controls	Yes	Yes
Geo Controls	Yes	Yes
Rounded Obs	58000	58000
C-D F-Stat	313.7	259.5
K-P F-stat	26.20	25.97

Notes: Unit of observation is census tract by race and education. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Fixed effects are at the CBSA (Core-based statistical area) by race and education level. Standard errors are cluster-robust with clusters at the tract-level. Conley standard errors for spatial correlation within a 1km radius are reported in brackets. The base controls are change in log rent, change in log pct White, and 5 binary indicators for distance from highways built between 1960 and 1970 in 1-mile wide bins, all interacted with race and education. Redlining fixed effects are included in all specifications. The geographic controls are log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads, all interacted with race and education. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. All specifications include the Borusyak and Hull (2023) control for CMA in large roads. Kleibergen-Paap rk Wald and Cragg-Donald Wald F statistics for weak instruments are reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.11: Commuting Gravity Equation – Additional Results

	(1)	(2)	(3)	(4)
Race x Educ	Black <HS	Black HS Grad	White <HS	White HS Grad
	Panel A – First-Stage – IV Plans			
Log Commute Time	0.988***	1.026***	1.023***	1.025***
	(0.00573)	(0.00475)	(0.00178)	(0.00145)
F-Stat (Rounded)	29710	46750	331400	501900
	Panel B – First-Stage – IV Rays			
Log Commute Time	0.999***	1.037***	1.027***	1.029***
	(0.00595)	(0.00492)	(0.00183)	(0.00152)
F-Stat (Rounded)	28150	44440	315400	455600
	Panel C – Log Commuting Share – IV Distance			
Log Commute Time	-5.198***	-4.325***	-5.205***	-4.485***
	(0.140)	(0.118)	(0.0502)	(0.0415)
R-squared	0.223	0.181	0.379	0.369
	Panel D – First-Stage – IV Distance			
Log Commute Time	0.492***	0.556***	0.662***	0.713***
	(0.00707)	(0.00609)	(0.00396)	(0.00404)
F-Stat (Rounded)	4840	8350	28020	31100
	Panel E – Log Commuting Share in Log Distance			
Log Distance	-2.556***	-2.406***	-3.447***	-3.199***
	(0.0642)	(0.0640)	(0.0336)	(0.0306)
R-squared	0.697	0.627	0.578	0.577
Rounded Obs	7000	8000	21500	25000
POR X Year FE	Yes	Yes	Yes	Yes
POW X Year FE	Yes	Yes	Yes	Yes

Notes: Unit of observation is Place of Work Zone by Place of Work Zone pair by year where commuting flows from residential tracts are aggregated up to the Place of Work Zone geography. Fixed effects are for POR (Place of Residence) by year at the Place of Work Zone scale although it does not represent workplace but rather residential location. POW by year fixed effects are for workplace at the Place of Work Zone level. The conditional commuting share is the share from a residential location that commutes to a workplace. Data comes from the restricted Census microdata in 1960 and 1970. The observation counts are lower for the Black population as some residences and workplaces have zero Black population. Standard errors are cluster-robust with clusters at the Place of Work Zone by Place of Work Zone level. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. The F-stat comes from testing a single coefficient on the excluded instrument and is rounded to four significant digits to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

Table A.12: Commuting Gravity Equation – Poisson Pseudo Maximum Likelihood IV

	(1)	(2)	(3)	(4)
Race x Educ	Black <HS	Black HS Grad	White <HS	White HS Grad
$\nu_{gr} = \kappa_{gr}\phi$	*Panel A* – Commuting Share (PPML) – IV Plans			
Log Commute Time	-4.706***	-3.940***	-3.888***	-3.260***
	(0.138)	(0.0857)	(0.0655)	(0.0526)
	Panel B – Commuting Share (PPML) – IV Rays			
Log Commute Time	-4.707***	-3.941***	-3.883***	-3.256***
	(0.140)	(0.0879)	(0.0655)	(0.0522)
Rounded Obs	20500	21000	26000	27000
POR X Year FE	Yes	Yes	Yes	Yes
POW X Year FE	Yes	Yes	Yes	Yes

Notes: Unit of observation is Place of Work Zone by Place of Work Zone pair by year where commuting flows from residential tracts are aggregated up to the Place of Work Zone geography. Fixed effects are for POR (Place of Residence) by year at the Place of Work Zone scale although it does not represent workplace but rather residential location. POW by year fixed effects are for workplace at the Place of Work Zone level. The conditional commuting share is the share from a residential location that commutes to a workplace. Data comes from the restricted Census microdata in 1960 and 1970. The observation counts are lower for the Black population as some residences and workplaces have zero Black population (while PPML addresses zeros in bilateral flows, it does not address zeros in entire rows or columns). As the coefficient is estimated via the control function approach of Wooldridge (2015), to obtain the correct standard errors, I bootstrap 200 samples to calculate standard errors with clusters at the Place of Work Zone by Place of Work Zone level. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

Table A.13: Residential Elasticity and Racial Preferences – Redlined Sample

	(1)	(2)
	$\Delta \log L_{igr}$ (Δ Log Population 1960-1970)	
Variables	OLS Base Geo Cont	+ SES Cont
θ_r: $\Delta \log CMA_{igr}$		
Black	1.573***	1.482***
	(0.504)	(0.481)
	[0.633]	[0.623]
White	0.648***	0.627**
	(0.246)	(0.246)
	[0.396]	[0.399]
$\tilde{\rho}_r = \theta_r \rho_r$: Δ log Pct White		
Black	-0.167*	-0.142
	(0.0984)	(0.0946)
	[0.131]	[0.131]
White	1.116***	1.108***
	(0.0719)	(0.0702)
	[0.0940]	[0.0928]
R-squared	0.322	0.337
CBSA X Group FE	Yes	Yes
Base Controls	Yes	Yes
Geo Controls	Yes	Yes
SES Controls		Yes
Rounded Obs	56500	56500

Notes: Unit of observation is census tract by race and education. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Fixed effects are at the CBSA (Core-based statistical area) by race and education group level. Standard errors are cluster-robust with clusters at the tract-level. Conley standard errors for spatial correlation within a 1km radius are reported in brackets. The base controls are change in log rent and 5 binary indicators for distance from highways built between 1960 and 1970 in 1-mile wide bins, all interacted with race and education. Redlining fixed effects are included in all specifications. The socio-economic status (SES) controls are change in log income, change in log percentage high school graduate, change in log percentage bottom income quintile, change in log percentage top income quintile, change in log home values, all interacted with race and education. The geographic controls are log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads, all interacted with race and education. All specifications include the Borusyak and Hull (2023) control for CMA in large roads interacted with race and education. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

Table A.14: Change in Amenities over Distance from Highway – IV

	(1)	(2)
	$\Delta \log b_{igr}$	
	IV – 2 mi bins	
Variables	Dist Plans	Dist Rays
Dist Highway (mi = 2)	-0.0469	0.519
	(0.133)	(0.668)
Dist Highway (mi = 4)	0.249*	0.312
	(0.149)	(0.502)
Dist Highway (mi = 6)	0.0766	-0.149
	(0.279)	(1.385)
R-squared	0.047	0.036
CBSA X Group FE	Yes	Yes
Geo Controls	Yes	Yes
Rounded Obs	51000	47000
C-D F-Stat	686.2	18.38
K-P F-stat	110.8	4.55

Notes: Unit of observation is census tract by race and education. Fixed effects are at the CBSA (Core-based statistical area) by race and education group level. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Standard errors are cluster-robust with clusters at the tract-level. There are 3 binary indicators for distance from highways built between 1960 and 1970 in 2-mile wide bins to increase power. The geographic controls are log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads, all interacted with race and education. Redlining fixed effects are included. The sample is limited to tracts within 10 miles of planned routes or the Euclidean ray network. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. Kleibergen-Paap rk Wald and Cragg-Donald Wald F statistics for weak instruments are reported. Parameters used to invert for dependent variables are the same as in Table 10. *** p<0.01, ** p<0.05, * p<0.1

Table A.15: Environmental Pollution Index (PM 2.5) over Distance from Highway

	(1)	(2)	(3)
	Log Particulate Matter 2.5		
Variables	1 mi bins	+ Geo Cont	0.5 mi bins
Dist Highway (mi = 1)	0.0245***	0.0204***	
	(0.000983)	(0.000976)	
Dist Highway (mi = 2)	0.0231***	0.0196***	
	(0.000980)	(0.000965)	
Dist Highway (mi = 3)	0.0197***	0.0174***	
	(0.00102)	(0.00100)	
Dist Highway (mi = 4)	0.0146***	0.0133***	
	(0.00114)	(0.00111)	
Dist Highway (mi = 5)	0.0108***	0.0103***	
	(0.00129)	(0.00126)	
Dist Highway (mi = 0.5)			0.0201***
			(0.00107)
Dist Highway (mi = 1)			0.0207***
			(0.00101)
Dist Highway (mi = 1.5)			0.0200***
			(0.00103)
Dist Highway (mi = 2)			0.0191***
			(0.00106)
Dist Highway (mi = 2.5)			0.0176***
			(0.00110)
Dist Highway (mi = 3)			0.0172***
			(0.00117)
Dist Highway (mi = 3.5)			0.0145***
			(0.00130)
Dist Highway (mi = 4)			0.0119***
			(0.00136)
Dist Highway (mi = 4.5)			0.0118***
			(0.00154)
Dist Highway (mi = 5)			0.00850***
			(0.00167)
Dep Var Mean	13.50		
R-squared	0.962	0.964	0.964
CBSA FE	Yes	Yes	Yes
Geo Controls		Yes	Yes
Observations	32,833	32,833	32,833

Notes: Unit of observation is census tract. Fixed effects are at the CBSA (Core-based statistical area) level. Data comes from the CDC Environmental Health Census Tract-Level PM2.5 Concentrations, 2001-2005 measures. There are 5 binary indicators for distance from highways in 1-mile wide bins in Columns 1–2 and 10 binary indicators in 0.5-mile wide bins in Column 3 (the value displayed is the upper end of the bin). Included in all specifications are redlining fixed effects and log distance from the central business district. The geographic controls are log distance from rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads. The sample is limited to tracts within 10 miles of highway routes. Standard errors are heteroskedasticity robust. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.16: Housing Expenditure Function

Variables	(1) Housing Expenditures
Predicted Income	0.119***
	(0.00294)
Constant	353.3***
	(9.263)
R-squared	0.080
Observations	20,786

Notes: Unit of observation is individual. Data comes from the Consumer Expenditure Surveys Public-Use Microdata in the year 1980. Predicted income is a linear prediction of income using categorical variables in age, education, marital status, occupation, sex, race and region. Income and housing expenditure is for quarterly amounts. Standard errors are heteroskedasticity robust. *** p<0.01, ** p<0.05, * p<0.1

Table A.17: Predicted Share of Income Spent on Housing

Race x Educ	Black <HS	Black HS Grad	White <HS	White HS Grad
Housing Exp. Share	0.34	0.22	0.30	0.21
Observations	1441	1908	5885	14712

Notes: Unit of observation is individual. Data comes from the Consumer Expenditure Surveys Public-Use Microdata in the year 1980. Income and housing expenditure is in quarterly amounts. Predicted share of income spent on housing uses the linear housing expenditure function from A.16 and the average level of income of the four race by education groups.

Table A.18: Additional Model Parameters

Parameters	Source
Production Labor Share $\alpha = 0.7$	Greenwood et al. (1997)
Elasticity of Substitution by Race and Education $\sigma^r = 8, \sigma^g = 2$	Card (2009), Boustan (2009)
Agglomeration $\gamma^A = 0.07$	Rosenthal and Strange (2004), Kline and Moretti (2014)
Housing Supply Elasticity $\mu^{cbd} = 0.35, \mu^{sub} = 0.25$	Baum-Snow and Han (2021)

Notes: Values are set following the literature.

Table A.19: Predicted and Observed Commute Flows in 1960 and 1970

	(1)	(2)	(3)	(4)
	Unweighted		Weighted	
Variables	Log Obs 1960	Log Obs 1970	Log Obs 1960	Log Obs 1970
Log Predicted 1960	0.855***		0.838***	
	(0.0260)		(0.0197)	
Log Predicted 1970		0.866***		0.950***
		(0.0178)		(0.0134)
Constant	0.456***	0.521***	2.018***	0.949***
	(0.136)	(0.102)	(0.111)	(0.186)
R-squared	0.560	0.613	0.861	0.950
Rounded Obs	12000	14000	12000	14000

Notes: Unit of observation is Place of Work Zone level by Place of Work Zone level. Data comes from restricted Census microdata in 1960 and 1970. Standard errors are cluster-robust with clusters at the CBSA (Core-based statistical area) level. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

Table A.20: Observed vs. Predicted Outcomes Over Commuter Market Access Improvements

Variables	(1) Δ Log Obs Rent	(2) Δ Log Pred Rent	(3) Δ Log Obs Pct White	(4) Δ Log Pred Pct White	(5) Δ Log Obs Income	(6) Δ Log Pred Income
Δ Log CMA	0.0455***	0.0219***	0.00580	0.00639***	0.174***	0.172***
	(0.00626)	(0.000895)	(0.00392)	(0.000351)	(0.0219)	(0.00611)
R-squared	0.230	0.194	0.097	0.105	0.039	0.530
CBSA FE	Yes	Yes	Yes	Yes	Yes	
Geo Controls	Yes	Yes	Yes	Yes	Yes	
Rounded Obs	58000	58000	58000	58000	58000	58000

Notes: Unit of observation is census tract by race and education. Data comes from the first difference of 1960 to 1970 using restricted Census microdata. Fixed effects are at the CBSA (Core-based statistical area) level. Standard errors are cluster-robust with clusters at the tract-level. All specifications have as controls log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large urban roads. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

Table A.21: Change in Log Productivity Over Distance from Highway (1960-1970)

Variables	(1) Δ Log Productivity
Dist from Highway (Miles)	-0.00269
	(0.00177)
Constant	-1.037***
	(0.0121)
R-squared	0.007
Rounded Obs	16000

Notes: Unit of observation is tract. Data comes from restricted Census microdata in 1960 and 1970. Standard errors are cluster-robust with clusters at the Place of Work Zone level because the variation in wages used to invert for productivity are at the Place of Work Zone level while housing prices used for inversion are at the tract level. Distance from the highway is in miles from segments of the highway network constructed between 1960 and 1970. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

Table A.22: Log Productivity Over Distance from Central Business District and Pct HOLC D in 1960 and 1970

Variables	(1) Log Prod 1960	(2) Log Prod 1970
Pct HOLC D	0.0954	0.0358
	(0.0761)	(0.0719)
Dist from CBD (Miles)	0.00212	-0.00106
	(0.00171)	(0.00137)
Constant	5.797***	4.829***
	(0.0397)	(0.0332)
R-squared	0.020	0.011
Rounded Obs	17000	14000

Notes: Unit of observation is tract. Data comes from restricted Census microdata in 1960 and 1970. Standard errors are cluster-robust with clusters at the Place of Work Zone level because the variation in wages used to invert for productivity are at the Place of Work Zone level while housing prices used for inversion are at the tract level. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

Table A.23: Changes in Equilibrium Outcomes (%) for Highway Impacts by Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Race	Black	Black	White	White	By Race		By Educ	
x Educ	<HS	HS+	<HS	HS+	Black	White	<HS	HS+
General Equilibrium								
Rent	0.32	0.47	0.23	0.14	0.37	0.18	0.24	0.16
Pct White	-0.47	-0.16	0.03	0.01	-0.37	0.02	-0.04	-0.00
Pct HOLC D	-0.19	-0.26	-1.06	-0.95	-0.21	-1.00	-0.93	-0.90
Amenities	-10.35	-9.43	-5.91	-4.82	-10.06	-5.33	-6.57	-5.13
Wages	-0.11	0.13	0.20	0.28	-0.03	0.24	0.15	0.27
Localized Costs	-7.99	-7.96	-6.37	-5.86	-7.98	-6.10	-6.61	-6.00
Dist from CBD	0.59	0.27	1.49	1.14	0.49	1.30	1.36	1.08
Commute Time	-3.72	-5.31	-3.47	-4.21	-4.23	-3.86	-3.51	-4.28
Commute Dist	4.81	3.95	6.16	4.91	4.53	5.50	5.96	4.84
General Equilibrium, No BD								
Rent	0.31	0.45	0.23	0.14	0.35	0.18	0.24	0.16
Pct White	-0.34	-0.15	0.03	0.01	-0.28	0.02	-0.03	-0.00
Pct HOLC D	-0.25	-0.33	-0.91	-0.86	-0.28	-0.88	-0.81	-0.82
Amenities	-8.67	-8.49	-5.99	-4.82	-8.61	-5.37	-6.39	-5.07
Wages	-0.13	0.12	0.20	0.27	-0.05	0.24	0.15	0.26
Localized Costs	-7.43	-7.55	-6.41	-5.88	-7.47	-6.13	-6.56	-5.99
Dist from CBD	0.61	0.27	1.50	1.15	0.50	1.31	1.37	1.09
Commute Time	-3.59	-5.15	-3.48	-4.22	-4.09	-3.87	-3.50	-4.28
Commute Dist	4.82	3.92	6.15	4.91	4.53	5.49	5.95	4.84
General Equilibrium, Same Fund Amen								
Rent	0.30	0.27	0.24	0.15	0.29	0.19	0.25	0.16
Pct White	0.09	0.08	-0.02	0.00	0.09	-0.01	-0.00	0.01
Pct HOLC D	-0.32	-0.29	-0.77	-0.77	-0.31	-0.77	-0.70	-0.74
Amenities	-6.00	-5.15	-6.17	-4.90	-5.73	-5.50	-6.14	-4.92
Wages	0.16	0.25	0.19	0.26	0.19	0.23	0.19	0.26
Localized Costs	-5.81	-5.80	-6.53	-5.99	-5.81	-6.24	-6.42	-5.98
Dist from CBD	0.67	0.47	1.52	1.18	0.61	1.34	1.39	1.13
Commute Time	-3.55	-4.16	-3.48	-4.21	-3.75	-3.87	-3.49	-4.21
Commute Dist	4.94	4.50	6.15	4.97	4.80	5.52	5.97	4.94

Notes: Equilibrium outcome calculations are based on data from the restricted Census in 1960. The general equilibrium simulation allows wages to respond in equilibrium. No institutions adjusts fundamental amenities for Black households by parameter E in redlined areas. The general equilibrium simulation with no institutions adds the highway impacts in the counterfactual world with no institutions. Parameter values are the same as in Table 9. All values are rounded to four significant digits to meet Census disclosure rules.

Table A.24: Alternative Exercises for Welfare Changes (%) by Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Race	Black	Black	White	White	By Race		By Educ	
x Educ	<HS	HS+	<HS	HS+	Black	White	<HS	HS+
General Equilibrium								
Baseline	-1.45	-0.16	2.69	3.01	-1.04	2.86	2.07	2.79
Highway Impacts Separately								
Commuting Benefits	7.32	8.77	10.16	9.87	7.78	10.01	9.74	9.80
Localized Costs	-8.08	-8.05	-6.57	-6.03	-8.07	-6.28	-6.79	-6.17
Full Interstate Network								
Welfare Change	15.36	23.45	25.53	27.59	17.95	26.62	24.01	27.31
Alternative Road Placements								
Planned Routes	14.83	23.15	25.23	27.67	17.49	26.52	23.68	27.36
Euclidean Rays	21.32	30.14	32.31	34.74	24.14	33.60	30.67	34.43
Alternative Spillovers								
$\rho'_W = 0$	-1.44	-0.19	2.79	3.03	-1.04	2.92	2.16	2.81
$\rho'_B = -0.2$	-0.90	-0.01	2.70	3.03	-0.62	2.87	2.16	2.82
Alternative Elasticities								
$\theta'_B = \theta_W = 0.8$	-1.47	-0.19	2.52	2.86	-1.06	2.70	1.93	2.65
$\theta'_r = 3\theta_r$	-1.26	0.02	3.28	3.52	-0.85	3.41	2.60	3.28
$\theta'_B = \theta'_W = 3\theta_W$	1.02	1.01	2.67	2.94	1.02	2.81	2.42	2.81

Notes: Welfare calculations are based on data from the restricted Census in 1960. All welfare changes are for the general equilibrium simulation of highway impacts but with different parameter values. $\rho'_N = -0.2$ comes from the estimate for $\tilde{\rho}_N = -0.07$ in Table 6 divided by the residential elasticity of $\theta_N = 0.35$. The alternative elasticities set the residential elasticity for Black and White households to the same values at the level of White households, to three times their original values, to three times the original level of White households. All values are rounded to four significant digits to meet Census disclosure rules.

Table A.25: Border Discontinuity on Additional Variables

	(1)	(2)	(3)	(4)	(5)
			Panel A – Pct White in 1960		
Variables	Standard	Balanced Sample	Border FE	Drop Roads, Schools (0.1 mi)	Drop Roads, Schools (0.3 mi)
Border RD	-0.189***	-0.175***	-0.180***	-0.171***	-0.166***
	(0.027)	(0.029)	(0.025)	(0.026)	(0.034)
Bandwidth (mi)	0.351	0.368	0.355	0.403	0.432
Border FE	No	No	Yes	Yes	Yes
Observations	12573	5914	12532	10703	5717
			Panel B – Socioeconomic Variables in 1960		
Variables	Pct HS	Pct Bottom Q5	Pct Top Q5	Home Value	Rent
Border RD	-0.064***	0.104***	-0.093***	-22248***	-110.06***
	(0.006)	(0.010)	(0.008)	(3309)	(12.05)
Dep. Var Mean	0.265	0.189	0.207	114238 (2010$)	534 (2010$)
Bandwidth (mi)	0.267	0.397	0.409	0.428	0.248
Border FE	Yes	Yes	Yes	Yes	Yes
Observations	12275	12310	12310	12260	12268
			Panel C – Pct White Over Time		
Variables	1950	1960	1970	1980	1990
Border RD	-0.141***	-0.187***	-0.185***	-0.151***	-0.146***
	(0.023)	(0.029)	(0.035)	(0.037)	(0.035)
Dep. Var Mean	0.945	0.911	0.852	0.773	0.668
Bandwidth (mi)	0.350	0.350	0.350	0.350	0.350
Border FE	Yes	Yes	Yes	Yes	Yes
Observations	9964	9964	9964	9964	9964
			Panel D – Land Types and Tree Cover		
Variables	Pct Open Water	Pct Woody Wetlands	Pct Decid Forest	Pct Highly Developed	Pct Tree Cover
Border RD	0.005	-0.004	-0.015**	0.033***	-0.056***
	(0.003)	(0.003)	(0.005)	(0.007)	(0.009)
Dep. Var Mean	0.014	0.021	0.050	0.063	0.197
Bandwidth (mi)	0.406	0.315	0.351	0.347	0.461
Border FE	Yes	Yes	Yes	Yes	Yes
Observations	11529	11529	11529	11529	11529

Notes: Unit of observation is census tract by redlining border. Data comes from 1950, 1960, 1970, 1980, and 1990 tract-level aggregates retrieved from IPUMS NHGIS. The dependent variable is residualized on border fixed effects for many specifications. The balanced sample has the same number of tracts on the redlined and non-redlined sides. The "Drop Roads, Schools" sample is limited to tracts that are at least 0.1 (or 0.3) miles away from possible physical barriers such as historical large urban roads, constructed highways in 1960, or historical railroads and 0.1 (or 0.3) miles away from a school district boundary. The bandwidth is chosen optimally following Calonico et al. (2014) except for in Panel C, where the bandwidth is set to 0.35 so the effective sample remains the same across decades. The order of polynomial is 1 for all specifications. Distance from the border is measured in miles. *** p<0.01, ** p<0.05, * p<0.1

Table A.26: Border Discontinuity Decomposition – Reduced Form Approach

	(1)	(2)	(3)	(4)
	Panel A – Black			
Variables	$\log L_{igr}$	Controls 1	Controls 2	Controls 3
ψ_B: Border RD	1.425***	1.414***	0.555***	0.489**
	(0.226)	(0.227)	(0.212)	(0.204)
Bandwidth (mi)	0.495	0.488	0.414	0.365
Order of Poly.	1	1	1	1
Education FE	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes
Rounded Obs	13000	13000	13000	13000
	Panel B – White			
Variables	$\log L_{igr}$	Controls 1	Controls 2	Controls 3
ψ_W: Border RD	-0.546***	-0.556***	-0.101	0.0205
	(0.122)	(0.122)	(0.0855)	(0.0794)
Bandwidth (mi)	0.358	0.364	0.380	0.397
Order of Poly.	1	1	1	1
Education FE	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes
Rounded Obs	13500	13500	13500	13500

Notes: Unit of observation is census tract by border in the redlining maps. Data comes from the 1960 restricted Census microdata. The dependent variable is residualized on fixed effects for education within race and on border fixed effects for all specifications. Controls 1 are log rent and log commuter access. Controls 2 includes Controls 1 and adds log percentage white. Controls 3 includes Controls 2 and adds log percentage high school grad, log population density, log average income, log percentage top quintile, log percentage bottom quintile, and log home values. Coefficients on controls are estimated with redlining fixed effects. Sample is limited to tracts that are at least 0.1 miles away from possible physical barriers such as historical large urban roads, constructed highways in 1960, or historical railroads and also at least 0.1 miles away from a school district boundary. The bandwidth is chosen optimally following Calonico et al. (2014). Distance from the border is measured in miles. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

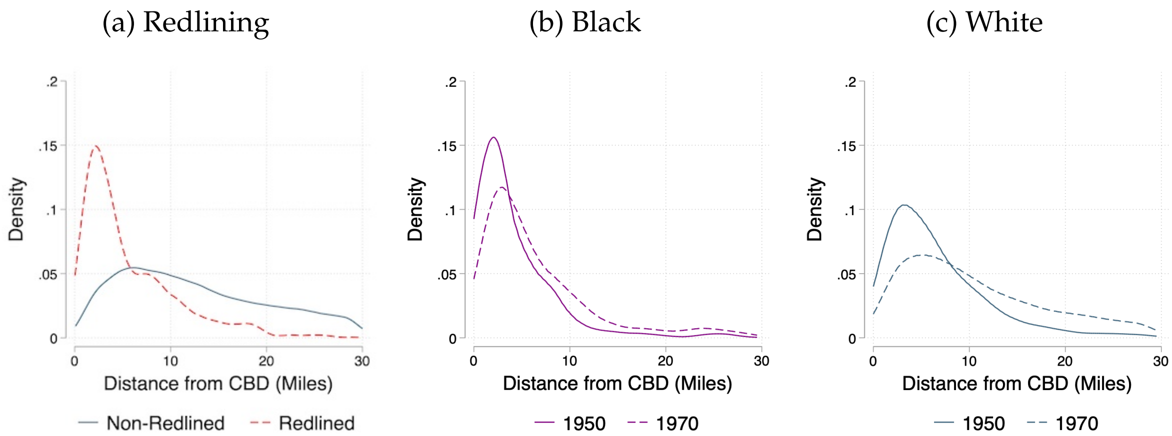
Table A.27: Changes in Welfare and Equilibrium Outcomes (%) for Removal of Institutional Barriers by Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Race	Black	Black	White	White	By Race		By Educ	
x Educ	<HS	HS+	<HS	HS+	Black	White	<HS	HS+
No BD								
Welfare Change	—	—	0.20	-0.50	—	-0.17	—	—
Rent	3.23	3.25	-0.17	-0.06	3.24	-0.11	0.34	0.17
Pct White	10.60	3.86	-0.29	-0.46	8.44	-0.38	1.33	-0.17
Pct HOLC D	-25.80	-31.02	6.06	5.51	-27.47	5.77	1.31	3.02
Dist from CBD	11.49	7.27	-0.57	-0.20	10.14	-0.37	1.23	0.31
Amenities	—	—	-0.19	-0.80	—	-0.51	—	—
Same Fund Amen								
Welfare Change	—	—	-0.03	-3.27	—	-1.75	—	—
Rent	9.35	11.62	-0.56	-0.33	10.08	-0.44	0.92	0.48
Pct White	136.3	124.0	-5.04	-6.12	132.36	-5.61	16.02	2.75
Pct HOLC D	-52.74	-46.97	12.67	14.01	-50.89	13.38	2.93	9.85
Dist from CBD	93.37	94.16	-4.48	-3.25	93.62	-3.83	10.10	3.39
Amenities	—	—	-1.87	-5.64	—	-3.87	—	—

Notes: Equilibrium outcome calculations are based on data from the restricted Census in 1960. The general equilibrium simulation allows wages to respond in equilibrium. No institutions adjusts fundamental amenities for Black households by parameter E in redlined areas. The general equilibrium simulation with no institutions adds the highway impacts in the counterfactual world with no institutions. Parameter values are the same as in Table 9. All values are rounded to four significant digits to meet Census disclosure rules.

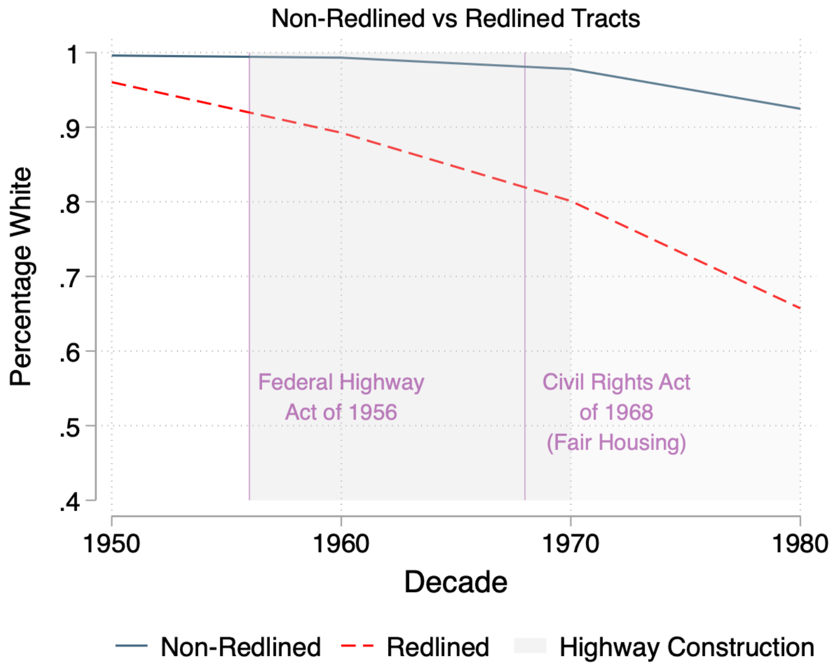
B Figures

Figure B.1: Spatial Distribution Population By Race in 1950 and 1970 and Redlined vs. Non-Redlined Tracts Over Distance from Central Business District



Notes: Data comes from IPUMS NHGIS in 1950 and 1970. Epanechnikov kernel density estimation for the spatial distribution of the Black vs. White population is over 60 bins of distance from the central business district in miles with population weights. Kernel density for redlined vs. non-redlined tracts uses the raw counts of tracts. Redlined tracts are tracts where more than 80% of the area is redlined.

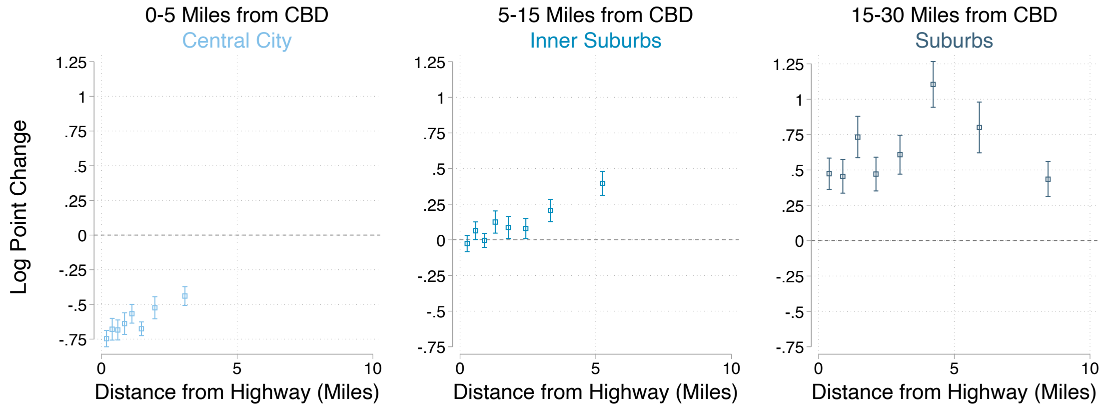
Figure B.2: Racial Composition of Median Tract 1950-1990



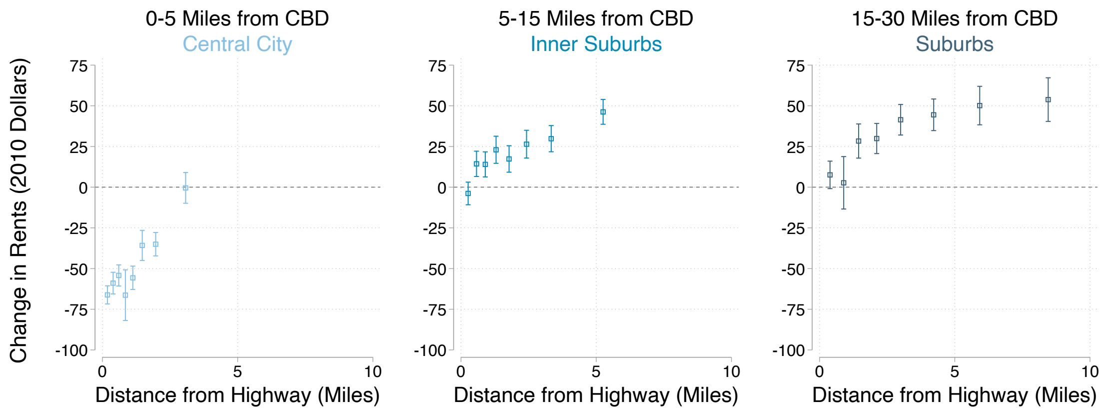
Notes: Data comes from IPUMS NHGIS tract-level aggregates from 1950 to 1990 for a constant sample of tracts that have population by race in 1950 and are in the sample of 100 cities with Yellow Book maps. Gray areas in the graph are for periods of highway construction starting in 1956.

Figure B.3: Changes Over Distance from Central Business District and Distance from Highway (1950-1960, 1960-1970)

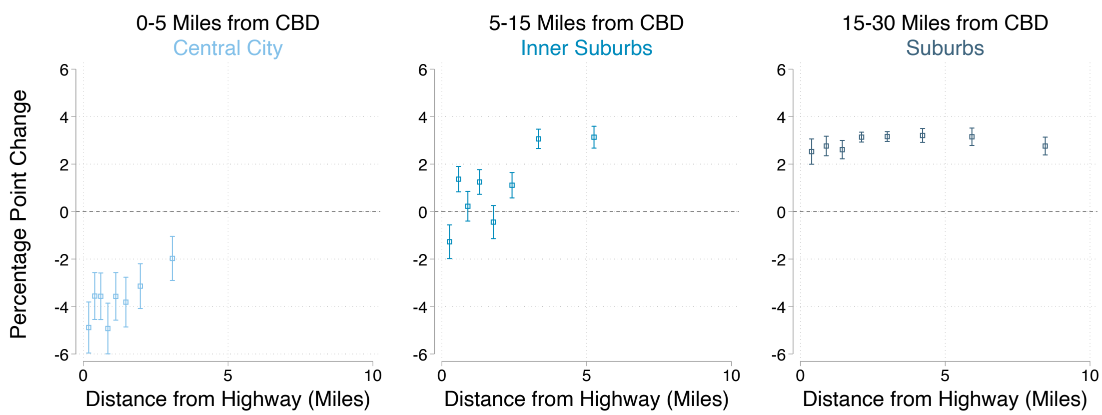
(a) Change in Log Population



(b) Change in Rents

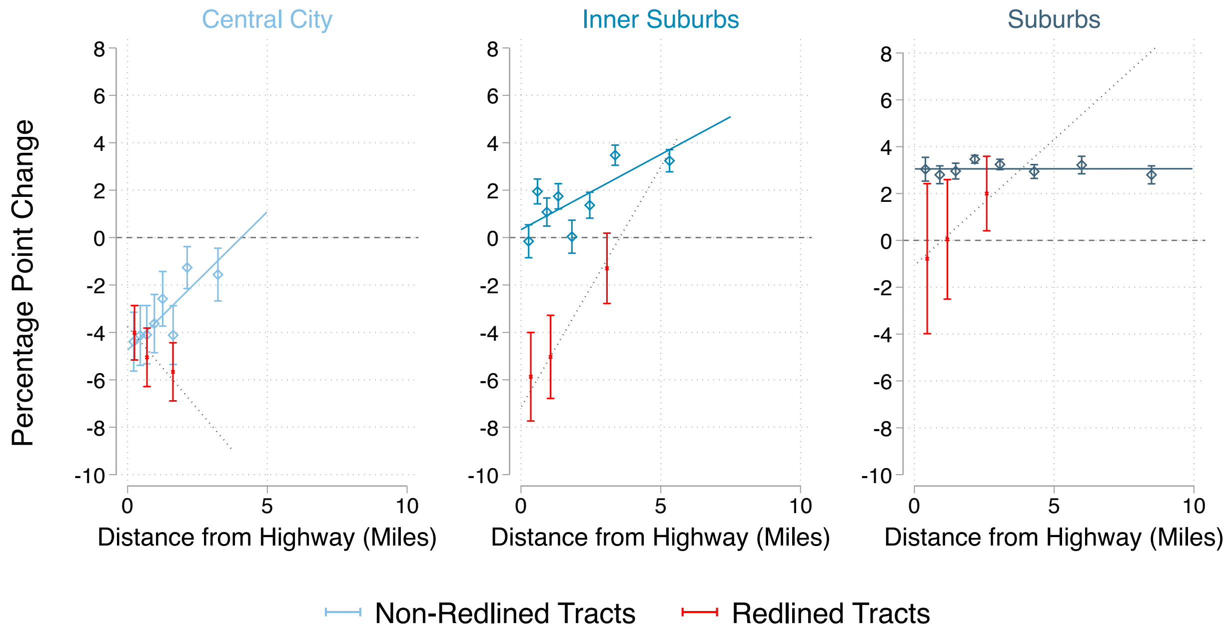


(c) Change in Percentage White



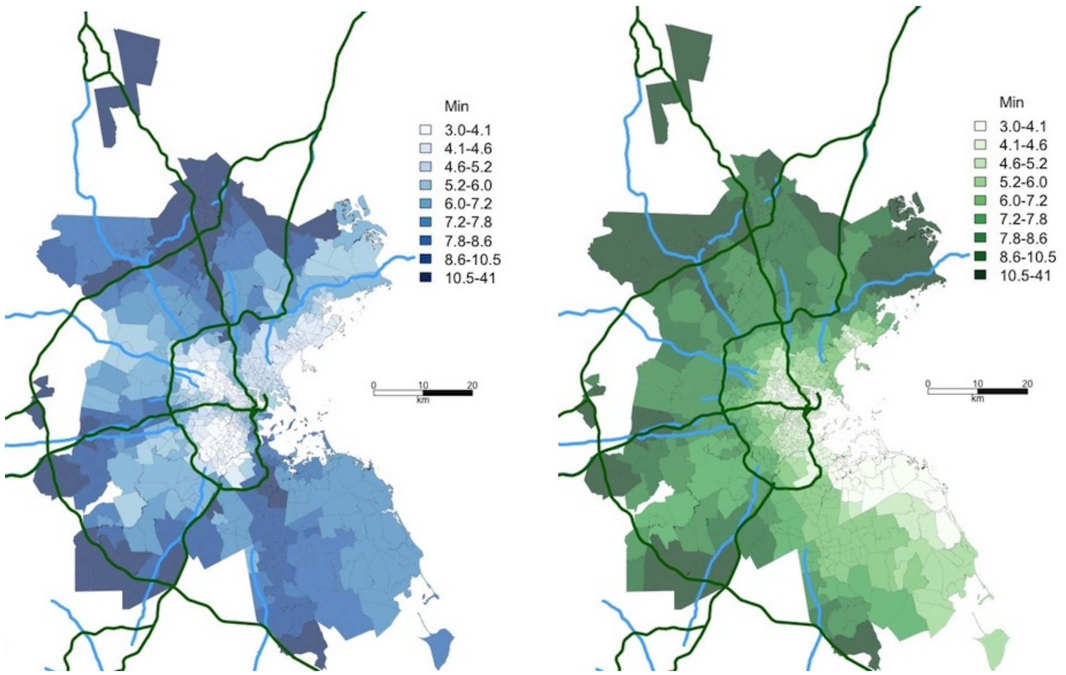
Notes: Unit of observation is census tract. Data comes from 1950, 1960, and 1970 tract-level aggregates retrieved from IPUMS NHGIS. The first difference is either over 1950 to 1960 or 1960 to 1970 and stacked into one panel depending on when highway construction started in the CBSA. All changes over time are de-meaned within CBSA. The sample of tracts for the central city panel is tracts within 5 miles of the constructed highway network, for the inner suburbs panel is tracts within 7.5 miles of the constructed highway network, and for the suburbs panel is tracts within 10 miles of the constructed highway network for legibility.

Figure B.4: Change in Percentage White by Redlining
Over Distance from Central Business District and Distance from Highway (1950-1960, 1960-1970)



Notes: Unit of observation is census tract. Data comes from 1950, 1960, and 1970 tract-level aggregates retrieved from IPUMS NHGIS. The first difference is either over 1950 to 1960 or 1960 to 1970 and stacked into one panel depending on when highway construction started in the CBSA. All changes over time are de-meaned within CBSA. The sample of tracts for the central city panel is those within 5 miles of the constructed highway network, for the inner suburbs panel is those within 7.5 miles of the constructed highway network, and for the suburbs panel is those within 10 miles of the constructed highway network for legibility. Redlined tracts are those where more than 80% of the area is redlined.

Figure B.5: Commute Time Reductions with Historical Roads as Interstates

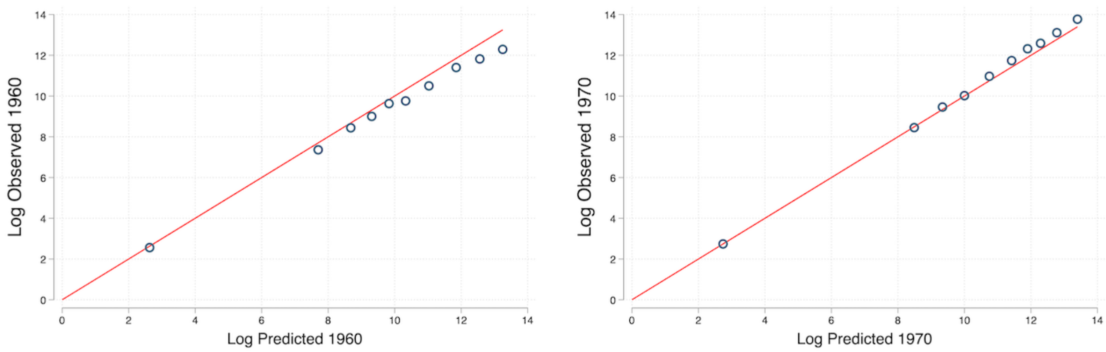


(a) Interstate Roads (b) Historical Large Roads as Interstates

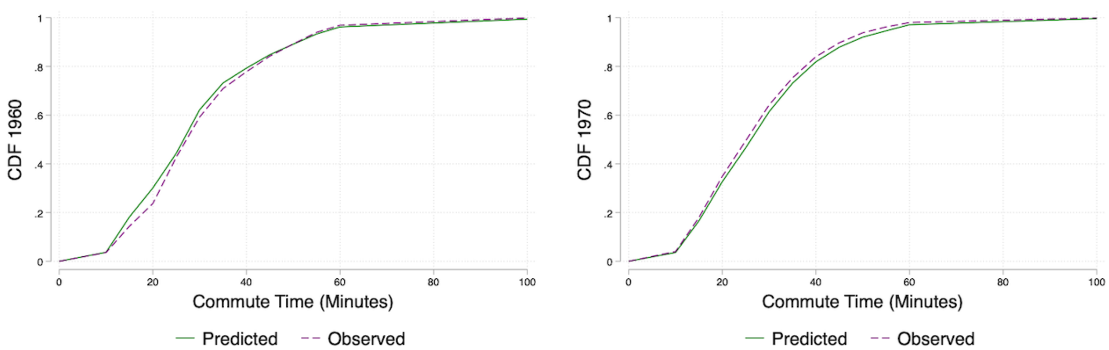
Notes: In Panel (a), commute time changes come from the author's calculations as the difference between commute times for the historical road network and for the entire Interstate network overlayed on the historical road network. In Panel (b) commute time changes come from the author's calculations as the difference between commute times for the historical road network and for the development of large roads as interstate highways.

Figure B.6: Predicted vs. Observed Commute Flows in 1960 and 1970

(a) Linear Fit and Scatter

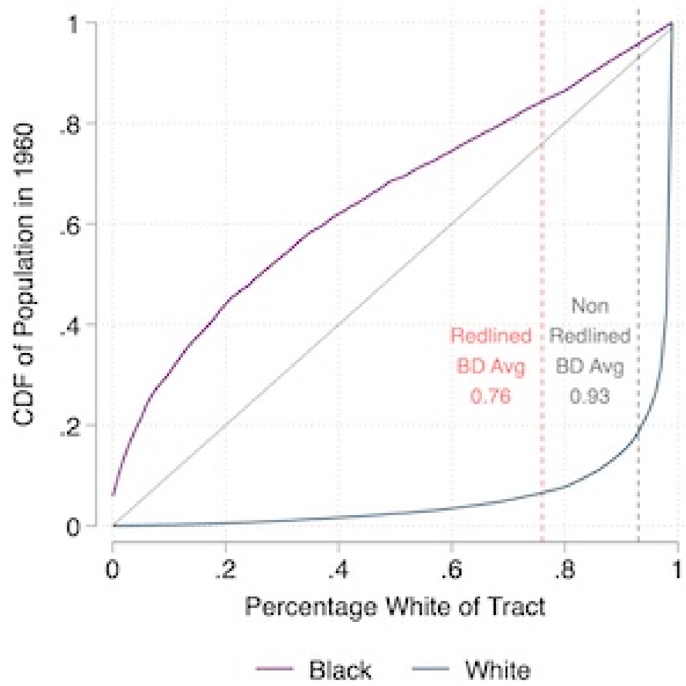


(b) Cumulative Distribution Function



Notes: Unit of observation is Place of Work Zone level by Place of Work Zone level. Data comes from restricted Census microdata in 1960 and 1970. In Panel (a), the scatter plot is created with 10 quantiles of predicted flows with analytical weights on the level of the observed commute flows. The red line is the 45 degree line. The linear fit is shown in Table A.19. In Panel (b), the cumulative distribution function over commute time in minutes is in predicted flows for the green line and in observed flows for the purple line.

Figure B.7: CDF of Black and White Population in 1960 over Racial Composition of Neighborhood and Neighborhood Average by Redlining Borders



Notes: Data comes from the 1960 tract-level aggregates retrieved from IPUMS NHGIS. The cumulative distribution function is calculated by applying analytical weights of each race group's population to the racial composition of census tracts. The average percentage White of redlined neighborhoods and non-redlined neighborhoods is calculated from the sample by the border of Figure 1.

C Descriptive Results

C.1 Instrument Validity

To test for instrument validity, I examine pre-trends in Table A.5 for changes between 1940 to 1950 or 1950 to 1960 depending on the timing of Interstate construction. As required for identification, the location of the planned routes and Euclidean rays is not correlated with demographic or economic changes before Interstate development, conditional on geographic controls. In Columns 8–9 of Table 2, there is also no cross-sectional correlation between the plans and rays with 1950 baseline characteristics after including controls.

Finally, I estimate the strength of the first-stage. To test that the planned routes and Euclidean rays are predictive of highway placement, I estimate two types of equations of the forms below where $IV \in \{Plans, Rays\}$.

$$\log(DistHW_i) = \phi \log(DistIV_i) + \mathbf{X}_i\theta + \lambda_{m(i)} + \nu_i$$
$$\mathbf{1}\{DistHW_i = 1\} = \pi\mathbf{1}\{DistIV_i = 1\} + \mathbf{X}_i\sigma + \delta_{m(i)} + \xi_i$$

The first compares log distance from the constructed routes to log distance from either the planned routes or the Euclidean rays, and the second compares a binary indicator for whether tracts are within 1 mile of the constructed route to the same indicator for the planned routes and rays to study placement at finer spatial scales. All the earlier controls and city fixed effects are included in the estimation. Results are shown in Table A.6. In both forms of first-stage regressions, the instruments are highly correlated with highway location as F-statistics on the excluded instrument are all above 100.

C.2 Instrument for CMA

In Appendix Table A.7, I report the first-stage regressions between CMA and corresponding measures with the Interstate, plan, and ray instruments. Because CMA includes both wage and commute cost changes, the first-stage coefficients on the planned and ray CMA instruments are lower than the first-stage coefficients reported for placement in Table A.6. However, when wages are fixed to 1960 levels, the first-stage coefficients for CMA look similar to those for placement as then the variation only comes from Interstate highway construction.

C.3 Additional Results on Changes over CMA Improvements

(i) I estimate how the equilibrium outcomes of rents and racial composition respond to CMA in Table A.8 Columns 1 and 3. Consistent with the long differences, elasticities for rents and racial composition are smaller compared to the White population response and presumably play a smaller role in the welfare assessment. Because these equilibrium responses in turn affect population responses through feedback channels, I probe their importance for the population elasticities by controlling for rents and racial composition successively in Columns 2 and 4 as conducted in Adão et al. (2019). They do not appear to be a large determinant of the population responses to CMA.

(ii) I construct two additional Borusyak and Hull (2023)-proposed CMA controls in Table A.9 Columns 1 and 2 where the planned routes and rays are converted into Interstates, and estimates remain unaffected when adding the controls. (iii) Pooling population elasticities by race is a fair approximation as in Table A.9 Column 4, I do not find substantial heterogeneity within race by education.

D Quantitative Model

D.1 Model Extensions

D.1.1 Stone-Geary

An alternative approach to incorporating non-homotheticity in housing consumption is to allow for Stone-Geary preferences. The consumer maximization problem then includes a minimum amount of housing consumption $\bar{l}_{gr}$ that can differ by group.

$$\max_{c_{ij}(o), l_i(o)} \quad \frac{z_i(o)\epsilon_j(o)B_{igr}}{d_{ijgr}} \left(\frac{c_{ij}(o)}{\beta_{gr}}\right)^{\beta_{gr}} \left(\frac{l_i(o) - \bar{l}_{gr}}{1 - \beta_{gr}}\right)^{1-\beta_{gr}}$$

$$\text{s.t.} \quad c_{ij}(o) + Q_i l_i(o) = \frac{w_{jgr}\epsilon_j(o)}{d_{ijgr}}$$

which leads to the indirect utility function of

$$u_{ijgr}(o) = B_{igr} z_i(o) Q_i^{\beta_{gr}-1} \left(\frac{w_{jgr}\epsilon_j(o)}{d_{ijgr}} - Q_i \bar{l}_{gr} \right)$$

Stone-Geary allows for income changes to generate sorting in contrast to Cobb-Douglas preferences.

D.1.2 Nested Frechet

With the indirect utility function defined as before, suppose that $z_i(o)$ is instead distributed with a nested Frechet structure where the cumulative distribution is

$$F(z_i(o)) = \exp\Big(- \Big(\sum_n \Big(\sum_{i \in S_n} z_i(o)^{-\theta_r} \Big)^{-\lambda_r/\theta_r} \Big) \Big)$$

where λ_r governs the substitutability across types of neighborhoods. When $\lambda_r = \theta_r$, the expression returns to the usual Frechet distribution as before. In this setting, suppose $\lambda_B < \theta_B$ where for Black households, there is more substitutability within type of neighborhood than across, and $\lambda_W = \theta_W$ where for White households, their choice behavior is not nested across the type of neighborhoods.

The choice probabilities are then

$$\begin{aligned} \pi_{igr} &= \pi_{n,gr} \pi_{igr|n} \\ &= \frac{\left(\sum_{s \in S_n} \left(B_{sgr} CMA_{sgr} Q_s^{\beta_{gr}-1} \right)^{\theta_r} \right)^{\lambda_r/\theta_r}}{\sum_m \left(\sum_{s \in S_m} \left(B_{sgr} CMA_{sgr} Q_s^{\beta_{gr}-1} \right)^{\theta_r} \right)^{\lambda_r/\theta_r}} \frac{\left(B_{igr} CMA_{igr} Q_i^{\beta_{gr}-1} \right)^{\theta_r}}{\sum_{s \in S_n} \left(B_{sgr} CMA_{sgr} Q_s^{\beta_{gr}-1} \right)^{\theta_r}} \end{aligned}$$

following a two step process. First, there is a choice of type n of neighborhoods, and then conditional on type, there is a choice of neighborhood i within type n. Define $V_{n,gr} = \left(\sum_{s \in S_m} \left(B_{sgr} CMA_{sgr} Q_s^{\beta_{gr}-1} \right)^{\theta_r} \right)^{1/\theta_r}$ as the inclusive value of living in type n neighborhoods. The share living in type n follows the usual gravity share formula with the shape parameter λ_r.

$$\pi_{n,gr} = \frac{V_{n,gr}^{\lambda_r}}{\sum_m V_{m,gr}^{\lambda_r}}$$

The population elasticity to CMA $\frac{\partial \pi_{igr}}{\partial CMA_{igr}}$ using the product rule and the definition of $\pi_{igr} = \pi_{n,gr}\pi_{igr|n}$ is

$$\begin{aligned}
\frac{\partial \pi_{igr}}{\partial CMA_{igr}} &= \frac{\partial \pi_{n,gr}}{\partial CMA_{igr}}\pi_{igr|n} + \frac{\partial \pi_{igr|n}}{\partial CMA_{igr}}\pi_{n,gr} \\
\frac{\partial \pi_{igr}}{\partial CMA_{igr}} &= \frac{\lambda_r \pi_{igr|n}^2}{CMA_{igr}}\pi_{n,gr}(1-\pi_{n,gr}) + \frac{\theta_r \pi_{n,gr}}{CMA_{igr}}\pi_{igr|n}(1-\pi_{igr|n}) \\
\Rightarrow \frac{\partial \pi_{igr}}{\partial CMA_{igr}}\frac{CMA_{igr}}{\pi_{igr}} &= \lambda_r \pi_{igr|n}(1-\pi_{n,gr}) + \theta_r(1-\pi_{igr|n})
\end{aligned}$$

When $\lambda_r = \theta_r$ (as is the case for White households), then the elasticity becomes

$$\begin{aligned}
\frac{\partial \pi_{igr}}{\partial CMA_{igr}}\frac{CMA_{igr}}{\pi_{igr}} &= \theta_r \pi_{igr|n}(1-\pi_{n,gr}) + \theta_r(1-\pi_{igr|n}) \\
&= \theta_r(\pi_{igr|n} - \pi_{igr}) + \theta_r(1-\pi_{igr|n}) = \theta_r(1-\pi_{igr})
\end{aligned}$$

which is the same as when there are no nests for types.

When $\lambda_r < \theta$ (as is the case for Black households), then the elasticity is lower

$$\lambda_r \pi_{igr|n}(1-\pi_{n,gr}) + \theta_r(1-\pi_{igr|n}) < \theta_r(1-\pi_{igr})$$

even though the conditional elasticity (conditional on type of neighborhood) is still approximately θ.

$$\frac{\partial \pi_{igr|n}}{\partial CMA_{igr}}\frac{CMA_{igr}}{\pi_{igr|n}} = \theta_r(1-\pi_{igr|n})$$

D.2 Separate Idiosyncratic Shocks

Two separate idiosyncratic shocks are received for residences and workplaces. Residential shocks $z_i(o)$ are drawn from distribution $F(z_i(o)) = \exp(-z_i(o)^{-\theta_r})$ and workplace shocks $\epsilon_j(o)$ are likewise distributed Frechet from $F(\epsilon_j(o)) = \exp(-T_{jgr}\epsilon_j(o)^{-\phi})$.

Previous estimates of the combined shock leverage variation on the workplace side, so in this model, ϕ represents the substitution elasticity across workplaces. The model implies residential choice follows the equation $L_{igr} = (B_{igr}\Phi_{igr}^{\frac{1}{\phi}} Q_i^{\beta_{gr}-1})^{\theta_r} / \sum_t (B_{tgr}\Phi_{tgr}^{\frac{1}{\phi}} Q_t^{\beta_{gr}-1})^{\theta_r}\mathbb{L}_{gr}$ where $\Phi_{igr} = \sum_j T_{jgr}(w_{jgr}/d_{ijgr})^{\phi}$. Under the null hypothesis that the residential elasticity and workplace elasticity are equivalent $\phi = \theta_r$, the coefficient λ_r in the estimating equation $\log L_{igr} = \lambda_r \log \Phi_{igr} + \gamma_{gr}$ should be approximately 1. Note that in Φ_{igr}, no assumptions are made on the value of ϕ because in the commuting gravity equation, $\nu_{gr} = \kappa_{gr}\phi$ is estimated directly from the data. See Appendix E.1 for details on the values in Φ_{igr}. In Appendix Table A.9, I test for whether the elasticities to residential and workplace shocks should be the same value. I find the coefficient on Φ_{igr} is significantly less than one, suggesting the residential elasticity is in fact lower than the labor supply elasticity to workplaces.

D.3 Spatial Barriers and Isomorphisms

To generate the capacity constraint $\bar{c}_{igr}$, as the constraint becomes tighter i.e. $\bar{c}_{igr} \to 0$, the barriers to entry for a neighborhood become larger. An equivalent way to arrive at the same allocation is to sufficiently increase the amenity or tax wedge. The amenity wedge, when no price wedge exists, must satisfy

$$
\begin{aligned}
\frac{L_{igr}}{\mathbb{L}_{gr}} =& \frac{\bar{c}_{igr}}{\mathbb{L}_{gr}} = \frac{\left((1-\tau^b_{igr})B_{igr}CMA_{igr}Q_i^{\beta_{gr}-1}\right)^{\theta_r}}{\sum_{t\neq i}\left(B_{igr}CMA_{igr}Q_i^{\beta_{gr}-1}\right)^{\theta_r} + \left((1-\tau^b_{igr})B_{igr}CMA_{igr}Q_i^{\beta_{gr}-1}\right)^{\theta_r}} \\
\Rightarrow& \frac{\bar{c}_{igr}}{\mathbb{L}_{gr}} \sum_{t\neq i} \left(B_{igr}CMA_{igr}Q_i^{\beta_{gr}-1}\right)^{\theta_r} = \left(1 - \frac{\bar{c}_{igr}}{\mathbb{L}_{gr}}\right)\left((1-\tau^b_{igr})B_{igr}CMA_{igr}Q_i^{\beta_{gr}-1}\right)^{\theta_r} \\
\Rightarrow& \frac{\bar{c}_{igr}/\mathbb{L}_{gr}\sum_{t\neq i}\left(B_{tgr}CMA_{tgr}Q_t^{\beta_{gr}-1}\right)^{\theta_r}}{(1-\bar{c}_{igr}/\mathbb{L}_{gr})\left(B_{igr}CMA_{igr}Q_i^{\beta_{gr}-1}\right)^{\theta_r}} = (1-\tau^b_{igr})^{\theta_r} = \mathbf{k}_{igr} \Rightarrow \tau^b_{igr} = 1 - \mathbf{k}_{igr}^{1/\theta_r}
\end{aligned}
$$

In the indirect utility function, an amenity wedge is isomorphic to a price wedge according to the relationship

$$
1 - \tau^b_{igr} = \left(1 + \tau^Q_{igr}\right)^{\beta_{gr}-1}
$$

so to attain the capacity constraint, the pride wedge is then $\tau^Q_{igr} = \mathbf{k}_{igr}^{1/(\theta_r(\beta_{gr}-1))} - 1$.

The average of the idiosyncratic shocks of individuals in each location can be derived using the properties of the Frechet distribution and generally follows $\bar{z}_{igr} = \Gamma\left(1 - \frac{1}{\theta_r}\right)\pi_{igr}^{1/\theta_r}$. Substituting $\mathbf{k}_{igr}$ and residential factors into π_{igr} leads to the expression for average shocks.

$$
\bar{z}_{igr} = \Gamma\left(1 - \frac{1}{\theta_r}\right)\left(\frac{\sum_{t\neq i}\left(B_{tgr}CMA_{tgr}Q_t^{\beta_{gr}-1}\right)^{\theta_r} + \mathbf{k}_{igr}\left(B_{tgr}CMA_{tgr}Q_t^{\beta_{gr}-1}\right)^{\theta_r}}{\mathbf{k}_{igr}\left(B_{tgr}CMA_{tgr}Q_t^{\beta_{gr}-1}\right)^{\theta_r}}\right)^{1/\theta_r}
$$

Note that while a capacity constraint, amenity wedge, and price wedge lead to the same allocation, the general equilibrium implications do differ. Suppose capacity constraints only bind for Black households such that $L_{igB} = \bar{c}_{igB}$ while the White population is determined endogenously and responds to neighborhood-level changes. If the capacity constraint is implemented via a price wedge, the housing market is subsequently affected by changes in housing demand across groups, versus via an amenity wedge, it is not directly impacted.

Concretely, the price wedge lowers housing demand (consumption). This then changes the expression for total housing supply, which is shared across all groups and is equated with total housing consumption.

$$H_i = \sum_g H_{igB} + \sum_g H_{igW} = \sum_g \frac{(1-\beta_{gB})\bar{w}_{igB} L_{igB}}{(1+\tau^Q_{igB})Q_i} + \sum_g \frac{(1-\beta_{gW})\bar{w}_{igW} L_{igW}}{Q_i} \tag{12}$$

D.4 Firms and Housing

Firms – As workers alter their labor supply to workplaces in response to reductions in commute costs, wages are determined in equilibrium by firms. While adjustments at firms are not a central theme of the empirical evidence or the question of the paper, I include this feature to close the model and allow for a comprehensive assessment of the impacts of Interstate highways. In the counterfactual exercises, I probe its importance for welfare by shutting down firm adjustments in wages and housing.

Across workplaces, there are representative firms with constant returns to scale production so that demand by firms translates into demand at each workplace. Perfectly competitive firms produce varieties with Cobb-Douglas technology over labor and commercial floorspace following $Y_j = A_j N_j^{\alpha} H_{Fj}^{1-\alpha}$, where α is the share of labor and A_j is a Hicks-neutral productivity shock. Combining heterogeneous workers, labor N_j is a CES aggregate over education where workers of different education levels are imperfect substitutes (Katz and Murphy, 1992; Card, 2009). N_{jg} is further a CES aggregate of different racial groups.

$$N_j = \left(\sum_g \alpha_{jg} N_{jg}^{\frac{\sigma^g - 1}{\sigma^g}} \right)^{\frac{\sigma^g}{\sigma^g - 1}} \quad \text{with} \quad N_{jg} = \left(\sum_r \alpha_{jgr} L_{Fjgr}^{\frac{\sigma^r - 1}{\sigma^r}} \right)^{\frac{\sigma^r}{\sigma^r - 1}}$$

This nested-CES structure accommodates imperfect substitutability across race as Boustan (2009) finds Black workers are closer substitutes to each other than to White workers. Imperfect substitutability can arise from occupational segregation preventing workers from switching into an occupation predominantly of another race or from unobserved skill gaps, even conditional on education (Higgs, 1977).[37]

Within education, locations employ workers from each race at varying intensities α_{jgr}, incorporating how firms in the central city may have different demands for Black workers compared to firms in the suburbs e.g. due to discrimination across space (Holzer and

[37]The average Black worker at this time attended lower quality schools, especially in the segregated South, compared to the average White worker which would lead equivalent years of schooling to translate into different skill levels (Margo, 2007).

Reaser, 2000; Miller, 2023). Moreover, it generalizes the labor aggregate structure of Tsivanidis (2022) by exploiting the detailed workplace wage Census data.

Firm profit maximization generates labor and commercial floorspace demand with the corresponding wage indices.

$$L_{Fjgr} = \left(\frac{w_{jgr}}{\alpha_{jgr}\omega_{jg}}\right)^{-\sigma^r}\left(\frac{\omega_{jg}}{\alpha_{jg}W_j}\right)^{-\sigma^g} N_j \quad \text{s.t.} \;\; W_j = \left(\sum_g \alpha_{jg}^{\sigma^g}\omega_{jg}^{1-\sigma^g}\right)^{\frac{1}{1-\sigma^g}} \quad \omega_{jg} = \left(\sum_r \alpha_{jgr}^{\sigma^r} w_{jgr}^{1-\sigma^r}\right)^{\frac{1}{1-\sigma^r}} \tag{13}$$

$$H_{Fj} = \left(\frac{1-\alpha}{Q_j}A_j\right)^{1/\alpha} N_j \tag{14}$$

The zero-profit condition from perfect competition combined with profit maximization leads to the subsequent condition for commercial rental prices, which rise when productivity is high and wages are low. Firms thus aim to locate in more productive, cheaper, and lower-wage areas.

$$Q_j = (1-\alpha)\left(\frac{\alpha}{W_j}\right)^{\frac{\alpha}{1-\alpha}} A_j^{\frac{1}{1-\alpha}} \tag{15}$$

Agglomeration – Within productivity of locations, the term A_j contains a fundamental component a_j that does not vary with equilibrium outcomes and an endogenous component representing agglomeration economies in density (L_{Fj}/K_j). In the definition of density, L_{Fj} is total employment, K_j is the land area, and γ^A is the strength of agglomeration.

$$A_j = a_j \left(L_{Fj}/K_j\right)^{\gamma^A} \tag{16}$$

Transportation infrastructure in conjunction with agglomeration can reallocate economic activity as in Faber (2014), Heblich et al. (2020), and Baum-Snow (2020) with racially disparate effects as studied by **?**. The model includes this channel of density affecting productivity (Rosenthal and Strange, 2004; Ellison et al., 2010).

Housing – Given that empirically, housing prices adjusted with highway construction, I allow for a housing construction sector that responds elastically to changes in demand from both residences and workplaces. In each location, there is H_i amount of floorspace that is allocated endogenously across residential versus commercial uses where θ_i is the share for residential use. Residential floorspace demand aggregates across the housing expenditures of each group Exp_{igr} so H_{Ri} is determined following

$$H_{Ri} = \theta_i H_i = \sum_{g,r} \frac{Exp_{igr}}{Q_i} \;\text{ with }\; Exp_{igr} = (1-\beta_{gr})\overline{w}_{igr}\varphi_{gr}L_{igr},\; \overline{w}_{igr} = \sum_j \pi_{j|igr} w_{jgr} \tag{17}$$

Distribution of rents to homeowners is constant across neighborhoods for each group within each city. Let total income by group gr be the sum of total labor income and total rental income from housing rents to each group based on the share of home values that the group owns in the portfolio of the city.

$$\underbrace{\varphi_{gr} \sum_i \overline{w}_{igr} L_{igr}}_{\text{total income}} = \underbrace{\sum_i \overline{w}_{igr} L_{igr}}_{\text{total labor income}} + \underbrace{\sum_i \hat{o}_{igr} \sum_{g,r} Exp_{igr}}_{\text{total rental income}}$$

$$\Rightarrow \varphi_{gr} = 1 + \frac{\sum_i \hat{o}_{igr} \sum_{g,r} Exp_{igr}}{\sum_i \overline{w}_{igr} L_{igr}}$$

The share of home values $\hat{o}_{igr}$ is observed in the data as the proportion of home values in homes owned by group gr out of total home values in a neighborhood.

Commercial floorspace demand comes from firm optimization in Equation (14), and with the two expressions for residential and commercial floorspace demand, the allocation across uses θ_i and total floorspace demand $H_i = H_{Ri} + H_{Fi}$ are then determined for land market clearing.

To parameterize how housing is supplied elasticity, I follow the literature where the housing production function is $H_i = K_i^{\mu} M_i^{1-\mu}$ with M_i as capital at universal price p and K_i as land at price r_i (Epple et al., 2010; Combes et al., 2021). The implied supply curve is

$$H_i = \left(\frac{1-\mu}{\mu}\right)^{\frac{1-\mu}{\mu}} K_i Q_i^{\frac{1-\mu}{\mu}} \tag{18}$$

D.5 General Equilibrium

Given the model's parameters $\{\beta_{gr}, \theta_r, \kappa_{gr}, \phi, \alpha, \alpha_{jg}, \alpha_{jgr}, \sigma^g, \sigma^r, \mu, \rho_r, \gamma^A\}$, city populations by education and race $\{\mathbb{L}_{gr}\}$, and location characteristics $\{T_{jgr}, t_{ijgr}, b_{igr}, a_j, K_i\}$, the general equilibrium is represented by the vector of endogenous objects $\{L_{igr}, L_{Fjgr}, Q_i, \theta_i, w_{jgr}, B_{igr}, A_j, U_{gr}\}$ determined by the following equations:

1. *Residential populations* in each neighborhood (5)
2. *Labor supply* at each workplace (3)
3. *Housing demand* from residences and firms (17) + (14)
4. *Housing supply* from the construction sector (18)
5. *Zero profit and profit maximization* by firms (13)
6. *Endogenous amenities* from racial composition (6)
7. *Endogenous productivity* from agglomeration (16)
8. *Closed City* where $\sum_i L_{igr} = \mathbb{L}_{gr}$

E Inversion and Estimation

E.1 Model Inversion

Parameters Estimated During Model Inversion

- $\alpha_{jg}, \alpha_{jgr}$ are labor intensities for the CES nested labor aggregate
- T_{jgr} is the scale parameter for workplaces

Observed data sources

- Observed wages $\hat{w}_{jgr}$ come from the Decennial microdata

Step 1 – Given $\{L_{Fjgr}, L_{igr}, t_{ijgr}\}$ and the semi-elasticity of commuting parameter $\{\nu_{gr}\}$, I invert for composite transformed wages $\omega_{jgr} = T_{jgr} w_{jgr}^{\phi}$ from the labor supply equation following

$$
\begin{aligned}
L_{Fjgr} &= \sum_i \frac{T_{jgr}(w_{jgr}/d_{ijgr})^{\phi}}{\sum_s T_{sgr}(w_{sgr}/d_{is})^{\phi}} L_{igr} \\
&= \sum_i \frac{\omega_{jgr}/\exp(\nu_{gr} t_{ijgr})}{\sum_s \omega_{sgr}/\exp(\nu_{gr} t_{isgr})} L_{igr}
\end{aligned}
$$

Commuting costs are in terms of commute times t_{ijgr} following $d_{ijgr} = t_{ijgr}^{\kappa_{gr}}$, therefore $d_{ijgr}^{\phi} = t_{ijgr}^{\nu_{gr}}$ with $\nu_{gr} = \kappa_{gr}\phi$. Labor supply is in the second line rewritten as a function of composite transformed wages ω_{jgr}. Wages are solved for iteratively following the process of Ahlfeldt et al. (2015) and wages are only identified up to a scaling factor.

Step 2 – Given $\{\omega_{jgr}\}$, the Frechet shape parameter for labor supply ϕ, and observed wages $\{\hat{w}_{jgr}\}$, I back out the Frechet scale parameter T_{jgr}. Following that $\omega_{jgr} = T_{jgr} w_{jgr}^{\phi}$, then the Frechet scale parameter is $T_{jgr} = \omega_{jgr}/w_{jgr}^{\phi}$. Compared to existing work where wages are not directly observed, this additional data allows for separately identifying the workplace amenity value T_{jgr} from the scale wages component ω_{jgr}.

Residential Side

Step 3 – Given $\{Q_i, \omega_{jgr}, t_{ijgr}, L_{igr}\}$ and the parameters $\{\beta_{gr}, \phi, \kappa_{gr}, \theta_r\}$, I can recover residential amenities B_{igr}. Returning to the residential choice equation, the share of each demographic group that lives in a location i follows

$$
\frac{L_{igr}}{\mathbb{L}_{gr}} = \frac{\left(B_{igr} CMA_{igr} Q_i^{\beta_{gr}-1}\right)^{\theta_r}}{\sum_t \left(B_{tgr} CMA_{tgr} Q_{tr}^{\beta_{gr}-1}\right)^{\theta_r}}
$$

which can be rearranged using the welfare equation (7).

$$\left(\frac{L_{igr}}{\mathbb{L}_{gr}}\right)^{1/\theta_r} = \frac{B_{igr} CMA_{igr} Q_i^{\beta_{gr}-1}}{U_{gr}}$$

Choosing units for amenities such that the geometric mean $\bar{B}_{igr} = \left[\prod_{i=1}^{S} B_{igr}\right]^{1/S} = 1$, and continuing with the bar notation for geometric mean, I calibrate amenities following

$$\frac{B_{igr}}{\bar{B}_{igr}} = \left(\frac{L_{igr}}{\bar{L}_{Rigr}}\right)^{1/\theta_r} \left(\frac{Q_i}{\bar{Q}_{ir}}\right)^{1-\beta_{gr}} \left(\frac{CMA_{igr}}{\overline{CMA}_{igr}}\right)^{-1}$$

Workplace Side

Step 4 – Given $\{L_{Fjgr}, w_{jgr}\}$ and the parameters $\{\sigma^r, \sigma^g\}$, I estimate the parameters α_{jg}, α_{jgr} with the following procedure. Using the labor demand equation from (13), the share of labor employed in a location and in an education group g that is of race r is

$$\frac{L_{Fjgr}}{L_{Fjg}} = \frac{(w_{jgr}/\alpha_{jgr})^{-\sigma^r}}{\sum_s (w_{jgs}/\alpha_{jgs})^{-\sigma^r}}$$

The share of labor and wages are observed, so this equation allows for determining α_{jgr} with the constraint that $\sum_r \alpha_{jgr} = 1$.

With a similar process, I solve for α_{jg}. First, I calculate $N_{jg} = \left(\sum_r \alpha_{jgr} L_{Fjgr}^{\frac{\sigma^r-1}{\sigma^r}}\right)^{\frac{\sigma^r}{\sigma^r-1}}$ which is a function of observed and previously estimated values. Using the CES demand form, I arrive at the equation

$$\frac{N_{jg}}{\sum_h N_{jh}} = \frac{(\omega_{jg}/\alpha_{jg})^{-\sigma^g}}{\sum_h (\omega_{jh}/\alpha_{jh})^{-\sigma^g}}$$

which is an equation for the unknown α_{jg} with the constraint that $\sum_g \alpha_{jg} = 1$. Recall that $\omega_{jg} = \left(\sum_r \alpha_{jgr}^{\sigma^r} w_{jgr}^{1-\sigma^r}\right)^{\frac{1}{1-\sigma^r}}$, which is a function of known values.

Step 5 – Given $\{q_i, w_{jgr}\}$ and the parameters $\{\alpha, \alpha_{jg}, \alpha_{jgr}\}$, I recover workplace productivity A_i. Productivity for each location i is inferred from the zero profit equation.

$$q_i = (1-\alpha)\left(\frac{\alpha}{W_j}\right)^{\frac{\alpha}{1-\alpha}} A_i^{\frac{1}{1-\alpha}} \text{ for } i \in Tracts_j$$

where $W_j = \left(\sum_g \alpha_{jg}^{\sigma^g} \omega_{jg}^{1-\sigma^g}\right)^{\frac{1}{1-\sigma^g}}$ the price index for labor is calculated after backing out wages w_{jgr} and the $\alpha_{jg}, \alpha_{jgr}$ relative productivity parameters at the POW zone j. Since prices are observable at the tract level for tract i, I assume that wages are the same for all tracts in POW zone j which is the set $Tracts_j$.

Housing Supply and Allocation

Step 6 – Given $\{Q_i, \omega_{jgr}, t_{ijgr}, L_{igr}, q_i, A_j, L_{Fjgr}\}$, the parameters $\{\beta_{gr}, \phi, \kappa_{gr}, \alpha, \alpha_{jg}, \alpha_{jgr}\}$, I recover total housing supply H_i and floorspace allocation θ_i across commercial and residential uses. Returning to the residential and commercial demand for floorspace equations, we have for the residential side

$$H_{Ri} = \theta_i H_i = \sum_{g,r} \frac{Exp_{igr}}{Q_i} \text{ with } Exp_{igr} = (1-\beta_{gr})\overline{w}_{igr}\varphi_{gr}L_{igr},\ \overline{w}_{igr} = \sum_j \pi_{j|igr} w_{jgr}$$

Distribution of rents to homeowners is calculated using total income by group gr as the sum of total labor income and total rental income to each group based on the share of home values that the group owns in the portfolio of the city.

$$\underbrace{\varphi_{gr} \sum_i \overline{w}_{igr} L_{igr}}_{\text{total income}} = \underbrace{\sum_i \overline{w}_{igr} L_{igr}}_{\text{total labor income}} + \underbrace{\sum_i \hat{o}_{igr} \sum_{g,r} Exp_{igr}}_{\text{total rental income}}$$
$$\Rightarrow \varphi_{gr} = 1 + \frac{\sum_i \hat{o}_{igr} \sum_{g,r} Exp_{igr}}{\sum_i \overline{w}_{igr} L_{igr}}$$

For the commercial side, I use that the production function is Cobb-Douglas

$$H_{Fi} = \left(\frac{W_j}{\alpha}\right)\left(\frac{1-\alpha}{q_i}\right)\frac{N_j}{S_j} \text{ for } i \in Tracts_j$$
$$\text{where } N_j = \left(\sum_g \alpha_{jg} N_{jg}^{\frac{\sigma^g-1}{\sigma^g}}\right)^{\frac{\sigma^g}{\sigma^g-1}} \text{ and } N_{jg} = \left(\sum_r \alpha_{jgr} L_{Fjgr}^{\frac{\sigma^r-1}{\sigma^r}}\right)^{\frac{\sigma^r}{\sigma^r-1}}$$

As the geographic unit on the workplace side is a POW zone while the geographic unit on the residential side is a census tract, I assume that on the workplace side, labor is supplied evenly across all the tracts within a POW zone.

Finally, θ_i where i is at the tract-level is set to follow

$$\theta_i = \frac{H_{Ri}}{H_i} = \frac{H_{Ri}}{H_{Ri} + H_{Fi}}$$

with housing supply at the tract level $H_i = H_{Ri} + H_{Fi}$.

Step 7 – Given $\{H_i, Q_i\}$ and the parameter μ, I recover the scaled amount of land used for development k_i as a location fundamental following profit maximization of the housing construction sector. Demand for capital can be derived in a straightforward manner as $M_i = Q_i H_i (1-\mu)/p$. Substituting this equation into the housing production function gives

$$H_i = K_i Q_i^{\frac{1-\mu}{\mu}} \left(\frac{1-\mu}{p}\right)^{1-\mu}$$
$$H_i = k_i Q_i^{\frac{1-\mu}{\mu}} \qquad \text{where } k_i = K_i \left(\frac{1-\mu}{p}\right)^{1-\mu}$$

In the quantitative implementation, I allow μ (the capital intensity of housing construction) which determines the housing supply elasticity to price to differ in the suburbs versus the central city following recent work by Baum-Snow and Han (2021) and Saiz (2010). Let $\mu = 0.3$ for neighborhoods within 5 miles of the CBD and $\mu = 0.2$ for neighborhoods further than 5 miles from the CBD, corresponding to floorspace supply elasticities of 2.33 and 4, respectively.

E.2 Parameter Estimation

E.2.1 Estimation of discriminatory pricing

Discriminatory pricing will be measured directly from home values and rents in the microdata. To test for differential pricing by race across neighborhoods, I look at the coefficient from the interaction of race and redlining. The estimating equation is across observations for each household h with either log home value or log rent as the dependent variable.

$$\log Q_h = \alpha_i + \alpha_r + \phi_1 D_i^{red} + \phi_2 D_i^{red} \times D_h^{non-white} + X_h + \epsilon_h$$

α_i is for neighborhood fixed effects, α_r is for race fixed effects, D_i^{red} is a dummy for being in a redlined neighborhood, D_h^{black} is a dummy for the household head being Black, and X_h is a set of household level characteristics on the quality of the home such as the availability of air conditioning, a freezer, a toilet, or a bathtub. The coefficient ϕ_2 is the differential increase in price black households have to pay to live outside of redlined neighborhoods compared to white households. In Table A.1, it appears that Black households pay less than White households for similar quality housing in non-redlined neighborhoods and more in redlined neighborhoods. These results do not suggest pricing is the reason why Black households are more likely to live in redlined areas.

E.2.2 Gravity Equation

Even with the aggregation, some bilateral pairs continue to have zero counts for the Black population. In addition to estimating the log-log specification above, I conduct the robustness checks suggested by the trade literature in Head and Mayer (2014) and estimate the commuting elasticity with Poisson Pseudo Maximum Likelihood (PPML) following Silva and Tenreyro (2006) to address sparsity. For the Black population, the commuting elasticity rises slightly with PPML estimates in Panel D. For White workers, their elasticities are lowered with the PPML estimator although the observation count only increases a small amount.[38] Overall, the pattern remains quite similar.

As the historical road network may also have been endogenously placed, I instrument commute times with Euclidean distance in Appendix Table A.11 Panel C (with the first stage in Panel D). The ordering of the elasticities across groups remains the same, although the magnitude is higher. Additionally, I report the coefficient for the reduced form regression of commuting share on Euclidean distance in Panel E and find that Black elasticities are about 20% lower because they commute via slower modes of transport. Lastly, In Appendix Table A.12, I instrument the PPML estimates via a control function approach following Wooldridge (2015) and bootstrap standard errors. These values concur with the previous PPML estimates, so instrumenting is not crucial.

E.2.3 Instruments for Estimation of Endogenous Amenities/Preferences

There are two endogenous variables $\{\Delta \log CMA_{igr}, \Delta \log(L_{iW}/L_i)\}$ with corresponding instruments. The instrument for CMA changes over time for all specifications comes from CMA where the plans or ray network are converted into Interstate highways. For example, CMA with the planned network is defined as $\mathbb{Z}_{igr}^{Plans} = \frac{1}{\phi}\left(\log \sum_j \omega_{jgr,1960}/d_{ijgr}^{Plans\,\phi}\right) - \frac{1}{\phi}\left(\log \sum_j \omega_{jgr,1960}/d_{ijgr,1960}{}^{\phi}\right)$ and $\mathbb{Z}_{igr}^{Rays}$ is the same measure with commute times in the post period from the ray network. The rest of the instruments described below are for racial composition changes.

Hausman Instruments – Instruments following Hausman (1996); Berry et al. (1995) are changes in rental prices and commuter market access (CMA) within the rings of 3-5 miles, 5-10 miles, and 10-15 miles away from each neighborhood. Commute times come from converting the planned routes and ray network into Interstate highways to produce more exogenous variation. For example, CMA changes with the planned routes for neighborhoods 3-5 miles away is denoted $\mathbb{Z}_{igr,3-5}^{Plans} = \{\mathbb{Z}_{sgr}^{Plans}\ \forall s : \text{dist}(i,s) \geq 3, \text{dist}(i,s) < 5\}$. Therefore, the set of instruments for racial composition changes $\Delta \log(L_{iw}/L_i)$ are $\{\Delta \log Q_{i,3-5}, \Delta \log Q_{i,5-10}, \Delta \log Q_{i,10-15}, \mathbb{Z}_{igr,3-5}^{Plans}, \mathbb{Z}_{igr,5-10}^{Plans}, \mathbb{Z}_{igr,10-15}^{Plans}\}$ or the corresponding set with rays.

Davis Instruments – Instruments following Davis et al. (2019) come from a 3-step process. The first step requires estimating Equation 6 with all the base and geographic controls and city effects. In addition, racial composition changes are included as a control rather than an endogenous variable of interest. The highway variation is only used for estimating residential elasticity θ_r as the coefficient on $\Delta \log CMA_{igr}$ where the instruments for CMA changes are $\mathbb{Z}_{igr}^{Plans}$ (or $\mathbb{Z}_{igr}^{Rays}$) as well as the CMA Hausman instruments for additional power $\{\mathbb{Z}_{igr,3-5}^{Plans}, \mathbb{Z}_{igr,5-10}^{Plans}, \mathbb{Z}_{igr,10-15}^{Plans}\}$ (or the set with rays). The elasticity

[38] Accounting for zeros in bilateral pairs still leaves the observation count of the less-educated Black population at 22000 below that of the higher-educated White population as there are cases of residential and workplace units without any Black workers, and PPML only adjusts for *bilateral* counts of zero.

estimates are presented in Table A.10 with values from Column 2 entering into the next step. Setting $\theta_N = 0.62, \theta_W = 0.75$ and taking the estimate of local costs from Brinkman and Lin (2022) where $b_{HW} = 0.175, \eta = 1.28$, I solve the quantitative model where endogenous amenities are removed. I simulate the construction of Interstate highways only for segments between 1960 and 1970. This counterfactual predicts racial composition changes under the assumption that other fundamentals of amenities and productivity are unchanged $\Delta\bar{b}_{igr} = 0$, $\Delta a_j = 0$. The prediction for racial composition L'_{iW}/L'_i is used for the calculation of racial composition changes in the instrument $\Delta \log(L_{iW}/L_i)' = \log(L'_{iW}/L'_i) - \log(L_{iW,1960}/L_{i,1960})$. The final set of instruments also includes the CMA Hausman instruments for additional power $\{\mathbb{Z}^{Plans}_{igr,3-5}, \mathbb{Z}^{Plans}_{igr,5-10}, \mathbb{Z}^{Plans}_{igr,10-15}\}$ (or the set with rays) in the last step.

CMA Instruments – Following that there are race-specific responses to CMA, the final set of instruments are CMA for each group separately. Variation in commute times again comes from either the planned routes or ray network for exogeneity. The instruments are $\{\mathbb{Z}^{Plans}_{iLN}, \mathbb{Z}^{Plans}_{iHN}, \mathbb{Z}^{Plans}_{iLW}, \mathbb{Z}^{Plans}_{iHW}\}$ or the corresponding set with the ray network.

E.2.4 Localized Costs

The population response is due to not just the direct negative consequences of highways but also the indirect changes in racial composition. I therefore set the composite amenity term $B_{igr} = b_{igr}(L_{iW}/L_i)^{\rho_r}$ as another outcome in Column 4 to include the indirect amenity impacts. I find endogenous amenities explain a small portion of the population drop by highways since the estimated value is only slightly more negative at $\Delta \log B_{igr} = -0.124$ (0.0517). Instrumented results are shown in Table A.14 and are too noisy to measure values precisely. In Table Appendix A.15, I project modern-day measures of environmental pollution over distance from Interstate roads and find a 2% increase within the first mile, which is a strong lower bound on pollution during Interstate construction as from the 1960s to today, car pollutants have been reduced by 99%.[39]

In a falsification test, I measure whether there were fundamental amenity changes near other historical large roads. Roads may have universally become more congested or polluted, and declines near Interstate highways may not be a distinctive feature that should be counted fully for welfare impacts. I replace the distance bins from Interstate roads with distance bins from historical control roads that were never re-built $\{\mathbf{1}\{DistLARGE_i = k\}_{k=1,\ldots,5}\}$. Falsification results in Column 4 indicate no change in amenities near large roads with the estimate at 1 mile being very close to zero at -0.0057 (0.137). The negative consequences are thus a unique aspect of Interstate routes where their massive size and elevated ramps were particularly unpleasant for neighboring areas (Rose and Mohl, 2012).

E.2.5 Linear prediction of housing consumption share from CEX data

I assign the housing consumption share for each race by education by first estimating a linear function for housing expenditure over income from the Consumer Expenditure

[39] The Clean Air Act of 1970 was the first of many federal legislative efforts to reduce air pollution.

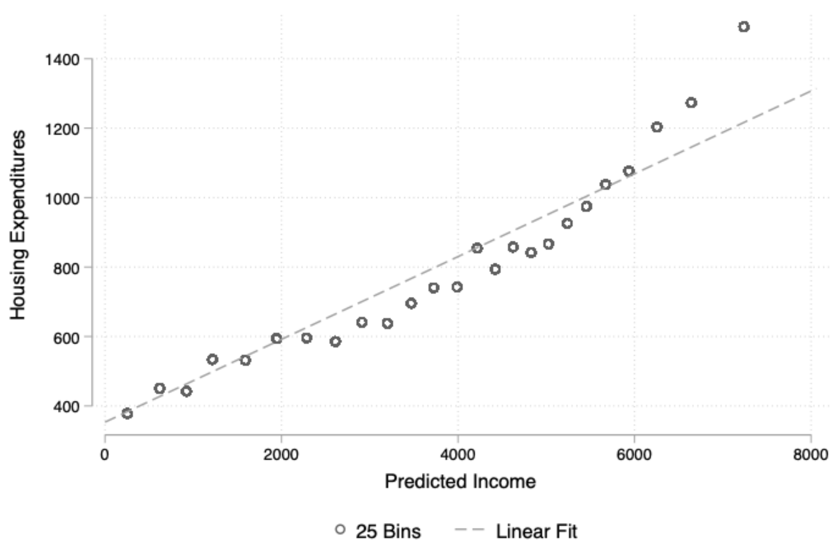
Surveys Public-Use Microdata in the year 1980.

$$E_i^{hous} = \beta_{gr}^0 + \beta_{gr}^1 PredIncome_i + \epsilon_i$$

E_i^{hous} is quarterly housing expenditure and $PredIncome_i$ is quarterly income predicted using categorical variables in age, education, marital status, occupation, sex, race and region. I use predicted rather than observed income given the variability in observed income that would lead to downward biased estimates of β_{gr}^1.

As depicted in Figure E.8, the assumption of linearity for the housing consumption Engel curve appears to be satisfied. From this expenditure function, I calculate the predicted housing expenditure for each race by education group given their average income and use the ratio of predicted housing expenditure to average income as the housing consumption share.

Figure E.8: Linear Housing Expenditure Function Over Income



Notes: Unit of observation is individual. Data comes from the Consumer Expenditure Surveys Public-Use Microdata in 1980. Predicted income is a linear prediction of income using categorical variables in age, education, marital status, occupation, sex, race and region. Income and housing expenditure is for quarterly amounts. 25 equally sized bins in predicted income (when predicted income is greater than zero) are created for the scatter. The linear fit uses the estimated coefficients from Table A.16.

E.2.6 External Parameters

In the production function, the labor share is set to 0.7 following findings in Greenwood et al. (1997). The elasticity of substitution by education σ^g in the CES labor aggregate comes from Card (2009) which uses the education categories of high school versus college educated. Estimates range from 1.4 to 3 and are corroborated by several other sources, so I set $\sigma^g = 2$ (Borjas, 2003; Ottaviano and Peri, 2012). The elasticity of substitution by race is taken from Boustan (2009) to be $\sigma^r = 8$. Housing supply elasticity values are obtained from Baum-Snow and Han (2021) and set to differ in the central city (within 5 miles of the CBD) where $\mu_{cbd} = 0.35$ versus the suburbs (all other neighborhoods) where $\mu_{sub} = 0.25$. Lastly, the agglomeration parameter is set to 0.07 within the range of Rosenthal and Strange (2004) and Kline and Moretti (2014).

E.2.7 Border Discontinuity

In Appendix Table A.26, I take a reduced form approach to decomposing the discontinuity, reducing the reliance on exact parameter magnitudes. Instead of using the parameters to invert for amenities, I residualize population on prices and commuter access, racial composition, and demographic controls successively with redlining fixed effects, using the cross-sectional variation within neighborhood types, and project the residuals onto the border. This cross-sectional variation likely contains bias compared to the estimated parameters, but I report the results as a robustness check. The estimates are broadly the same where in Column 4, the discontinuity is still large for Black households at 0.489 (0.204) and continues to be zero for White households at 0.021 (0.079).

Lastly, I present additional results in Appendix Table A.25. In Panel A, I probe the sensitivity of the drop in percent White across the redlined border by: (1) adding and removing the border fixed effects, (2) forming balanced samples where the number of tracts on the redlined and non-redlined sides is the same, and (3) altering the restrictiveness of how many neighborhoods are dropped away from physical barriers and school district borders. These adjustments do not greatly alter the findings. I further display in Panel B the border discontinuity estimates for control variables used to residualize the fundamental amenities. Lastly, I show how segregation along the border has changed over time from 1950 to 1990. The discontinuity in racial composition was largest in 1960 and 1970 and declined dramatically in 1980 after a decade of fair housing initiatives post Civil Rights legislation.

F Welfare and Counterfactuals

F.1 Derivation of Direct Impacts to Welfare

This section derives the approximation of changes in welfare from total differentiating Equation (7) with respect to the two variables that are changing due to the Interstate highway system: commute times t_{ijgr} and amenities B_{igr}. Assuming that commute times only affect commuter access and amenities do not affect any other indirect residential characteristics such as prices, the approximation is then

$$d \log U_{gr} = \sum_{i,j} \frac{\partial \log U_{gr}}{\partial t_{ijgr}} \Delta t_{ijgr} + \sum_{i} \frac{\partial \log U_{gr}}{\partial B_{igr}} \Delta B_{igr}$$

For ease of notation, define the location-specific utility shifter for neighborhoods, ignoring the idiosyncratic shock, as $V_{igr} = B_{igr} CMA_{igr} Q_i^{\beta_{gr}-1}$. Calculating the partial derivative for amenities first, the expression is as follows

$$\begin{aligned}\frac{\partial \log U_{gr}}{\partial B_{igr}} &= \frac{1}{\theta_r}\frac{\partial V_{igr}^{\theta_r}/\partial B_{igr}}{\sum_s V_{sgr}^{\theta_r}} \\ &= \frac{V_{igr}^{\theta_r-1}}{\sum_s V_{sgr}^{\theta_r}} CMA_{igr} Q_i^{\beta_{gr}-1} \\ &= \pi_{igr}/B_{igr}\end{aligned}$$

where the last step substitutes in the residential share. A similar first step precedes calculating the partial derivative for commute times.

$$\begin{aligned}\frac{\partial \log U_{gr}}{\partial t_{ijgr}} &= \frac{1}{\theta_r}\frac{\partial V_{igr}^{\theta_r}/\partial t_{ijgr}}{\sum_s V_{sgr}^{\theta_r}} \\ &= \frac{V_{igr}^{\theta_r-1}}{\sum_s V_{sgr}^{\theta_r}} B_{igr} Q_i^{\beta_{gr}-1} \left(\partial CMA_{igr}/\partial t_{ijgr}\right) \\ &= \frac{V_{igr}^{\theta_r-1}}{\sum_s V_{sgr}^{\theta_r}} B_{igr} Q_i^{\beta_{gr}-1} \left(-\Phi_{igr}^{\frac{1}{\phi}} \frac{T_{jgr}(w_{jgr}/d_{ijgr})^{\phi}}{\Phi_{igr}} \frac{\kappa_{gr}}{t_{ijgr}}\right) \\ &= -\frac{V_{igr}^{\theta_r}}{\sum_s V_{sgr}^{\theta_r}} \frac{T_{jgr}(w_{jgr}/d_{ijgr})^{\phi}}{\Phi_{igr}} \frac{\kappa_{gr}}{t_{ijgr}} \\ &= -\pi_{igr}\pi_{j|igr}\frac{\kappa_{gr}}{t_{ijgr}}\end{aligned}$$

where the last step substitutes in the residential share and the conditional commuting share. Finally, note that $\Delta B_{igr}/B_{igr} = (-b_{highway}\exp(-\eta d_{i,highway}))$ so the direct impact to welfare is

$$d\log U_{gr} = -\sum_{i,j} \pi_{igr}\pi_{j|igr}\kappa_{gr}\Delta t_{ijgr}/t_{ijgr} - \sum_i \pi_{igr} b_{highway}\exp(-\eta d_{i,highway})$$

F.2 Solving for the Partial Equilibrium Counterfactual

To solve for the model counterfactuals, I employ a combination of observed data on travel times and city-level population $\{t_{ijgr}, \mathbb{L}_{gr}\}$, model parameters $\{\beta_{gr}, \kappa_{gr}, \phi, \theta_r, \mu\}$ with the externality parameter $\{\rho_r\}$, location fundamentals from the inversion process $\{b_{igr}\}$, and other location characteristics inferred during model inversion $\{k_i\}$. Equilibrium objects on the workplace side are fixed to their initial values for $\{w_{jgr}^0, \theta_i^0\}$. I assume starting values for the endogenous variables that correspond to the observed equilibrium for housing prices and the partially endogenous amenities $\{Q_i^0, B_{igr}^0\}$. From these starting values, I iterate following the equilibrium conditions of the model to reach a new equilibrium

$\{Q_i^1, B_{igr}^1\}$.

$$\pi_{Rigr}^1 = \frac{\left(B_{igr}^0 CMA_{igr}(Q_i^0)^{\beta_{gr}-1}\right)^{\theta_r}}{\sum_t \left(B_{tgr}^0 CMA_{tgr}(Q_{tr}^0)^{\beta_{gr}-1}\right)^{\theta_r}} \quad \text{with } CMA_{igr} = \Phi_{igr}^{\frac{1}{\phi}}$$

$$\Phi_{igr} = \sum_s T_{sgr}(w_{sgr}^0/d_{isgr})^{\phi}$$

$$L_{Rigr}^1 = \pi_{Rigr}^1 \mathbb{L}_{gr}$$

$$Q_i^1 = \left(\frac{Exp_i}{\theta_i^0 k_i}\right)^{\mu} \quad \text{with } Exp_i = \sum_{g,r}(1-\beta_{gr})\left(\sum_j \pi_{j|igr} w_{jgr}^0\right) L_{Rigr}^1$$

$$\text{and } \pi_{j|igr} = \frac{T_{jgr}(w_{jgr}^0/d_{ijgr})^{\phi}}{\sum_s T_{sgr}(w_{sgr}^0/d_{isgr})^{\phi}}$$

$$B_{igr}^1 = b_{igr}(L_{RiW}^1/L_{Ri}^1)^{\rho_r^R}$$

I continue the iterative procedure until the endogenous variables converge such that

$$\left\| \{Q_i^0, B_{igr}^0\} - \{Q_i^1, B_{igr}^1\} \right\| < \epsilon$$

for some tolerance level ϵ. Before I reach that point, I update the endogenous variables as weighted averages of the initial values and the predicted values with $\lambda \in (0,1)$ following

$$Q_i^2 = \lambda Q_i^1 + (1-\lambda) Q_i^0$$
$$B_{igr}^2 = \lambda B_{igr}^1 + (1-\lambda) B_{igr}^0$$

F.3 Solving for the General Equilibrium Counterfactual

To solve for the model counterfactuals, I employ a combination of observed data on travel times and city-level population $\{t_{ijgr}, \mathbb{L}_{gr}\}$, model parameters $\{\beta_{gr}, \kappa_{gr}, \phi, \theta_r, \alpha, \alpha_{jg}, \alpha_{jgr}, \sigma^g, \sigma^r, \mu\}$ with the externality parameters $\{\rho_r, \gamma^A\}$, location fundamentals from the inversion process $\{b_{igr}, a_i\}$, and other location characteristics inferred during model inversion $\{k_i, T_{jgr}\}$. I assume starting values for the endogenous variables that correspond to the observed equilibrium for wages, prices, distribution of rents, floorspace allocation and the partially endogenous amenities and productivity $\{w_{jgr}^0, Q_i^0, \theta_i^0, B_{igr}^0, A_i^0\}$. From these starting values, I iterate following the equilibrium conditions of the model to reach a new equilibrium $\{w^1_{jgr}, Q^1_i, \theta^1_i, B^1_{igr}, A^1_j\}$.

$$\pi^1_{Rigr} = \frac{\left(B^0_{igr} CMA_{igr} (Q^0_i)^{\beta_{gr}-1}\right)^{\theta_r}}{\sum_t \left(B^0_{tgr} CMA_{tgr} (Q^0_{tr})^{\beta_{gr}-1}\right)^{\theta_r}} \quad \text{with } CMA_{igr} = \Phi_{igr}^{\frac{1}{\phi}}$$

$$\Phi_{igr} = \sum_s T_{sgr} (w^0_{sgr}/d_{isgr})^{\phi}$$

$$L^1_{Rigr} = \pi_{igr} \mathbb{L}_{gr}$$

$$\pi^1_{j|igr} = \frac{T_{jgr}(w^0_{jgr}/d_{ijgr})^{\phi}}{\sum_s T_{sgr}(w^0_{sgr}/d_{isgr})^{\phi}}$$

$$L^1_{Fjgr} = \sum_i \pi_{j|igr} L^1_{Rigr}$$

$$Y^1_i = A_i N_i^{\alpha} H_{Fi}^{1-\alpha} \quad \text{with } N_{jg} = \left(\sum_r \alpha_{jgr} (L^1_{Fjgr})^{\frac{\sigma^r - 1}{\sigma^r}}\right)^{\frac{\sigma^r}{\sigma^r - 1}} \quad N_j = \left(\sum_g \alpha_{jg} N_{jg}^{\frac{\sigma^g - 1}{\sigma^g}}\right)^{\frac{\sigma^g}{\sigma^g - 1}}$$

$$N_i = N_j / S_j \text{ for } i \in Tracts_j$$

$$H_{Fi} = (1 - \theta^0_i) k_i (Q^0_i)^{\frac{1-\mu}{\mu}}$$

$$Q^1_i = \left(\frac{Exp_i + (1-\alpha) Y^1_i}{k_i}\right)^{\mu} \quad \text{with } Exp_i = \sum_{g,r} (1 - \beta_{gr}) \left(\sum_j \pi^1_{j|igr} w^0_{jgr}\right) L^1_{Rigr}$$

$$\theta^1_i = \frac{Exp_i}{(Q^1_i)^{\frac{1}{\mu}} k_i}$$

$$w^1_{jgr} = (\alpha_{jgr} \omega_{jg}) \left(\frac{\alpha_{jg} W_j}{\omega_{jg}}\right)^{\frac{\sigma^g}{\sigma^r}} \left(\frac{\alpha Y^1_j}{W_j L^1_{Fjgr}}\right)^{\frac{1}{\sigma^r}} \text{ with } \omega_{jg} = \left(\sum_r \alpha_{jgr}^{\sigma^r} (w^0_{jgr})^{1-\sigma^r}\right)^{\frac{1}{1-\sigma^r}}$$

$$W_j = \left(\sum_g \alpha_{jg}^{\sigma^g} \omega_{jg}^{1-\sigma^g}\right)^{\frac{1}{1-\sigma^g}} \qquad Y^1_j = \sum_{i \in Tracts_j} Y^1_i$$

$$B^1_{igr} = b_{igr} (L^1_{RiW} / L^1_{Ri})^{\rho_r}$$

$$A^1_i = a_i (L^1_{Fj} / K_j)^{\gamma^A} \text{ for } i \in Tracts_j$$

I continue the iterative procedure until the endogenous variables converge such that

$$\left\| \{w^0_{jgr}, Q^0_i, \theta^0_i, B^0_{igr}, A^0_j\} - \{w^1_{jgr}, Q^1_i, \theta^1_i, B^1_{igr}, A^1_j\} \right\| < \epsilon$$

for some tolerance level ϵ. Before I reach that point, I update the endogenous variables as weighted averages of the initial values and the predicted values with $\lambda \in (0,1)$ following

$$\begin{aligned}
w_{jgr}^2 &= \lambda w_{jgr}^1 + (1-\lambda) w_{jgr}^0 \\
Q_i^2 &= \lambda Q_i^1 + (1-\lambda) Q_i^0 \\
\theta_i^2 &= \lambda \theta_i^1 + (1-\lambda) \theta_i^0 \\
B_{igr}^2 &= \lambda B_{igr}^1 + (1-\lambda) B_{igr}^0 \\
A_j^2 &= \lambda A_j^1 + (1-\lambda) A_j^0
\end{aligned}$$

F.4 Sufficient Conditions for Uniqueness of Equilibria

The equilibrium defined has many sources of spillovers. The most immediate are through endogenous amenities and productivity from racial composition and agglomeration. Additional spillovers emerge through inelastic land generating a congestion force in housing supply and the idiosyncratic preferences of individuals creating dispersion forces. As the wages of each group depend on the labor supply of other workers, there are productivity spillovers across groups at workplaces.

I follow Allen et al. (2022) where I rewrite the equilibrium conditions as a set of H types of economic interactions conducted by the set of N heterogeneous agents. I then construct the $H \times H$ matrix of the uniform bounds of the elasticities on the strength of economic interactions. The equilibrium system falls under a constant elasticity form that is commonly used in spatial economics. Building on Tsivanidis (2022), I reformulate the CMA measures as solutions to a system of equations in residential and workplace populations and commute costs. With these conditions on model parameters, I derive theory-consistent equations to estimate parameter values in the next section.

First, I rewrite the equilibrium conditions in a form that adheres to the constant elasticity system of Allen et al. (2022) where spillovers are of an exponential form. I further allow the elasticities to differ by the type of the agent.

$$x_{ih} = f_{ijh}(x_j) = \sum_{j \in \mathcal{N}} K_{ijh} \prod_{h' \in \mathcal{H}} x_{jh'}^{\alpha_{ihh'}}$$

In this setting, type $\mathcal{N}$ can be a combination of location $i \in \{1, \ldots, S\}$, education $g \in \{L, H\}$, and race $r \in \{B, W\}$. The set of economic interactions $\mathcal{H}$ include population, prices, amenities, and productivity. Define the city-level constant following $\lambda_{gr} = \mathbb{L}_{gr} U_{gr}^{-\theta_r}$.

The equilibrium conditions are the stacked set of equations

$$
\begin{aligned}
L_{igr} &= \lambda_{gr}\left(B_{igr}Q_i^{\beta_{gr}-1}\Phi_{igr}^{\frac{1}{\phi}}\right)^{\theta_r} \\
L_{Fjgr} &= \lambda_{gr}T_{jgr}w_{jgr}^{\phi}\Phi_{Fjgr} \\
\Phi_{igr} &= \lambda_{gr}\sum_j d_{ijgr}^{-\phi}\frac{L_{Fjgr}}{\Phi_{Fjgr}} \\
\Phi_{Fjgr} &= \lambda_{gr}\sum_i d_{ijgr}^{-\phi}\frac{L_{igr}}{\Phi_{igr}} \\
N_i^{(\sigma_g-1)/\sigma_g} &= \sum_g \alpha_{ig}N_{ig}^{(\sigma_g-1)/\sigma_g} \\
N_{ig}^{(\sigma_r-1)/\sigma_r} &= \sum_r \alpha_{igr}L_{Figr}^{(\sigma_r-1)/\sigma_r} \\
Y_i &= A_i^{1/\alpha}N_i(1-\alpha)^{(1-\alpha)/\alpha}Q_i^{(\alpha-1)/\alpha} \\
\overline{w}_{igr} &= \sum_j T_{jgr}w_{jgr}^{\phi+1}d_{ijgr}^{-\phi}\Phi_{igr}^{-1} \\
Q_i^{\frac{1}{\mu}} &= k_i^{-1}\left(\sum_{g,r}(1-\beta_{gr})\overline{w}_{igr}L_{igr}+(1-\alpha)Y_i\right) \\
w_{jgr} &= \alpha_{jgr}(\omega_{jg})^{\frac{\sigma_r-\sigma_g}{\sigma_r}}\alpha_{jg}^{\frac{\sigma^g}{\sigma^r}}W_j^{\frac{\sigma^g-1}{\sigma^r}}\left(\alpha Y_j\right)^{\frac{1}{\sigma^r}}L_{Fjgr}^{-\frac{1}{\sigma_r}} \\
\omega_{jg}^{1-\sigma^r} &= \sum_r \alpha_{jgr}^{\sigma^r}w_{jgr}^{1-\sigma^r} \\
W_j^{1-\sigma^g} &= \sum_g \alpha_{jg}^{\sigma^g}\omega_{jg}^{1-\sigma^g} \\
L_{iW} &= \sum_g L_{igW} \\
L_i &= \sum_{g,r} L_{igr} \\
B_{igr} &= b_{igr}L_{iW}^{\rho_r}L_i^{-\rho_r} \\
A_j^{1/\gamma^A} &= \frac{a_j^{1/\gamma^A}}{K_j}\sum_{g,r}L_{Fjgr}
\end{aligned}
$$

Almost all of the elasticities $\epsilon_{ijh,jh'}(x_j) = \frac{\partial \log f_{ijh}(x_j)}{\partial \log x_{jh'}}$ are of the form $\epsilon_{ijh,jh'}(x_j) = \alpha_{hh'}$ except for the elasticity to price and the spillovers of racial composition on residential location choices. Let $\beta = \min_{g,r}\{\beta_{gr}\}$ where $\beta_{g,r} > 0$, $\rho = \max_r\{|\rho_r|\}$, and $\theta = \max_r\{\theta_r\}$. Then the $H \times H$ matrix $(\mathbf{A})_{hh'}$ where $H = 16$ is

$$\begin{bmatrix}
0 & 0 & \theta/\phi & 0 & 0 & 0 & 0 & 0 & \mu(\beta-1)\theta & 0 & 0 & 0 & 0 & 0 & \theta & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & \phi & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & \frac{(\sigma_g-1)\sigma_r}{(\sigma_r-1)\sigma_g} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & (\frac{\sigma_r-1}{\sigma_r}) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & (\frac{\sigma_g}{\sigma_g-1}) & 0 & 0 & 0 & \mu(\frac{\alpha-1}{\alpha}) & 0 & 0 & 0 & 0 & 0 & 0 & \frac{\gamma^A}{\alpha} \\
0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & \phi+1 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & -\frac{1}{\sigma_r} & 0 & 0 & 0 & 0 & \frac{1}{\sigma_r} & 0 & 0 & 0 & \frac{\sigma_r-\sigma_g}{\sigma_r(1-\sigma_r)} & -\frac{1}{\sigma_r} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-\sigma_r & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1-\sigma_g}{1-\sigma_r} & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho^R & -\rho^R & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

Following Allen et al. (2022) Theorem 1 Part (i), a sufficent condition for uniqueness is that the spectral radius $\rho(A) < 1$. At the current parameter values in Table 8, $\rho(A) > 1$. However, unique equilibria may exist with the listed parameters as the above condition is sufficient but not necessary for uniqueness.

G Data

Decennial Census Microdata

The Decennial Census is the data source for all of the quantitative estimation. Residential population, workplace population, commute flows, rental prices, and other characteristics of locations come from the Decennial Census microdata in 1960 and 1970. The decade between these two censuses covers a substantial portion of highway construction as by 1960, 20% of the national network was completed, and by 1970, 71% was completed.

- **Residences** – Residential geographic units are census tracts that represent neighborhoods with the usual tract containing 2,500 to 8,000 people. In 1960, there were 42,689 tracts across the United States but not all of the country was contained within tracts. By 1990, the entire country fell under some tract definition, and in 2010, there were 73,175 tracts. Tracts are re-defined across census surveys as population levels across neighborhoods change, so I interpolate all tract-level aggregates to consistent tract definitions with the Longitudinal Tract Database to match 2010 Census delineations (see more below) (Logan et al., 2014). The shapefile for 2010 census tract definitions is retrieved from IPUMS NHGIS.

- **Workplaces** – I construct geographic units which I define as Place of Work (POW) Zones from the Journey to Work questions of the 1960 Census, the first survey in which the Census Bureau asked for location of employment. County and municipality of place of work are reported as 1960-specific Universal Area Codes (UAC), and from these UACs, I calculate the smallest intersection of county and municipality to create the POW Zone. These POW Zones are then overlayed on 1960 tract definitions to create a spatial unit and mapped into 2010 tract boundaries with a crosswalk between 1960 and 2010 tracts. As the UAC for place of work is missing for some observations, I reweight the microdata by calculating inverse probability weights based on observed demographic variables of age, age squared, educational attainment, employment status, total income, wages, industry, occupation, a poverty indicator, race, gender, mode of transport, weeks worked, and a urban/rural indicator. In 1970, place of work is available for UACs, although 1970 UACs are different units from 1960 UACs. For some observations, place of work at the tract level is observed. The inverse probability weights for the 1970 Census are based on whether UAC is observed. For those with tract-level place of work, I assign them to the tract. For those with only UAC, I evenly distribute them across the tracts that are in the UAC. The 1970 tract reweighted sums are then mapped into the 1960 POW zones using a crosswalk between 1970 tracts and 2010 tracts to create a panel of workplace data from 1960 to 1970.

- **Cities** – Cities are represented by Metropolitan Statistical Areas out of the Core-Based Statistical Areas (CBSAs) from 2010 Census definitions. The quantitative analysis requires granular data on commute flows to workplaces from the Decennial microdata in 1960 and 1970. To create the POW Zone, the sample of cities is smaller. While some cities have many unique counties and municipalities, others have very few. For there to be sufficient spatial granularity in place of work, I limit the sample of cities to 25 of the largest, and these cities in total contain 406 POW Zones. I provide the list of cities with available data in Appendix Table G.29. For the motivating empirical analysis, the sample of cities is limited to the 100 cities with Yellow Book maps using public-use tract-level aggregates from NHGIS (see below).

- **Commuting** – With residences as tracts and workplaces as POW zones, commute flows are constructed from population counts over the cross-product of residences and workplaces and are comparable to the widely used Census Transportation Planning Package (CTPP) for commuting after 1990. Starting with the 1980 census, commute times are reported in the Journey to Work section. While individuals may be using non-automobile modes of transport during this time, the lack of data on public transit across a large set of cities makes analysis of other modes difficult. I account for commuting through other methods by assuming public transit systems and walking have not changed in speed from 1960 to 1980 and take reported commute times from the 1980 Decennial Census microdata, the first census survey with commute time data. I non-parametrically estimate non-automobile commute times over 15 bins of Euclidean distance for bilateral pairs of tract of residence and POW Zone and 3 bins of distance from the CBD for both residences and workplaces. The

15 bins of Euclidean distance are fully interacted with the 3 residential bins and 3 workplace bins. Adjusting for distance from the central city captures how car usage is greater when workers live in the suburbs or commute to the suburbs for employment. For each race and education group, I similarly create mode of transport weights over the interaction of bins of Euclidean distance in 1960 and 1970 and bins of distance from the CBD for residences and workplaces. Weighted commute times are averages using the weight for automobile modes (private auto, carpool, van or truck) with the computer generated commuting times for the road network (see below) and the weight for non-automobile modes with the binned commute times from above.

- **Race by Education Tabulations** – To tabulate the population counts, the Census Long-Form person-level sample (25% in 1960 and 15% in 1970) is limited to workers and divided into race and education categories. Person-level sampling weights from the Census are used for all tabulations. Race is divided into White and Non-White as finer splits of race leave too few counts for smaller geographic units. Education is also separated into two categories where those with a high school degree or higher are considered highly-educated and those without a high school degree are considered less-educated. Wages are then calculated for each geographic unit by race and education.

- **Housing Prices** – Housing price data come from the household-level sample with household sampling weights used for all tabulations. Quality-adjusted rents per unit are calculated by taking the rent and residualizing out housing characteristics of the number of rooms, bedrooms, and bathrooms,the availability of a basement, kitchen, heat, hot water, shower/bathtub, indoor toilet, and the year built (setting as the base price the average over the fitted values of housing characteristics for the CBSA and then adding in the neighborhood fixed effects for each neighborhood).

Digitized Roads and Highway Routes

- **Historical Urban Roads** – To capture commuting on the road network prior to Interstate construction, I digitize maps of historical U.S. and state highways and major roads from Shell Atlases in 1951 and 1956 (Rumsey, 2020). To create maps of the historical roads, I start with a highly accurate digital map of modern day major roads from ESRI (2019). I remove Interstate highways and keep major roads less than a freeway, other major roads, and secondary roads as a starting point for the historical map roads. I then georeference the Shell map images in ArcMap and edit the modern day major roads file to match the historical roads maps. I categorize the historical roads into two groups: Superhighways and other major roads following the legend of the Shell Atlases. Maps from 71 cities were digitized as shown in Appendix Table G.29. Examples for Baltimore, MA and San Francisco, CA are shown in Figure G.9.

- **Yellow Book Plans** – I retrieve maps of the planned routes from the *General Location of National System of Interstate Highways Including All Additional Routes at Urban*

Areas Designated in September 1955, commonly known as the Yellow Book, for plans of Interstate highways within cities. While maps for 100 cities are available, some cities are located within the same CBSA (e.g. Dallas and Fort Worth) and some are Micropolitan Statistical Areas. For these reasons, in Appendix Table G.29, only 96 cities are shown. These planned maps were originally used by Brinkman and Lin (2022), and I manually digitized them for this project in ArcMap by georeferencing the map images and creating the spatial lines. Examples for Atlanta, GA and Cleveland, OH are depicted in Figure G.10.

- **National 1947 Plan** – I digitize a map of the 1947 plan of national highway routes from Baum-Snow (2007). This map has less spatial granularity compared to the Yellow Book plans but conveys the direction of routes between cities and which cities the Interstate system was designed to connect. The 1947 plan and Yellow Book maps are consolidated into one planned network.

- **Euclidean Rays** – I construct an additional network of highway routes following the planned routes where I connect cities and towns in the planned maps with straight line rays. This network follows the "inconsequential units" approach where neighborhoods that happen to be located between major cities are treated by the Interstate highway system.

- **Constructed Highways** – The constructed Interstate system comes from MIT Libraries' file of Interstate Highways in 1996 (ESRI, 1996). I exploit the panel variation in when different segments were built by combining this constructed network map with the PR-511 database on dates of construction from Baum-Snow (2007) to examine changes only on routes constructed between 1960 and 1970.

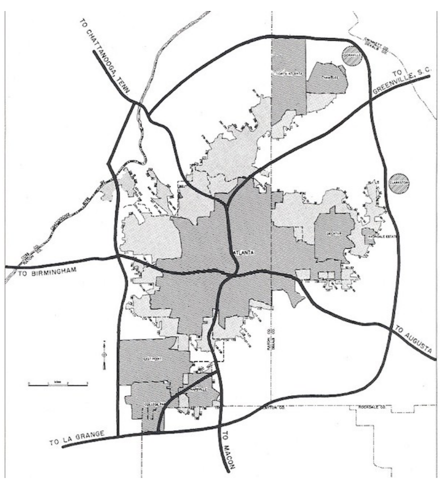
Figure G.9: Historical Roads from Shell Atlases for Baltimore and San Francisco

(a) Baltimore, Maryland

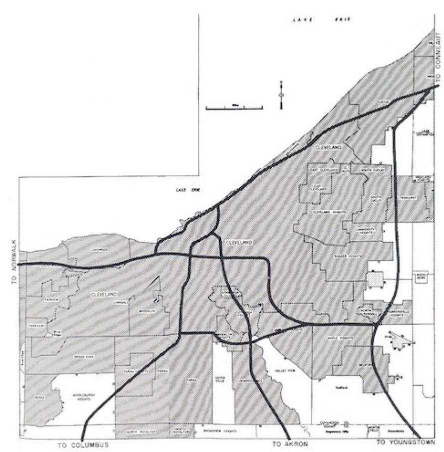
(b) San Francisco, California

Notes: Shell Atlases by the H.M. Gousha Company in 1956 retrieved from the Rumsey Collection for Baltimore and San Francisco.

Figure G.10: Yellow Book Maps for Atlanta and Cleveland



(a) Atlanta, Georgia



(b) Cleveland, Ohio

Notes: Yellow Book (General Location of National System of Interstate Highways Including All Additional Routes at Urban Areas Designated in September 1955) maps retrieved from the Bureau of Public Roads.

Commuting Networks

- **Speeds** – To calculate commute times on the road networks, I assume speeds for different segments of the routes. For the historical urban roads, large roads (superhighways) are set to have a speed of 40 mph while other major roads are set to have a speed limit of 30 mph following travel surveys conducted during the 1950-1960 period (Gibbons and Proctor, 1954; Walters, 1961). For constructed highways, I use the speed limit for each segment of the highway. The consolidated planned routes of the 1947 plan and Yellow Book maps do not have associated speed limits, so I assign each 2500 meter segment the speed limit of the nearest constructed highway. The Euclidean ray spanning network is set to 60 mph. Minor errors in assignment of speed limits should not affect the results too much given that for urban highways, speed limits cover a narrow range of 55 mph to 65 mph.

- **Commuting Matrices** – For the period prior to highway construction, I calculate commuting times from each 2010 delineated tract centroid to other tract centroids within the same CBSA using ArcNetwork Analyst. The only road network that is traversable is the major roads from the historical road maps. For the period during highway construction, I retrieve the highway network at two stages mid-construction: for all routes built before 1960 and for all routes built before 1970. I overlay these semi-completed highway networks on the historical road network to calculate commuting times during these intermediate periods to align with the years when data is available from the Decennial Census. Using the planned maps and Euclidean ray networks, I construct commute times for the instruments by overlaying the planned and ray networks instead of the Interstate routes on the historical road network. Since there is some distance from tract centroids to the nearest road, and ArcGIS sets the starting point as the point on the traversable network that is closest to the centroid, I add in the additional travel time from the centroid to the road assuming a travel speed of 20 mph. Least cost travel times between tracts are then generated following Dijkstra's algorithm in ArcGIS Network Analyst for 49 million pairwise comparisons. I validate that the computer generated commute times for the fully constructed highway network overlayed on the historical road network are closely correlated with reported commute times by automobile in the 1980 Census (despite possible further road development) in Table G.28. The 1980 Census is the first census survey with commute time data.

Table G.28: Commuting Time Comparison in 1980

Variables	Reported 1980 Commute Time (Minute)
Generated Commute Time (Minute)	0.683***
	(0.0122)
Constant	10.52***
	(0.395)
R-squared	0.537
Correlation Coefficient	0.733
Rounded Obs	11500

Notes: Unit of observation is Place of Work Zone by Place of Work Zone. Data comes from the 1980 Census for survey reported commute times of workers whose mode of transport is private automobile. Computer generated commute times use the full constructed highway network and historical urban roads. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. Robust standard errors are included in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Geographic Features

- **Historical Rail, Canals, Rivers** – Historical railroad networks from 1826-1911, 19th century canals, and 19th century steam-boat navigated rivers are included as controls (Atack, 2015, 2016, 2017).

- **Natural Features** – Distances to natural features including lakes, shores, and ports come from Lee and Lin (2017) and are included as controls.

- **Central Business Districts** – Centroids of the central business districts of MSAs come from Holian and Kahn (2015) although their list does not cover the full list of cities studies in this paper. To obtain the location of other central business districts, I search for where central business districts are in the modern day (assuming most downtowns do not change their location) for cities in Google Earth.

- **HOLC Redlining** – Redlining maps for the Home Owners' Loan Corporation come from a group of digital historians at Mapping Inequality: Redlining in New Deal America (Nelson et al., 2020). Examples for Los Angeles, CA and New York City, NY are in Figure G.11.

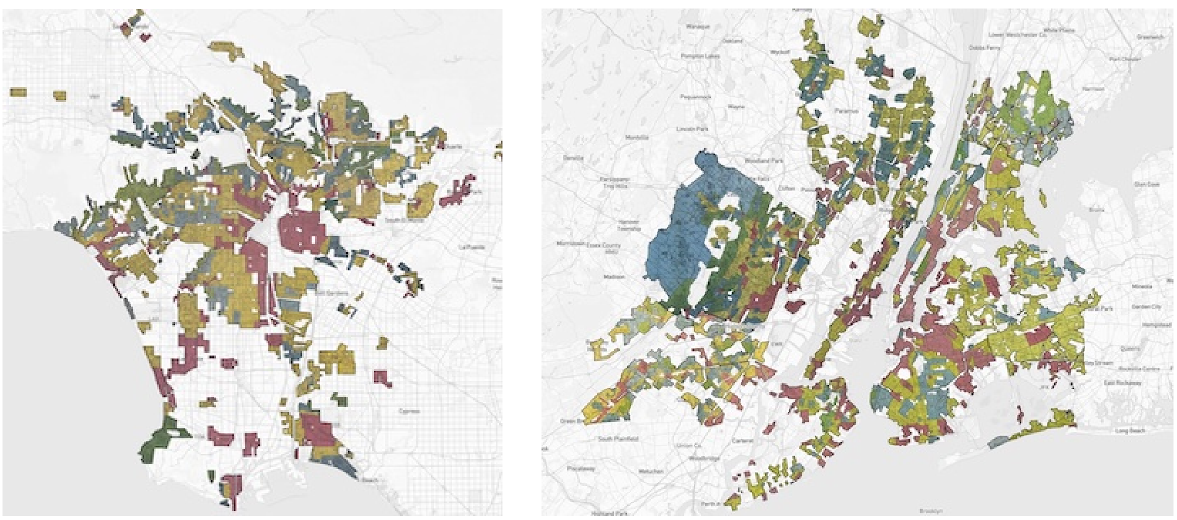
  - **Borders** – To calculate distances from tracts to borders in the HOLC maps for the border discontinuity, I find for each tract the distance to all HOLC map borders. I keep all borders that are within 2 km of the tract centroid. If the tract is redlined, then it has a positive distance from the redlining border. If the tract is non-redlined, the distance is negative.

- **Redlined/Non-Redlined** – I calculate the percentage of each census tract that is redlined by overlaying the 2010 tract boundaries on the HOLC redlining maps. Tracts that are more than 80% covered by HOLC grade D areas are considered redlined. The results are not sensitive to the percentage cut-off as 70 percent of tracts are either 100% or 0% graded D. At the 80% cutoff, 3050 out of 13436 tracts are redlined while at a 50% cutoff, 3761 tracts are redlined.

- **School District Borders** – School district boundaries used for the border design are acquired from the National Center for Education Statistics (NCES) for the 1989-1990 school year.

- **Distances to Features** – I calculate the distance from tract centroids to each of the geographic features above. For the POW zones, I take the average of the distances from tract centroids for the tracts within a POW zone.

Figure G.11: Redlining Maps for Los Angeles and New York City



(a) Los Angeles, California (b) New York City, New York

Notes: HOLC Maps for Los Angeles and New York City from Mapping Inequality: Redlining in New Deal America.

Natural Amenities

- **Land Cover** – The National Land Cover Database (NLCD) from the U.S. Geological Survey provides data nationwide on land cover types at high spatial resolution (30m). I obtain the dataset for 2011 and limit the characteristics to the land cover types of open water, woody wetlands, developed high-intensity, and deciduous forest. Other land cover types that are available include barren land, cultivated crops, and perennial ice and snow.

- **Tree Canopy Cover** – The U.S. Forest Service Science provides a dataset on Tree Canopy Cover (TCC), and I obtain the 2011 version. It is a 30m spatial resolution file with one variable representing the percentage of canopy cover.

- **Overlap of Tracts with Natural Amenities** – I calculate the overlap between each 30m square from the NLCD and TCC datasets with each tract from the census tracts (with 2010 boundaries) shapefile. A weighted average is computed across the squares that overlap with census tracts.

Air Pollution Index

- **Environmental Pollution** – The Centers for Disease Control and Prevention (CDC) National Environmental Public Health Tracking Network generates air quality measures at the census tract-level using the Environmental Protection Agency (EPA)'s Downscaler model for the mean predicted concentration of PM 2.5. I obtain the 2001-2005 daily estimates and aggregate over the 5 years of data to create a tract-level average.

IPUMS NHGIS Public-Use Aggregates

- I construct a panel of tract-level characteristics from the public-use aggregates available at IPUMS NHGIS (Manson et al., 2017) starting from 1950 and ending in 2010. Aggregates include tract-level population by education, race, income, and housing rents and home values. This dataset is interpolated to be consistent with 2010 tract definitions and spans the full set of cities with planned (Yellow Book) maps in the U.S. The panel is unbalanced however as it was not until 1990 that the Census defined tract geographic units for the entire United States.

Longitudinal Tract Crosswalks

- Tract cross-walk weights derived using population overlaps from the Longitudinal Tract Database are available for 1970 to 2010 from Logan et al. (2014) to harmonize tract-level data across decades to 2010 boundaries. Weights for 1950 and 1960 come from Lee and Lin (2017) and are derived from area overlaps.

Table G.29: Cities and Map/Data Availability

Metropolitan Statistical Area	Yellow Book	HOLC	Historical Roads	Census
Albany-Schenectady-Troy, NY	X	X	X	X
Allentown-Bethlehem-Easton, PA-NJ	X	X	X	X
Atlanta-Sandy Springs-Marietta, GA	X	X	X	X
Baltimore-Towson, MD	X	X	X	
Bangor, ME	X			
Baton Rouge, LA	X		X	
Battle Creek, MI	X	X	X	
Birmingham-Hoover, AL	X	X	X	
Boston-Cambridge-Quincy, MA-NH	X	X	X	X
Buffalo-Niagara Falls, NY	X	X	X	
Burlington-South Burlington, VT	X			
Chattanooga, TN-GA	X	X	X	
Chicago-Joliet-Naperville, IL-IN-WI	X	X	X	X
Cincinnati-Middletown, OH-KY-IN	X	X	X	
Cleveland-Elyria-Mentor, OH	X	X	X	X
Columbia, SC	X	X	X	
Columbus, OH	X	X	X	
Dallas-Fort Worth-Arlington, TX	X	X	X	X
Davenport-Moline-Rock Island, IA-IL	X	X		
Denver-Aurora-Broomfield, CO	X	X		
Des Moines-West Des Moines, IA	X	X		
Detroit-Warren-Livonia, MI	X	X	X	X
Erie, PA	X	X	X	
Eugene-Springfield, OR	X			
Flint, MI	X	X	X	
Fort Smith, AR-OK	X		X	
Gadsden, AL	X		X	
Grand Rapids-Wyoming, MI	X	X	X	
Great Falls, MT	X			
Greenville-Mauldin-Easley, SC	X		X	
Harrisburg-Carlisle, PA	X	X	X	
Hartford-West Hartford-East Hartford, CT	X	X	X	X
Houston-Sugar Land-Baytown, TX	X	X	X	X
Indianapolis-Carmel, IN	X	X	X	
Jackson, MS	X	X	X	
Kansas City, MO-KS	X	X	X	X
Kingsport-Bristol-Bristol, TN-VA	X			
Kingston, NY	X		X	
Knoxville, TN	X	X	X	
Lake Charles, LA	X		X	
Lansing-East Lansing, MI	X	X	X	
Lincoln, NE	X	X	X	
Little Rock-North Little Rock-Conway, AR	X	X	X	
Los Angeles-Long Beach-Santa Ana, CA	X	X	X	X
Louisville/Jefferson County, KY-IN	X	X	X	
Macon, GA	X	X		
Manchester-Nashua, NH	X	X		

Notes: The table displays 96 cities because while there are 100 cities in the Yellow Book, not all of them have an associated Metropolitan Statistical Area. Some constitute Micropolitan Statistical Areas, and two cities (Dallas and Fort Worth) are combined into one MSA. The HOLC redlining maps are available for more cities than those listed, but the table is restricted to the sample of Yellow Book maps. Historical road maps are also available for more cities, but for this paper, only 71 are digitized. The Census column indicates which cities are included in the quantitative analysis using Decennial microdata for estimation.

Table G.29: Cities and Map/Data Availability CONTINUED

Metropolitan Statistical Area	Yellow Book	HOLC	Historical Roads	Census
Memphis, TN-MS-AR	X	X	X	
Miami-Fort Lauderdale-Pompano Beach, FL	X	X	X	
Milwaukee-Waukesha-West Allis, WI	X	X	X	
Minneapolis-St. Paul-Bloomington, MN-WI	X	X	X	X
Monroe, LA	X		X	
Montgomery, AL	X	X	X	
Nashville-Davidson–Murfreesboro–Franklin, TN	X	X	X	
New Orleans-Metairie-Kenner, LA	X	X	X	
New York-New Jersey-Long Island, NY-NJ-PA	X	X	X	X
Oklahoma City, OK	X	X	X	
Omaha-Council Bluffs, NE-IA	X	X	X	
Pensacola-Ferry Pass-Brent, FL	X			
Peoria, IL	X	X	X	
Philadelphia-Camden, PA-NJ-DE-MD	X	X	X	X
Phoenix-Mesa-Glendale, AZ	X	X		
Pittsburgh, PA	X	X	X	X
Pocatello, ID	X			
Portland-South Portland-Biddeford, ME	X			
Portland-Vancouver-Hillsboro, OR-WA	X	X	X	X
Providence-New Bedford-Fall River, RI-MA	X	X	X	X
Rapid City, SD	X			
Reading, PA	X		X	X
Richmond, VA	X	X		
Roanoke, VA	X	X		
Rochester, NY	X	X	X	
Saginaw-Saginaw Township North, MI	X	X	X	
St. Joseph, MO-KS	X	X		
St. Louis, MO-IL	X	X	X	X
Salem, OR	X			
San Antonio-New Braunfels, TX	X	X		
San Francisco-Oakland-Fremont, CA	X	X	X	X
Seattle-Tacoma-Bellevue, WA	X	X		
Shreveport-Bossier City, LA	X	X	X	
Sioux Falls, SD	X			
Spartanburg, SC	X		X	
Springfield, MA	X	X	X	X
Syracuse, NY	X	X	X	
Tampa-St. Petersburg-Clearwater, FL	X	X	X	
Toledo, OH	X	X	X	
Topeka, KS	X	X		
Tucson, AZ	X			
Tulsa, OK	X	X	X	
Tuscaloosa, AL	X		X	
Utica-Rome, NY	X	X	X	
Virginia Beach-Norfolk-Newport News, VA-NC	X	X	X	X
Washington-Arlington, DC-VA-MD-WV	X		X	X
Wheeling, WV-OH	X	X	X	
Wichita, KS	X	X		
Worcester, MA	X		X	X

Notes: The table displays 96 cities because while there are 100 cities in the Yellow Book, not all of them have an associated Metropolitan Statistical Area. Some constitute Micropolitan Statistical Areas, and two cities (Dallas and Fort Worth) are combined into one MSA. The HOLC redlining maps are available for more cities than those listed, but the table is restricted to the sample of Yellow Book maps. Historical road maps are also available for more cities, but for this paper, only 71 are digitized. The Census column indicates which cities are included in the quantitative analysis using Decennial microdata for estimation.