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

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Abstract

This paper measures the Interstate Highway System's impact on welfare inequality in cities separately by race and education. I quantify the incidence of commute benefits from connecting residences to workplaces, costs where highways are built, and equilibrium responses using novel data on commuting and historical maps nationwide. Given the concentration of benefits in suburbs and costs in the urban core, differential suburbanization by race, more pronounced than by education, contributes to racial gaps in welfare gains. Using a spatial equilibrium framework, opening access to peripheral areas for minority families eliminates the majority of the gap while preserving aggregate welfare improvements.

JEL Classifications: N92, R13, R23, R41
Keywords: Infrastructure, segregation, inequality

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1 Introduction

Cities worldwide display stark differences in quality of life as access to public services and opportunity vary widely between neighborhoods segregated by socioeconomic status. With the rapid rise in urbanization globally, inequality within cities has become progressively more important for inequality overall (Beall et al., 2011). Transportation infrastructure is a broadly relied upon tool for economic development by connecting places to employment and economic prospects, but locally, it imposes negative environmental and social costs. The extent to which infrastructure reduces or worsens inequality depends crucially on how these benefits and costs are shared across groups.

In the U.S., the Interstate Highway System (IHS) continues to be the largest transportation and public works project, with investment exceeding \$500 billion in 2020 dollars.[1] Funded by the Federal-Aid Highway Act of 1956, it marked an unparalleled national push to develop infrastructure as 90% of the financing was from the federal government. The most intensive building phase between 1960 and 1970 added over 25,000 miles of highways and permanently reshaped cities through two main channels: faster commuting from residences to workplaces, and negative harms by routes such as heightened pollution, traffic, and the physical barrier of highways.

This paper employs a spatial equilibrium framework to quantify which groups receive the benefits, bear the costs, and are affected by equilibrium responses to the IHS, separately by race and education. Before this analysis, a few simple facts already suggest the welfare impacts were unequal, particularly by race. From 1960 to 1970, levels of racial segregation peaked as the Civil Rights Act of 1968 had not yet effectively lowered housing discrimination (Cutler et al. 1999). Minority households were more likely than White households to reside in the urban core, where commute benefits were more muted with jobs mostly downtown and where highways intersected, before and after Interstate development (Caro 1974, Jackson 1985, Rose 1990). They were also less likely to commute via automobile.

While these patterns are informative for the distributional impacts, open questions remain on whether race vs. economic differences are more central, which mechanisms are the key contributors, and the magnitude of the rise in welfare inequality from the IHS. This paper leverages new data to address these questions and advance the literature in three main ways.

First, is improving the measurement of the primary benefit of highways: reducing commute costs. Using restricted microdata from the 1960–1970 Journey to Work surveys of the Census, this study builds commute flows disaggregated by race and education across 25 major U.S. metro areas (CBSAs) and significantly expands on previous work focused on Chicago and Detroit (Brinkman and Lin 2022, Bagagli 2024). This prior research does not have socioeconomic traits in the com-

[1] The original cost of the system was \$114 billion, equivalent to roughly \$500 billion today. Investment in highways has continued, including the \$110 billion allocated by the Infrastructure Investment and Jobs Act of 2021 for roads, bridges, and surface transportation.

muting data, making it more suited for aggregate analysis, while the microdata contain rich individual characteristics necessary to understand *inequality*. Yet, even within the Census data, *travel time* is not available until 1980, so changes in neighborhood time to workplaces are calculated from newly digitized historical maps for 71 metro areas that cover 49 million tract-to-tract pairs.

Second, transportation infrastructure is a multifaceted policy with myriad equilibrium consequences, and existing studies on the Interstates each consider a subset of factors. This paper presents a *unifying framework* to separate multiple mechanisms behind unequal incidence. Like Brinkman and Lin (2022), this study estimates local disamenity costs concentrated downtown where roads intersected. Combined with improved connectivity in the suburbs, these two effects lead to migration outwards i.e. suburbanization. Beyond aggregate population responses, which are also the focus of Baum-Snow (2007), I document substantial heterogeneity in migration by race, with less variation by education within race. Similar to Mahajan (2024) and Bagagli (2024), this paper examines how disamenities, income differences, and racial homophily contribute to increased racial segregation from highways. They omit other factors which the disaggregated Census data capture, such as public transit use that differs substantially by race and education across routes, and firm location that is group-specific and can change with highways (as in Miller 2023).

Third, the historical narrative has pointed to an *alternative mechanism* for low Black suburbanization rates from Interstate development: discrimination by race prevalent in suburban neighborhoods. While previous work models sorting as a result of residential choice (e.g. Bayer et al. 2007), this paper demonstrates that barriers to choice play an outsize role in the neighborhood locations of minority households. Further, they *interact* with place-based policies, such as infrastructure, to create unequal policy impacts.[2] These barriers are proxied using maps created by the Home Owners' Loan Corporation (HOLC) in 1932 to indicate high credit risk and racially integrated "redlined" areas, often located in city centers. As Fishback et al. (2020, 2022) note, HOLC followed existing segregation patterns rather than necessarily creating them. Still, these patterns may have reflected informal discrimination since outside redlined areas, Black families faced landlords and property owners who resisted integration e.g. by including racial covenants to restrict home sales to only White households (Rothstein, 2017).[3]

In the empirical analysis to follow, I rule out other explanations besides discrimination as fully explaining racial differences in residential sorting from highways, including income, transit usage, and place of work. Within the microdata, all variables are cross-tabulated by race (White/Non-White, primarily Black in 1960) and *education* (less than high school/high school+) rather than *in-*

[2]Recent experimental studies by Christensen and Timmins (2022, 2023) show that housing discrimination leads to welfare losses and is a determinant of neighborhood choice. This study focuses on an observational, rather than experimental, setting that occurs during a period when discrimination was more pervasive.

[3]Though ruled unenforceable by Shelley v. Kraemer in 1948, these covenants continued to appear in property records until 1955 in Minnesota. The "Fair Housing" Civil Rights Act of 1968 outlawed these practices nationally.

come as income can rise endogenously with improved workplace connections. Summary statistics show that higher-educated Black households have similar weekly earnings, rents, and home values (\$500, \$460, \$92k) as less-educated White households (\$570, \$440, \$94k) while higher-educated White households average much higher (\$730, \$610, \$130k). Comparing the migration of these three groups then informs whether education/economic differences or race is the key mediator for differential sorting.

I employ a difference-in-differences strategy using variation across census tracts within metro areas that differ by intensity of treatment from Interstate segments built between 1960 and 1970 (including CBSA fixed effects). Changes in population levels are measured against changes in Commuter Market Access (CMA). CMA summarizes infrastructure impacts and is micro-founded by the general equilibrium model, which builds on existing work by Ahlfeldt et al. (2015), Donaldson and Hornbeck (2016), and Tsivanidis (2023) to consider a within-city context with commuting. It aggregates over (a) *commuting costs* which, exploiting the microdata, embeds differential public transit use by group and route, and (b) *workplace wages and employment* by race and education, capturing how the location of good jobs differs by group. Interstate development directly raises CMA by lowering travel costs for commuting via car.

The results show that within White households across education, there is no significant difference in migration to CMA improvements despite large economic gaps between the two groups. Higher-educated Black versus less-educated White households, despite economic similarities, show statistically different migration responses. Further ruling out that economic differences are the primary driver, controlling for changes in rent, e.g., from the suburbs becoming higher rent, does not affect the results by race. Notably, the Black CMA coefficient is not just lower than for Whites but often indistinguishable from zero. I also find that migration away from neighborhoods immediately by highways and their disamenities follows a similar pattern. In summary, low Black responsiveness to highway impacts cannot be explained by economic, mode of transport, or workplace variables alone, and an alternative mechanism remains.

As suggestive evidence for discrimination as a factor, I measure Black responses to CMA within redlined areas, and population changes are no longer zero and are significantly positive.[4] The limited response previously to CMA improvements, which are greater in the suburbs, may then result from barriers that inhibit free movement to the suburbs. However, racial homophily is not yet ruled out since preferences to be with same-race families can lead Black families to remain in integrated redlined areas. In the model section, I estimate linear parameters for racial homophily that show White homophily is greater than Black homophily, and this social preference is not

[4] While racial covenants were in place across the U.S., existing records of covenants are currently only available in the Minneapolis-St. Paul metropolitan area. The specification is underpowered when using observations for a single metro area, so the empirical test focuses on redlining maps instead, which are available for the whole country.

quantitatively large enough to account for Black clustering in central, redlined areas. Additionally, controlling for changes in racial composition, i.e. that downtown areas become less White, does not substantially affect the low Black migration coefficient on CMA changes.

For these results, I develop an identification strategy to address the non-random placement of routes. Urban highway routing was influenced by political considerations, often leading to their location in socioeconomically disadvantaged and declining neighborhoods and thus the unequal incidence of their costs. Consequently, in estimation, OLS conflates selection with treatment effects. For cleaner comparisons, within the digitized historical maps, major roads are considered candidates for Interstate construction. Not all were converted, and the historic roads that remain form a natural control group. Covariates for the location of historical railroads, ports, canals, rivers, and the central business district are also included to create areas with similiar propensity of receiving an Interstate road. Lastly, I construct two instruments by (1) drawing a Euclidean ray network to intersect intermediate cities where neighborhoods coincidentally between them are treated (Chandra and Thompson, 2000), and (2) digitizing for 100 cities planned engineering maps that were less subject to political influences. This paper cannot use instruments from past studies on city-level Interstate impacts, such as the national 1947 plan in Baum-Snow (2007) or exploration routes in Duranton and Turner (2012), as they are insufficiently granular for neighborhood (tract) outcomes.

Then, to pinpoint the Interstates' effects on migration rather than suburbanization already occurring, in all specifications, I control for distance from the central business district and exploit variation between suburbs connected by Interstates and other suburbs connected by comparison historical roads.[5] Furthermore, I conduct the Borusyak and Hull (2023) method of re-centering against pre-existing market connectivity.

While the empirical analysis is transparent in its findings, it does not provide a framework for measuring how multiple forces simultaneously impact welfare, necessitating a more formal model. After Interstate highways raise commuting access and impose disamenities, migration in equilibrium changes several components in welfare such as housing prices, wages at firms, and endogenous amenities (as a function of racial composition, similar to Diamond 2016). Moreover, *counterfactual* questions cannot be answered absent a model, which can simulate removing each channel to measure their role in welfare. For example, while the empirical results indicate there is differential migration, possibly due to discrimination, they do not quantify the size of the contribution to inequality. Consequently, in the second section of the paper, I parameterize the model and employ it to separate the mechanisms behind welfare gains.

In model estimation, I leverage the Interstate shock in a theory-consistent way for several esti-

[5] 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).

mating equations. After running a gravity equation of commuting, changes in CMA are measured, which then provide variation for a key parameter behind segregation—racial homophily. I construct instruments for racial composition following Davis et al. (2019) by simulating how race-specific mobility to the CMA Interstate shock implies percent White is declining in parts of the urban core. Importantly, estimation of homophily employs variation within redlined areas, which are already racially integrated, to avoid conflating preferences with barriers. As noted earlier, I find that racial preferences are greater for the White population compared to the Black population. Additionally, I estimate highway costs as the decline in amenities by highways, which are reflected in migration/price changes, through a revealed preference approach.

Using the estimated parameters and additional calibrated ones, in the general equilibrium framework, development of Interstate highways changes welfare by -1.5%, -0.2%, 2.7%, and 3.0% for less-educated Black, higher-educated Black, less-educated White, and higher-White households, respectively. Commute cost reductions constitute most of the gains, so properly measuring changes in network connectivity using the data developed in this study is central to policy evaluation. As is evident, the race gap is substantially larger than the education gap within race, and the IHS widened racial inequality. Importantly, these values are *within-city* estimates of welfare impacts and do not include more aggregate gains, which could alleviate the welfare losses for Black households. Previous research by Michaels (2008), Duranton et al. (2014), and Allen and Arkolakis (2022) indicate that highways also improved trade across cities for certain sectors and aided regional economic development.

Breaking down the impacts further, the direct channels of commute benefits and disamenities alone lead to large welfare differences, as initially, Black families resided near Interstate routes and commuted with cars at a lower rate. Allowing for reallocation via migration increases racial inequality by 30% since White households suburbanize more and magnify their gains from road development. Equilibrium adjustments in wages, housing prices, and endogenous amenities are less significant and somewhat offset each other for welfare.

These estimates provide evidence on the distributional impacts of the Interstate system in cities, which have not yet been comprehensively quantified and are valuable in their own right, even without a strong stance on whether discrimination is involved.

Now turning to the role of discrimination, I classify neighborhood barriers as the difference between White and Black households in residential location, *after removing factors related to neighborhood choice* of housing prices, the location of good workplaces by group, mode of transport availability and use by group, and racial homophily. The model-implied location residual without these other components commonly corresponds to the fundamental amenity term in urban models.

I test whether this measure of barriers coincides with empirical proxies for discrimination using a border discontinuity design along borders in the redlining maps. As measured directly in the data, there is an immense 140% increase in the Black population when entering redlined areas, and a still sizeable 50% decrease in the White population. These large population jumps are not fully explained by house price differences (a more modest 20% drop at the border), and adding additional socioeconomic controls only somewhat reduces the discontinuity. Given parameter estimates, the biggest factor behind White households not residing in integrated redlined neighborhoods is racial homophily, and this same-race preference also partially accounts for Black clustering on the redlined side. Notably, the fundamental amenity residual is smooth across the border for White households, indicating the identification assumption of similar characteristics at the border is satisfied.[6] Yet, for Black households, a large residual remains, and the asymmetry across the two groups at the border is strongly suggestive of race-specific determinants.

These model-implied barriers play a large role in inequality in welfare impacts. After simulating opening neighborhood access in the spatial equilibrium framework by removing these barriers, which are especially large in the suburbs, the development of Interstate highways raises welfare levels of the Black population by 1%, and the racial gap in impacts closes by a substantial 54%. All groups benefit from highway development, and impacts for the White population remain the same, so gains for Black households do not lead to a zero-sum game for aggregate highway impacts. These results show how the limited mobility of disadvantaged groups can lead to unequal consequences from place-based policies, even if they are not inherently racially-targeted. In this setting of the Interstate highway system, reducing barriers to choice goes far in closing the gap.

2 Historical Context and Data on the Interstates and Inequality

In this section, I describe the context related to the Interstate highway system's impacts on cities and which data sources are needed for measurement.

There were several intended economic benefits that motivated highway development when the Federal-Aid Highway Act of 1956 was passed. The 42,800-mile road network, the largest in the world, would lower road congestion that was rising as a result of the ongoing relocation of families into the suburbs. Postwar programs encouraged residential migration outward and greater commuting to workplaces. For example, the GI Bill subsidized homeownership for millions of veterans, and the Federal Housing Act of 1949 expanded mortgage insurance for newly constructed suburbs while simultaneously funding the clearance of blighted downtown areas (Rose, 1990).

As commute cost reductions are a core impact of highways, precise measurement of the change in commute times is essential. However, travel time surveys were conducted sparsely in the period

[6] 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. Additionally, fundamental amenities often refer to natural amenities, and in robustness checks, land cover types of open water and wetlands are continuous along the border, supporting the identification assumption of no change in fundamental amenities.

of Interstate construction.[7] I build commute time matrixes using Shell Atlases in 1951 and 1956 that I digitized for 71 cities (Rumsey, 2020). Road networks are categorized into superhighways and other major roads, and these two categories are assigned different speeds following historical surveys (Gibbons and Proctor, 1954; Walters, 1961). I assign each Interstate segment its posted speed limit (55–65 mph) and use the PR-511 database from Baum-Snow (2007) to exploit decade-by-decade variation in segment openings. Commute times are generated in ArcGIS Network Analyst by overlaying the Interstate and historical road networks. To incorporate 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 by decade over bins of bilateral distance and distance from the central business district (CBD).

Beyond the benefits, the harms and inequities of highways were quickly evident as they displaced and polluted surrounding communities, often low-income ones targeted for urban renewal by city planners (Hirsch, 1983). In response, freeway revolts aimed to halt construction or shift the course of routes.[8] Revolts were occasionally effective, though far less often when initiated by disadvantaged groups (Rose and Mohl, 2012).

To measure disparities in Interstate incidence, I collect the location of residences and workplaces separately by race and education from Decennial Censuses in 1960 and 1970. The decade in between covers 51% of network construction. Residential units are census tracts, and workplace units are Place of Work zones, which I constructed for this study 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 metro areas i.e. CBSAs, listed in Supp. Appendix Table G.26, as smaller ones have few Place of Work zones. In some specifications measuring residential changes, I expand the sample to 96 CBSAs 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).[9] Education is split into high school graduates and those without a high school degree, approximately a 50-50 cut. For each group and geographic unit, I calculate average wages and quality-adjusted housing prices. Supp. Appendix G contains more details.

In Table 1, I display summary statistics for 1960, and Column 5 indicates which variables are

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

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

[9] 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.

newly available using the microdata, such as detailed neighborhood and commuting characteristics. Large differences are present by race *conditional on education*: 49% of Black higher-educated workers commute by car compared to 66% for White higher-educated workers, but conditional on car usage, the distance is similar. Among the higher educated, Black workers are located 3.6 miles closer to the CBD, where commuting improvements are muted, and reside 0.8-0.9 miles closer to a highway, which can be due to political influences leading to unequal route placement.

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 substantial differences in location relative to highways and the central city, so wages/prices alone do not appear to be the largest explanatory factor (Bayer et al., 2021).

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	(5) New Microdata
Economic Variables – Mean (SD)					
Weekly Wages (2010$)	402.3 (115.6)	495.2 (131.6)	569.4 (97.6)	726.7 (159.1)	
Rent (2010$)	382.9 (124.6)	464.6 (136.0)	444.9 (140.8)	607.7 (194.8)	
Home Value (2010$)	65,900 (29,850)	92,200 (35,740)	93,700 (32,050)	130,000 (40,200)	
Home Ownership Rate	0.334 (0.238)	0.379 (0.273)	0.599 (0.266)	0.626 (0.280)	
Neighborhood Variables – Mean (SD)					
Pct HOLC D	0.661 (0.405)	0.554 (0.436)	0.303 (0.409)	0.189 (0.342)	✓
Dist to Highway (mi)	1.779 (4.072)	1.643 (3.753)	2.578 (4.891)	2.565 (4.781)	✓
Dist to CBD (mi)	6.187 (7.703)	6.337 (6.888)	9.743 (9.485)	9.892 (9.086)	✓
Commuting Variables – Mean (SD)					
Commute Time (min)	26.86 (11.07)	26.76 (10.75)	26.65 (12.03)	27.74 (12.42)	✓
Commute Dist (mi)	9.30 (7.38)	9.36 (7.03)	9.22 (7.20)	10.11 (7.25)	✓
Pct Auto	0.392 (0.324)	0.488 (0.361)	0.561 (0.315)	0.663 (0.293)	
Auto Commute Time (min)	28.56 (14.89)	28.27 (13.97)	28.02 (14.66)	28.31 (13.93)	✓
Auto Commute Dist (mi)	11.07 (7.56)	10.84 (7.34)	10.56 (7.38)	10.68 (7.19)	✓
Rounded Count	N=2,834,000	N=1,334,000	N=16,190,000	N=18,240,000	

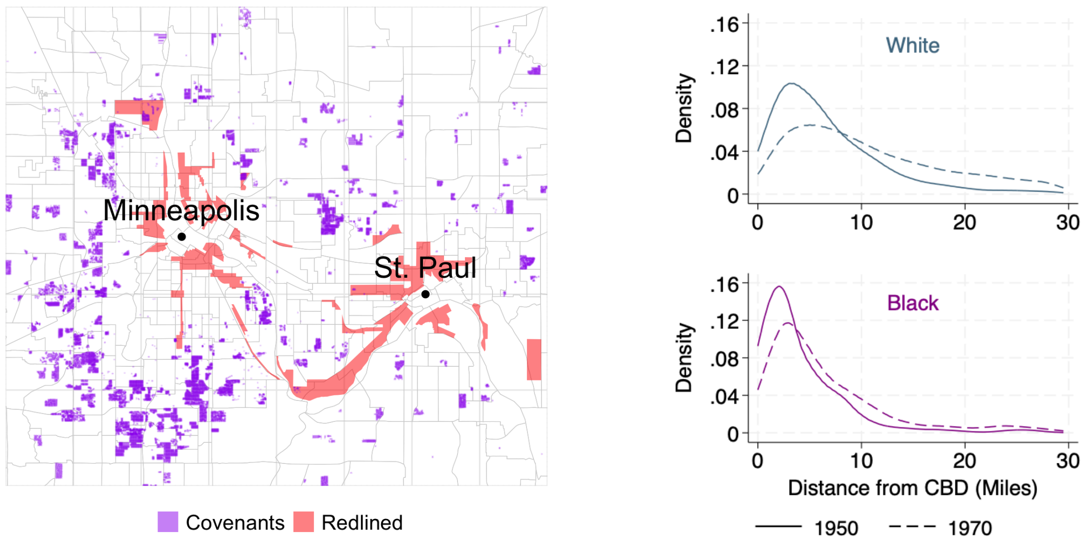
Notes: Data from the 1960 Census restricted microdata. Weekly wages are for employed workers; rents are monthly. All values CPI-adjusted to 2010 dollars. Pct HOLC D calculated on tracts with redlining maps. Distance from highway uses 1960 locations and constructed Interstates. Percent auto is share of workers using private vehicles. Counts and values are rounded following Census disclosure rules.

This segregation may have been shaped by various obstacles that discriminated against minority families. Although some policies ended before the 1960s, others persisted.[10] During the decade of

[10] 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 v. Warley in 1917. Restrictive covenants were ruled unenforceable in Shelley v. Kraemer in 1948, yet they continued to be found in property deeds until the 1950s Corey et al. (2025).

this study, segregation reached its peak after an extended period of Black migration from the rural South into neighborhoods in Northern cities (Cutler et al., 1999; Boustan, 2010). It began declining after the 1968 Civil Rights Act—also known as the Fair Housing Act—but uneven enforcement meant reductions were gradual over time.

Figure 1: Suburbanization and Neighborhood Institutions



(a) Racial Covenants & Redlining in Minneapolis-St. Paul

(b) Suburbanization by Race

Notes: Kernel density plots of population use tract-level aggregates from IPUMS-National Historical Geographic Information System (NHGIS). Racial covenants were collected by researchers at the University of Minnesota (Corey et al., 2025). Redlining maps come from the American Panorama Project (Nelson et al., 2020).

Discrimination occurred through various formal and informal institutions that constrained residential choice (North, 1991). Figure 1a presents the Minneapolis metro area as an example where restrictive racial covenants in property deeds prevented sales to non-White households (Jones-Correa, 2000). These covenants were present mostly in suburban neighborhoods, which Figure 1b shows is where White families migrated out towards from 1950 to 1970. Conversely, Black households remained in the center, which were marked "redlined" in maps by the Home Owners' Loan Corporation (HOLC), a federal agency formed in 1933 after the Great Depression to identify high-risk neighborhoods for mortgage financing.[11] Some researchers such as Faber (2020) and Aaronson et al. (2021) argue the HOLC maps directly increased segregation, but other scholars such as Fishback et al. (2020, 2022) demonstrate the maps reflected existing racial and economic characteristics and that HOLC did not itself discriminate in mortgage provision.

[11]Concurrently, 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). 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.

This paper does not assume that segregation associated with the maps was necessarily caused by HOLC policies. For this study's purposes, the HOLC maps proxy geographic borders where discrimination occurred, including from private actions such as racial covenants or refusal by landlords to rent to Black families outside of redlined neighborhoods. In later sections, using the microdata and estimated parameters, I decompose how much of the sorting by these maps is likely due to discrimination and how much is also attributable to economic differences, commuting patterns to workplaces, and social preferences of homophily (which can reinforce segregation at the borders). I provide evidence that discrimination is an important factor in the spatial distribution of households, which then interacts with highway infrastructure to have unequal impacts.

3 Empirical Evidence on Interstate Impacts

In this section, I develop an empirical strategy for causal identification and 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 Identification Strategy

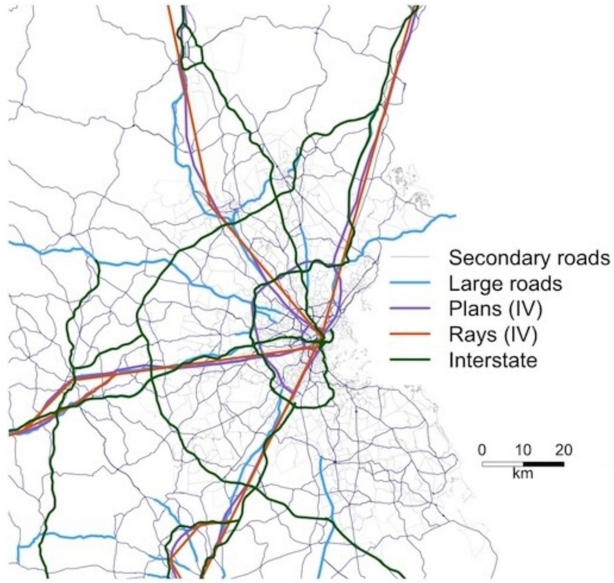
Non-random placement of Interstate routes can lead changes by highways to be contaminated by selection on trends. To obtain cleaner identification, I create comparison areas likely to have received an Interstate highway.

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 infrastructure.[12] Related to (1), I 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 2, I overlay the Interstate system on the historical network for the Boston area and illustrate that the two are closely aligned. Several historical roads were never re-built as Interstate highways, and these serve as the control routes. Related to (2), maps on railroads, canals, steam-boat navigable rivers for the late 19th century, bodies of water, shores, and ports are included as geographic controls since they influenced highway placement (Atack, 2015, 2016, 2017; Lee and Lin, 2017).

While previous research has employed historical routes as instruments, past infrastructure influ-

[12] The introduction to *Interregional Highways* recommends that the "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."

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



Notes: Historical urban roads are split into two categories: secondary roads and large roads (superhighways in the legend of Shell Atlases), where large roads are candidates for Interstates. Planned routes are digitized from Yellow Book maps. Euclidean rays connect cities in the plans.

ences subsequent economic development and risks violating the exclusion restriction (Donaldson and Hornbeck, 2016). This paper instead purges these historical influences by including them as controls and consequently compares areas with similarly high levels of economic activity/traffic to areas that ultimately received Interstates.

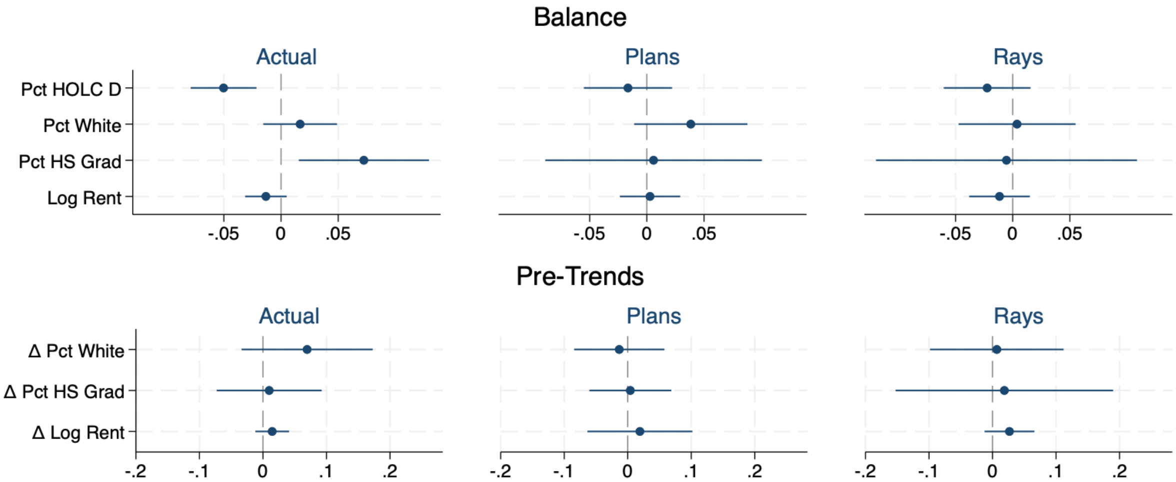
Conditional on geographic features, the final placement of highway routes may continue to be biased due to local political factors, e.g. protests in high-income areas. To address this bias, transportation plans can be used as instruments since they were decided on before external influences occurred 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). The Euclidean ray network is thus likely to be more quasi-random than the plans.

Figure 2 plots the two instruments next to the Interstate network for the Boston metro area and shows they are often adjacent.

Figure 3: Pre-Period Correlation & Pre-Trends for Highways and Instruments

Coefficient on Distance from Route



Notes: Data is 1940, 1950 and 1960 tract-level aggregates (IPUMS NHGIS). Tracts are limited to those within 5 miles of the nearest constructed route. The pre-trends cover either 1940 to 1950 or 1950 to 1960, depending on when highway construction started in the CBSA. Fixed effects are at the CBSA level. Standard errors are clustered by county. The geographic controls are log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large roads. *** p<0.01, ** p<0.05, * p<0.1

I measure the correlation at baseline and in pre-trends between distance from the various routes and neighborhood characteristics in a multivariate regression. Figure 3 shows the constructed highways were built further from more-educated areas and closer to redlined ones that were becoming less White over time. Both instruments are not significantly correlated with tract features at baseline or in trends, although estimates for some variables are similar in direction to the Interstate ones (with larger standard errors). Note that identification relies only on pre-trends being satisfied since estimation is based on the time variation. Later, I present results using both instruments to provide a range of what the magnitudes could be. The first-stage regressions, shown in Supp. Appendix C.1, indicate that F-statistics are all above 100.

3.2 Population and Equilibrium Responses By Highways

Using this identification strategy, I first present some stylized facts on the effects by highways as indicative of their costs. The long differences specification estimates 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, educational, and racial composition.

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

Differences 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.[13] The coefficient on distance from highways $DistHW_i$ represents the costs. Distance from the central business district $DistCBD_i$ is used as a control to absorb commuting access benefits correlated with suburbanization. A redlined indicator captures heterogeneity in redlined versus non-redlined areas, so the empirical variation comes from within the two types of neighborhoods. CBSA fixed effects $\gamma_{m(i)}$ for each city m are included to exploit only within-metro area variation. Standard errors adjust for spatial correlation following Conley (1999) within a radius of 1 kilometer.

Results are presented in Figure 4, which shows significant declines by highways in population and rents, and that neighborhoods become less White.[14] The changes in racial makeup are driven by White households leaving, as there is no statistically measurable response by Black households. Interestingly, there is very little effect on educational composition, only racial composition. Home values also do not adjust significantly, as shown in Supp. Appendix Table A.1.

Comparing magnitudes of outcomes, the changes in rents and racial composition are smaller than the White population response, so for welfare impacts, the large reallocation of White households may be more meaningful for their gains than adjustments in these two characteristics.

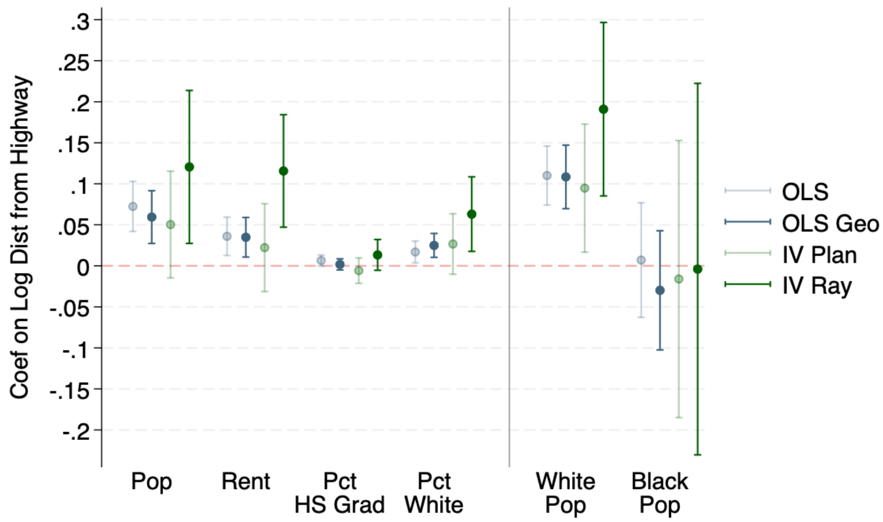
These results are consistent across all the specifications. Including geographic controls does not substantially alter the effect sizes, so selection is minimal once $DistCBD_i$ is controlled for. Instrumenting with the plans also does not affect the size of the estimates greatly, although instrumenting with the rays tends to raise the standard errors and the point estimate.

Feedback channels link the neighborhood 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 leads to more out-migration of White households. Migration then transmits into housing prices. The equilibrium system should thus aim to characterize how the channels are determined simultaneously and measure the importance of each.

[13] 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 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.

[14] In Supp. Appendix Figures B.1 and B.2, I present results in non-parametric bins over distance from highways in panels grouped 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.

Figure 4: Changes Over Distance from Highway (1950-1960, 1960-1970)



Notes: Observations are census tracts (5 mi from nearest highway; ≤30 mi from CBD), differenced over 1950–60 or 1960–70 depending on highway construction timing in the CBSA (IPUMS NHGIS). CBSA fixed effects included; Conley SEs (1 km) are reported. All specifications include Dist CBD and the gradient (Dist CBD/Dist Highway) as controls. Specifications OLS Geo, IV Plan, IV Ray also control for log distance from rivers, lakes, shores, ports, historical railroads, canals, and historical large roads. Redlined tracts are those with $>$ 80% area redlined. Kleibergen-Paap rk Wald F statistics are 613.2, 466.7 for the plan and ray instruments, respectively.

3.3 Population Elasticities to Commuter Market Access

Next, I measure population responses to the commuting benefits of highways, which contribute to suburbanization during this period. Similarly to the results for migration away from highway costs, I examine whether race versus education is more important and the differences between White vs. Black households for residential reallocation towards highway benefits.

To pinpoint highway impacts separately from ongoing migration away from city centers, I exploit the growth in Commuter Market Access (CMA) from the reduction in travel time from Interstate construction. These connectivity improvements are compared against existing connections from the historical roads while controlling for $DistCBD_i$. The variation is then between suburbs connected by Interstates to other suburbs not connected.

Residential CMA is defined for each tract i and aggregates over workplaces denoted with j:

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

CMA is always heterogeneous by education $g \in \{L, H\}$, for less-educated and high-educated, and race $r \in \{B, W\}$, for Black and White. Using the richness of the microdata, I measure how workplaces pay group-specific wages ω_{jgr} (scaled by employment) and calculate the commute costs d_{ijgr} as a weighted average of commute times by car and *other modes of transit* with weights that differ by group and ij pair. The change in CMA from Interstate development then accounts for the pre-existing presence of public transit and the location of high-wage jobs, which differentially affects each race $\times$ education group. Parameter ϕ is a substitution elasticity over workplaces and is set to 3 in the middle of estimates from the literature for the stylized facts (Ahlfeldt et al., 2015; Morten and Oliveira, 2018; Severen, 2021).

In the Decennial microdata, I measure the elasticity of how population L_{igr} responds to improvements in CMA from 1960 to 1970.

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

The controls X_i include $DistCBD_i$ to exploit variation in concentric rings around cities, i.e. within the suburbs, as well as other geographic controls of railroads, canals, etc., and CBSA fixed effects.

The empirical 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 (displayed in Supp. Appendix Figure B.3). Borusyak and Hull (2023) argues this re-centering addresses non-exogenous exposure where areas connected by highways are systematically different in the existing network.

Results are reported in Table 2 with standard errors clustered at the tract level and Conley (1999) standard errors in brackets. The population elasticity is around 1.4 for the White population across Columns 1–2 where Column 2 includes counterfactual CMA with historical large roads 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 much lower than for White households at 0.1 and are insignificant. Consistent with the previous results on the lack of movement away from highway costs, Black households do not respond to the benefits of highways.

This differential migration is not explained by the education differences across racial groups. Column 3 shows that less-educated White households are just as responsive to CMA improvements as their higher-educated counterparts, yet Black households remain far less mobile at both education levels. This pattern also indicates that economic status is not a key driver of racial differences in migration since Table 1 demonstrates that higher-educated Black households earn wages and pay home prices similar to less-educated White ones. In a similar vein, declining rents in city centers over time cannot explain the gap since controlling for changes in prices leaves the Black population elasticity to CMA virtually unchanged (see Supp. Appendix C.2).

The previous descriptive evidence in Section 2 suggested that barriers to choice could be important for the low mobility response of the Black population. I explore how this shapes the population elasticities in Column 4, which includes redlining by race fixed effects. The specification then uses variation within types of neighborhoods, i.e. within redlined neighborhoods that are already racial integrated and less likely to exhibit housing discrimination.

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 around 0.3 and statistically significant, though still lower than for White households. Their dampened overall elasticities mask how Black households respond to CMA changes in redlined areas and how spatial frictions inhibit the Black population from leaving centrally located, redlined neighborhoods for suburban, non-redlined one. Lastly, to show that racial homophily is not leading Black households to stay in the center, which is becoming more diverse over time, Supp. Appendix C.2 includes a result that controls for changing racial composition, and again, the estimate remains the same. In the model simulations, I will further decompose the sources of segregation after directly estimating the homophily parameter.

Table 2: Elasticity of Population to Commuter Access

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \log L_{igr}$ (Δ Log Population 1960–1970)					
Variables	OLS	+ BH (2023)	Race $\times$ Educ	+ Redlining FE	Plans IV	Rays IV
$\Delta \log CMA_{igr}$						
Black	0.0907	0.0941		0.273***	–1.757	–3.062*
	(0.0968)	(0.0968)		(0.100)	(1.276)	(1.564)
	[0.110]	[0.110]		[0.116]	[1.490]	[1.838]
White	1.401***	1.410***		1.083***	0.648**	0.719**
	(0.115)	(0.115)		(0.125)	(0.323)	(0.340)
	[0.143]	[0.143]		[0.157]	[0.456]	[0.458]
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	0.139	0.118	0.099	0.072
CBSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes
Rounded Obs	N = 60 500					

Notes: Observations are census tracts by race and education in first differences from 1960–70. Data is restricted Census microdata. Tract-clustered SEs are reported with Conley SEs (1 km) in brackets. Included are CBSA fixed effects and controls: log distances to CBD, river, lakes, shorts, ports, railroads, canals, historical roads, all interacted with race (and education for Col 3). The Borusyak and Hull (2023) control for CMA in large roads is interacted with race in Col 2 (and education in Col 3). Redlining fixed effects are interacted with race. Col 5-6 include the Borusyak and Hull (2023) control interacted with race and CBSA fixed effects. Kleibergen-Paap rk Wald and Cragg-Donald Wald F statistics for Col 5-6 are 35, 25 and 203, 139. Counts rounded to the nearest 500 to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

In the endogenous variable of $\Delta \log CMA_{igr}$, wages and employment in ω_{jgr}, not only commute costs, adjust from 1960 to 1970. Employing only commuting variation from the highway shock, I define the instrument $\Delta \log CMA^{IV}_{igr} = \frac{1}{\phi}\left(\log \sum_j \omega_{jgr,1960}/{d^{IV}_{ijgr}}^{\phi}\right) - \frac{1}{\phi}\left(\log \sum_j \omega_{jgr,1960}/{d_{ijgr,1960}}^{\phi}\right)$ where I fix scaled wages to 1960 levels and only adjust the commute costs in d^{IV}_{ijgr} using the change in commute times from the plans or the Euclidean rays.[15]

I report IV estimates in Columns 5-6.[16] Coefficients are smaller than with OLS, so the previous estimates may include responses to endogenous wage and employment changes rather than solely the Interstate shock or selection of highway routes in growing places. Black population responses are imprecisely estimated as standard errors are large. Yet overall, the estimated coefficients indicate strong treatment effects on migration.

3.4 Discussion

Building on these empirical facts, in the next section, I lay out a quantitative urban model that expands the analysis in several ways. To start, while the reduced form evidence is informative for some of the impacts, it comingles both direct and indirect effects (such as endogenous reallocation and adjustments in equilibrium outcomes) which simultaneously shape welfare. The model is rich enough to encompass all channels and carefully consider the forces at play for welfare.

Additionally, the empirical estimates recover treatment effects (i.e. coefficients), but they are silent on *incidence*, which depends on the extent of exposure by groups to the treatment and is central to distributional measurement. The model framework provides a structure to allocate benefits, costs, and equilibrium changes across groups.

Finally, how discrimination shapes highway effects has been examined incompletely since the empirical sample includes only areas where Black households resided, leaving out those where they are never observed because of neighborhood discrimination. The model enables asking counterfactual questions, such as how opening up neighborhood access changes sorting by race and inequality in Interstate impacts.

4 A Quantitative Model of Cities

In the sections below, I describe the key pieces of the spatial equilibrium framework to measure the impacts of the Interstate highway system, which is quantified for the 25 metro areas in the Census microdata. Extending previous advances by Allen and Arkolakis (2014), Ahlfeldt et al. (2015), and Tsivanidis (2023), the general equilibrium model maps the sources of segregation to components of classic urban models and incorporates residential barriers that ultimately influence

[15] 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, also explained in the model section.

[16] I find the Kleibergen-Paap rk Wald and Cragg-Donald Wald F-statistics are all far above 10. Additional details on how the instruments are defined and the first-stage regressions are in Supp. Appendix C.3.

welfare inequality. Neighborhoods are linked via commuting networks, and transportation infrastructure lowers the costs of travel, which in turn affects the rest of the spatial economy.

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 metro area consists of neighborhoods indexed by $i = 1, \ldots, S$ and contains fixed population levels $\mathbb{L}_{gr}$ by education and race. I focus on a closed city set-up to emphasize the *within-city* impacts of highways since the literature has previously examined regional impacts and in the empirical estimation, CBSA fixed effects absorb any city-level migration.

Workers – Individuals (o) choose where to live (i) and work (j) depending on idiosyncratic shocks and location characteristics to maximize the utility function:

$$\max_{c_{ij}(o), l_i(o)} \quad \frac{z_i(o)\varepsilon_j(o)(1-\tau^b_{igr})B_{igr}}{d_{ijgr}} \left(\frac{c_{ij}(o)}{\beta_{gr}}\right)^{\beta_{gr}} \left(\frac{l_i(o)}{1-\beta_{gr}}\right)^{1-\beta_{gr}}$$
$$\text{s.t.} \quad c_{ij}(o) + (1+\tau^Q_{igr})Q_i l_i(o) = w_{jgr}\varphi_{gr}$$

Preferences are Cobb-Douglas over consumption $c_{ij}(o)$ and residential floorspace $l_i(o)$. Amenities B_{igr} are group-specific and contribute to heterogeneous choices. 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).[17] Wage w_{jgr} at workplaces j are set by firms in equilibrium, and 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.

Incorporating homeownership in φ_{gr}, the budget constraint includes income from redistributed rents based on the ratio of home values owned by each group, akin to holding a portfolio of homes, such that total income for each group equals the sum of labor and rental income.

$$\underbrace{\varphi_{gr}\sum_i \bar{w}_{igr}L_{igr}}_{\text{total income}} = \underbrace{\sum_i \bar{w}_{igr}L_{igr}}_{\text{total labor income}} + \underbrace{\sum_i \hat{o}_{igr}\sum_{g,r}(1-\beta_{gr})\bar{w}_{igr}\varphi_{gr}L_{igr}}_{\text{total rental income}}$$
$$\Rightarrow \varphi_{gr} = 1 + \frac{\sum_i \hat{o}_{igr}\sum_{g,r}(1-\beta_{gr})\bar{w}_{igr}\varphi_{gr}L_{igr}}{\sum_i \bar{w}_{igr}L_{igr}} \qquad \text{where} \quad \bar{w}_{igr} = \sum_j \pi_{j|igr}w_{jgr}$$

The share of home values $\hat{o}_{igr}$ is observed in the data as the fraction of the value of homes owned

[17] 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 Supp. Appendix D.1.1, I provide an extension with Stone-Geary preferences.

by group gr out of the value of all homes in a neighborhood.

Spatial barriers can arise in a couple 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. 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.[18]

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 $\varepsilon_j(o)$ from $F(\varepsilon_j(o)) = \exp(-T_{jgr}\varepsilon_j(o)^{-\phi})$ where T_{jgr} is a scale parameter representing the size of the workplace and 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. Likewise, ϕ is a workplace elasticity governing the responsiveness of choices to workplace changes.[19]

After utility maximization, indirect utility is expressed as:

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

With this indirect utility expression, population levels at locations are derived using the Frechet properties of $\varepsilon_j(o)$. 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 before following $CMA_{igr} = \Phi^{1/\phi}_{igr}$. Labor supply L_{Fjgr} aggregates over all residences and the probability each residence sends workers to j

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

where L_{igr} is the population of group gr workers at residence i.[20] The probability a worker lives in i is of a similar form using the Frechet properties of the residential shocks, and combined with the

[18] In Supp. Appendix D.1.2, I include an extension with a Nested structure such that mobility is differential across types of neighborhoods. For a more parsimonious framework, this feature is not included in the main model.

[19] 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 Supp. Appendix D.2 for an expanded discussion of this choice.

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

total city population of a group $\mathbb{L}_{gr}$, we arrive at the key equation for residential sorting:

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

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

Sources of Segregation – With the factors characterizing residential choice, sorting by race and education arises from (1) group-specific commuter market access, including differential firm location and mode of transport usage, (2) differing substitution elasticities, (3) housing prices which, while not group-specific, are valued differentially by race and education,[21] (4) group-specific amenities, and (5) spatial barriers as residual wedges. I expand on a couple components below.

Racial preferences such as homophily appear in amenities through the component that is endogenous in racial composition L_{iW}/L_i.

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

Preference parameter ρ_r can capture how retail amenities or public goods like school quality are correlated with racial composition, or taste-based factors such as prejudice or cultural similiarity (Becker, 1971; Diamond, 2016; Almagro and Dominguez-Iino, 2020). The remaining fundamental component b_{igr} is for time-invariant factors such as persistent natural geography.

Spatial barriers appear in the model as wedges that are invariant to highway policy.[22] In estimation, they will mapped to residual differences in location that remain after accounting for the other factors in the choice expression. Some of sorting can be related to differences directly observed in the data, such as in sensitivity to home prices and CMA (encompassing firm location, wages, and public transit use). In addition, racial homophily must be measured credibly before estimating the wedge since stronger homophily would lower how much is attributed to barriers.

Within the set of barriers, further disambiguating them is challenging since they are often correlated with each other. Resistance to racial integration by property owners may produce preference (amenity) wedges around the same neighborhood borders that divided rental units from single-family developments, where price wedges also arise through the limited access to low-interest

[21] 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 Supp. Appendix Table E.13.

[22] 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).

mortgages from the Federal Housing Administration (Rothstein, 2017). However, data on credit access is scarce for this time, so price wedges are difficult to measure. Direct discrimination in prices seems minimal, since I find Black and White households pay essentially the same to live in any particular area (see Supp. Appendix E.2.1).[23]

In Supp. Appendix D.3, I show how all barriers can be mapped to a single wedge, given the isomorphisms between the amenity and price wedges. They are also equivalent to a capacity constraint that fixes the number of households from the minority group. Intuitively, given the Cobb-Douglas form of utility, higher amenities translate into lower prices, which provides a mapping from amenity wedges to price wedges (however, price wedges have different implications for welfare since they also affect the housing market). To attain the same allocation as the capacity constraint, either of the two wedges must sufficiently increase to reduce residential population. In conclusion, I include a single residential barrier that is essentially the amenity wedge.

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 Supp. 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.

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

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

[23]While the qualitative literature has 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 for similar quality housing. In Supp. Appendix E.2.1, after including neighborhood fixed effects and house quality controls, Black households face 3% higher rents in non-redlined areas and 8% higher rents in redlined areas. As the 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 positive race differential suggests some discrimination.

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 direct highway impacts and with equilibrium adjustments across residences and workplaces.

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

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 greatly affect Black residential locations, in line with the observed low Black migration in the stylized facts.

Impacts to Welfare in Equilibrium – Welfare changes are tightly tied to residential choices 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

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

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. If Black households have lower residential elasticities, i.e. $\theta_B < \theta_W$, their incidence to the shocks is stronger. Furthermore, low elasticities imply that initial residential locations, which may be heavily determined by time-invariant wedges, are even more important for welfare impacts.

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 $\{L_{igr}, L_{F\,jgr}, Q_i, w_{jgr}, B_{igr}, U_{gr}\}$ 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 Supp. 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 1. *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 Supp. Appendix F.4 □

I follow Allen and Arkolakis (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 begin by summarizing the overarching goals. Throughout this summary, I briefly include results for parameters that are more standard to estimate in the literature. Later, I present the full estimating equation for the residential parameters since they are central to inferring how much of segregation comes from discrimination and the population responses to the Interstate highway system.

5.1 Estimation and Inversion Overview

Parameter Estimation – The focus of estimation is on two main groups 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. This equation is derived from the commute shares in Eq. (2) and the functional form of commute costs as $d_{ijgr} = t_{ijgr}^{\kappa_{gr}}$. Using the planned and ray instruments and the Poisson-Pseudo Maximum Likelihood (PPML) estimator following Silva and Tenreyro (2006), I obtain commuting elasticities $\nu_{gr} = \kappa_{gr}\phi$ around 4 for all groups. Parameter ν_{gr} combines the commute cost parameter κ_{gr} with the workplace substitution elasticity ϕ, and it enters into the CMA measures. The workplace elasticity is assigned from the literature to $\phi = 3$ following studies with settings similar to this paper.[24] Supp. Appendix E.2.2 provides more details on gravity estimation.

Commuting elasticities on hand, I construct 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 population responds in race-specific ways to CMA, providing variation for ρ_r.

Housing price sensitivity, i.e. the consumption share of housing $1-\beta_{gr}$, is calibrated using the Consumer Expenditure Surveys (CEX) microdata in 1980. Supp. Appendix E.2.3) describes how calibration occurs.

With the parameters θ_r, β_{gr}, and ρ_r, I invert the model to obtain fundamental amenities b_{igr} (including the 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. I find that amenities drop by 19% in the first 0.5 mile by highways, and 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 the estimated values. In Supp. Appendix E.2.4, I additionally conduct a placebo check around historical large roads and show that local costs are correlated with modern-day pollution measures.

Lastly, in Section 7, I return to the residual component of residential choice b_{igr} to infer discriminatory barriers as a location-race-specific wedge. As a time-invariant term, however, it is not necessary for quantification of highway impacts and will only be used for *counterfactual* analysis.

Model Inversion – In tandem with parameter estimation described above, model inversion occurs in the background to acquire components that enter estimation. As described in greater detail in Supp. Appendix E.1, inversion uses the set of parameters (partially estimated, partially from the literature) to map observed data on residential and workplace populations, commute times, housing prices, and wages to productivity and residential amenities. During this process, several location characteristics such as T_{jgr} are also inferred.

Using the commuting equation for labor supply in Eq. (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

[24] 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.

observed wages with the scale parameter T_{jgr}.[25] Aggregating the workplace factors into the CMA measure and combining CMA, rents, and the estimated parameters θ_r and β_{gr}, I infer amenities B_{igr} up to scale following the residential share expression in Eq. (4).

Not central to the paper but necessary for the equilibrium analysis, I calibrate parameters in the production function using the Nested CES structure for labor demand, wages by group, 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, 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. The additional parameters on the production function and housing supply construction sector are described in Supp. Appendix E.2.5.

5.2 Residential Elasticity and Preferences as Endogenous Amenities

I now estimate the residential elasticity θ_r and racial preferences ρ_r with the equation below which relates population flows to changes in CMA and racial composition, similar to the stylized facts.

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

The first difference is between 1960 and 1970 using the Census microdata. CMA contains the inverted values for scaled wages ω_{jgr} and the commuting elasticities ν_{gr}.

This equation is derived by combining the residential share expression (4), endogenous amenities in (6), and local highway costs in (8) where the vector of controls $\mathbf{X}_i$ contains changes in rental prices and bins over distance from highways for the local costs (all interacted with race and education). Rents and highway costs need to be controlled for as they are correlated with changing residential choice, commuter access improvements, and changing demographics.[26] To obtain cleaner variation in the Interstate shock, all the previous geographic features of historical roads, railroads, etc. as well as the Borusyak and Hull (2023)-proposed control for CMA are also in $\mathbf{X}_i$. All controls are interacted with race and education.

[25] 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 that captures variation in the size of the POW Zone units and workplace amenities beyond wages that are differential by group across locations, including discrimination.

[26] 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.

Since multiple cities are pooled together in estimation, CBSA by group fixed effects $\gamma_{m(i)gr}$ are included to capture factors such as changes in average welfare U_{gr} and aggregate population $\mathbf{L}_{gr}$ such as migration across cities, leading the variation to come from within cities. Importantly, this equation also contains redlining fixed effects $\alpha_{red(i)}$ 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 estimated ρ_r parameter then more closely represents racial preferences since within integrated, redlined areas, discrimination is less significant.

OLS results with all controls described above are presented in Table 3 Column 1. Standard errors are clustered by tract with Conley (1999) standard errors in brackets. Estimates of the residential elasticity for Black households are 0.119 (0.172) and smaller than the value of 0.802 (0.183) for White households, in line with the stylized facts indicating lower Black responsiveness.

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. (2007) (although with larger magnitudes for White families). In Column 2, I add controls for average income, home values, percentage high school graduates, bottom/top income quintile. These covariates lower how much Black households care about racial composition, so some of the earlier estimate came from preferences for SES correlated with race. However, the estimated values for White households are unchanged, so their preferences are mostly related to race.

These results are similar when limiting the sample to only redlined neighborhoods, as shown in Supp. Appendix Table A.2.

Moreover, instruments are needed for consistent estimation of the parameters. For θ_r, the variable $\Delta \log CMA_{igr}$ is endogenous and needs to be instrumented with $\Delta \log CMA_{igr}^{Plans}$, $\Delta \log CMA_{igr}^{Rays}$, which are the same measures as in the empirical evidence section. For ρ_r, omitted variable bias is a concern as the error term ε_{igr} corresponds to changing location characteristics not yet included as covariates. As an example, policies targeted to particular populations, such as steering by real estate agents, affect residential choice and are correlated with changing racial composition. Exogenous shifters of racial composition are then needed, and I construct two types of instruments that exploit *only variation from the highway shock*. The identification assumption behind the racial preferences parameter is then the same as for the rest of the highway parameters: that the empirical strategy isolates exogenous variation in Interstate placement.

The first type follows the 3-step approach of Davis et al. (2019). In an initial step, I estimate a simpler version of Eq. (11) that has only the residential elasticities θ_r (no endogenous amenities) as the estimand while instrumenting for CMA changes with the plans/ray network. Next, using the estimated elasticities by race, I solve a pared-down version of the model that shuts off equilibrium outcome adjustments 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. In the final step, I use the predictions for racial composition $\Delta\log\widehat{(L_{iW}/L_i)}$ as instruments.

Leveraging the migration responses to CMA changes, the second type of instruments directly uses the group-specific CMA measures $\{\Delta\log CMA^{IV}_{iLB}, \Delta\log CMA^{IV}_{iHB}, \Delta\log CMA^{IV}_{iLW}, \Delta\log CMA^{IV}_{iHW}\}$ with $IV = Plans$, or $Rays$ as instruments. Since households migrate as group-specific CMA changes, then racial composition changes, and the instruments have a first-stage.

The exclusion restriction is satisfied for both sets of instruments since conditional on $\Delta\log CMA_{igr}$, they do not affect residential choice except through how they affect racial composition. Additional information on how the instruments are constructed is in Supp. Appendix E.2.6.

Table 3: Residential Elasticity and Racial Preferences

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\log L_{igr}$ (Δ Log Population 1960–1970)					
	OLS		IV Davis		IV CMA	
Variables	Base	+ SES Cont	Plans	Rays	Plans	Rays
θ_r: $\Delta\log CMA_{igr}$						
Black	0.119	0.224	1.281***	1.284***	0.00593	0.412
	(0.172)	(0.171)	(0.374)	(0.324)	(0.378)	(0.290)
	[0.196]	[0.196]	[0.626]	[0.585]	[0.672]	[0.494]
White	0.802***	0.802***	0.576***	0.918***	0.228	0.493**
	(0.183)	(0.183)	(0.167)	(0.161)	(0.244)	(0.203)
	[0.213]	[0.214]	[0.225]	[0.237]	[0.282]	[0.253]
$\tilde{\rho}_r = \theta_r\rho_r$: $\Delta\log$ Pct White						
Black	-0.364***	-0.283***	-0.0616	-0.0766	-0.0737	-0.0418
	(0.0546)	(0.0523)	(0.111)	(0.0894)	(0.151)	(0.137)
	[0.0722]	[0.0720]	[0.176]	[0.147]	[0.238]	[0.214]
White	1.049***	1.066***	1.202***	1.173***	1.170***	1.016***
	(0.0244)	(0.0246)	(0.0556)	(0.0526)	(0.181)	(0.154)
	[0.0436]	[0.0434]	[0.0957]	[0.0939]	[0.221]	[0.193]
R-squared	0.190	0.202	0.531	0.527	0.565	0.568
SES Controls		Yes	Yes	Yes	Yes	Yes
Rounded Obs	N=56500		N=56000		N=38000	
S-W F-Stat (θ_B, θ_W)			6.45, 26.26	10.09, 28.55	5.76, 11.96	14.90, 16.98
S-W F-Stat ($\tilde{\rho}_B$, $\tilde{\rho}_W$)			4.26, 17.22	5.55, 18.61	2.68, 5.66	3.53, 6.02

Notes: Observations are differences over 1960–70 for tracts by race and education (restricted microdata). CBSA FE by group are included. SEs are clustered by tract. Conley SEs (1 km) in brackets. All specifications include controls for change in log rent, five 1-mile-wide bins over distance from highways built 1960-1970, geographic controls, and Borusyak and Hull (2023) control for CMA in large roads, all interacted with race and education. Redlining FE included. SES controls: changes in log of average income, pct high school graduate, pct bottom/top income quintile, home values, all interacted with race and education. Observations rounded to 500 for Census disclosure rules. Sanderson-Windmeijer multivariate F statistics are reported. *** p<0.01, ** p<0.05, * p<0.1

In Table 3 Columns 3–6, I report IV estimates. Residential elasticities for White households are in the range of 0.228 (0.244) 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. The most stable estimate across all specifications is racial preferences for White households, which range from 1.016 (0.154) to 1.202 (0.056) and are highly statistically significant. Interestingly, I find that in the IV estimates, Black racial preferences are fairly weak with point estimates in the range of -0.042 (0.137) to -0.077 (0.089) and many not statistically significant. These results suggest that the previous findings on Black preferences may result from correlations with changing unobserved characteristics.

At the bottom of Table 3, 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.

5.3 Validation Exercises

After completing estimation and parametrizing the model, I conduct several tests to validate that the model's predictions match the empirical moments. For non-targeted variables, Supp. Appendix Table A.3 shows that the relationship between changes in rent prices, racial sorting, and income with CMA improvements exhibits similar qualitative and quantitative patterns for the predicted and observed values. Supp. Appendix Figure B.4 shows the tight relationship between predicted vs observed commute flows in 1960 and 1970.

To validate the modeling assumptions, in Supp. Appendix Table A.4, I show that changes in log productivity are uncorrelated with distance from routes, so there is no reallocation of economic activity to areas by routes. This result rules out trade costs as an important channel for firm relocation because the productivity term is the residual component after removing the commuting channel of labor supply to workplaces. I do not model discrimination at workplaces because firm productivity is unrelated to redlining in either 1960 or 1970 (see Supp. Appendix Table A.5).

6 Welfare Analysis

Having estimated the set of key model parameters, I conduct several simulations to investigate the impacts of Interstate highways on welfare inequality. I leave the quantification of the role of discrimination to Section 7 since neighborhood barriers are assumed to be invariant to highway policy, so I take the constraints on residential choice as given and proceed with the welfare assessment.

6.1 The Impacts of the Interstates

Returning to the welfare impacts expression in Eq. (10), changes in commute costs, disamenities, and equilibrium outcomes are weighted by initial shares in the cross-sectional distribution and aggregated using substitution elasticities across locations. Because of the low residential elasticities of the Black population, their initial shares being centrally concentrated suggests that shocks to the urban core come close to fully determining their welfare impacts. To illustrate this result more definitively, I break down specific channels in the equilibrium framework and measure how welfare changes when different parts are allowed to adjust.

In the equilibrium analysis, I simulate the construction of highways starting in 1960 as the reduction in commute times and the addition of localized costs along routes built from 1960 to 1970.[27] Across the 25 metro areas in the analysis, I calculate a weighted average with city-level population weights and report these averages as the main counterfactual numbers. Supp. Appendix F.3 lists the full set of equations for the general equilibrium system. Solving for equilibria follows the iterative procedure described by Allen and Arkolakis (2014).

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 (Dekle et al., 2008). I infer counterfactual changes with predicted flows generated using the estimated commuting elasticities to avoid 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.

For parameters, residential elasticities are obtained from Table 3 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 for White households, $\rho_W = 1$ at the low range of the confidence intervals.[28] 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. All model parameters are listed in Table 4.

After conducting the welfare analysis under different scenarios, Figure 5a displays the values for the change in welfare across the race and education groups. Starting from the left, the *direct impacts* ignore reallocation or equilibrium adjustments and is a transparent weighted average of the changes in commute times and fundamental amenities from the Interstate system with weights

[27] 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.

[28] 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 Supp. Appendix F.4. However, the conditions are not necessary for uniqueness, and I do not encounter multiple equilibria with the smaller preference parameters.

Table 4: 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	
$\nu_{LB} = 4.20$, $\nu_{HB} = 3.65$, $\nu_{LW} = 4.71$, $\nu_{HW} = 4.15$	Estimated in Table E.14
$\kappa_{LB} = 1.4$, $\kappa_{HB} = 1.22$, $\kappa_{LW} = 1.57$, $\kappa_{HW} = 1.38$	Implied with $\phi = 3$
Residential Elasticity $\theta_B = 0.35$, $\theta_W = 0.8$	Estimated in Table 3
Racial Preferences $\rho_B = 0$, $\rho_W = 1$	Estimated in Table 3
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.2.3
Highway Localized Costs $b^{HW} = 0.203$, $\eta = 0.612$	Estimated in Table E.18

Notes: ϕ is set to a value from the literature. Parameter ν_{gr} comes from Table E.14 Panel B. θ_r comes from the midpoint of estimates in Table 3. ρ_B is set to 0 since the estimates from Table 3 are not distinguishable from zero. ρ_W is set to be within the lower range of the confidence intervals from Table 3 and not greater than 1. β_{gr} comes from Table E.17. b^{HW} and η come from fitting two values in Table E.18 Column 5.

that are the initial shares at residences and workplaces.[29]

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

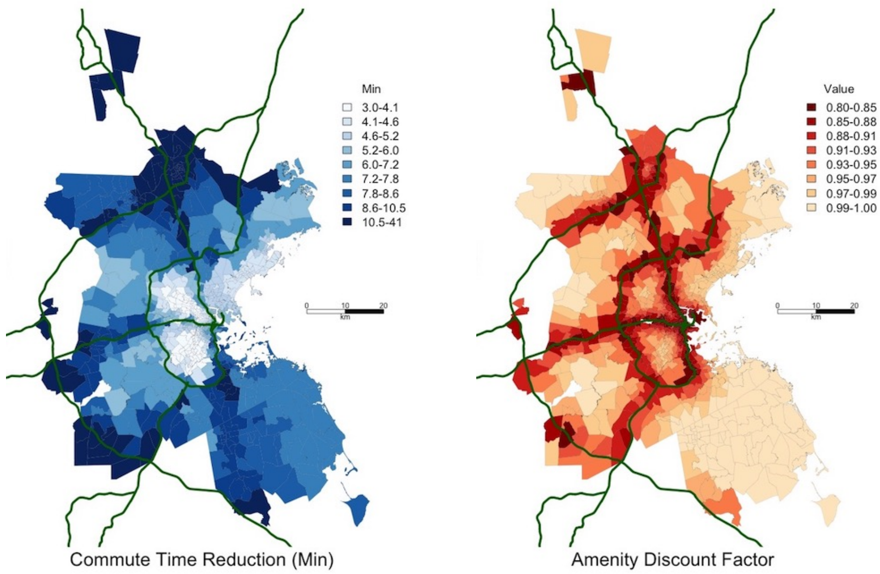
These direct impacts are visualized in Figure 5 for the city of Boston where the spatial distribution of the Black population is also provided for comparison. Given the disparate placement of highways (leading to unequal distribution of costs) as well as lower Black car usage and commute time reductions being muted in the central city (leading to unequal receipt of benefits), it is unsurprising that the welfare changes are more positive for White households. Gaps are small across education within race, but large across race. Direct impacts are around -1.5% for the Black population (slightly lower for the less-educated) and 1.7% for the White population (slightly higher for the more-educated).

Next, I allow for household *reallocation* across locations, but no equilibrium outcome adjustments, so that 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 Eq. (10). By allowing for spatial mobility, welfare losses are

[29] A derivation that starts from the welfare equation (7) is available in Supp. Appendix F.1.

Figure 5: Interstate Highway Impacts for Boston Metro Area in 1960

Commute time reductions | Localized costs



Notes: Observations are census tracts limited to those where population is observed in 1960 in IPUMS-NHGIS. Commute time changes calculated 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 parameter estimates from Table 4 and applying it to census tracts using the distance from the tract to the nearest Interstate.

then around -1% for the Black population and gains are 3% 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.

As most of the empirical evidence was related to residential changes, I only allow equilibrium outcome adjustments for residential characteristics and shut down those on the firm side in a *partial equilibrium* counterfactual. Any changes in labor supply do not affect wages paid to workers or housing demand from firms (see Supp. Appendix F.2 for exact equations). I find that the welfare results look broadly similar. Relatedly, moving to the full *general equilibrium* system only slightly changes the values, suggesting that equilibrium outcome adjustments play a small role in welfare. This lack of effect can be due to outcomes offsetting each other, 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.

Finally, 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% to -1.3% while White welfare increases from 2.9% to 3.1%. 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.

Additional Results – In Supp. Appendix Table A.6, I probe how the changes to welfare are affected by slight modifications in key parameters. Removing White homophily preferences or agglomeration forces do not substantially alter the results. Increasing homophily for Black households somewhat offsets the losses from Interstate development, since racial segregation increase. Raising the residential elasticity to larger values found in the literature boosts the welfare gains for all groups, but especially for Black households, which suggests that increasing residential mobility across all locations could be another policy solution for reducing racial disparities.

In the same table, I conduct counterfactual exercises on alternative designs for transportation infrastructure could be informative for policy. 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 unequal impacts by race because Interstate highways were required to intersect central cities, further highlighting the importance of residential barriers, and because of differences in car usage. Mitigating highway costs (calculated as only including the commuting benefits) increases welfare, especially for Black households, which suggests that an effective policy would be reducing highway harms. Indeed, regulation of Interstate construction has strengthened over time to limit the negative consequences, leading to rising construction costs (Brooks and Liscow, 2020).

Lastly, Supp. Appendix Table A.7 shows the changes in equilibrium outcomes from the simulations. Black households experience large drops in amenities, slightly lower wages, lower commute times, but increased commute distance. They move marginally further outwards and away from redlined areas. 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. These equilibrium adjustments, in addition to the direct impacts, contribute to inequality in highway impacts.

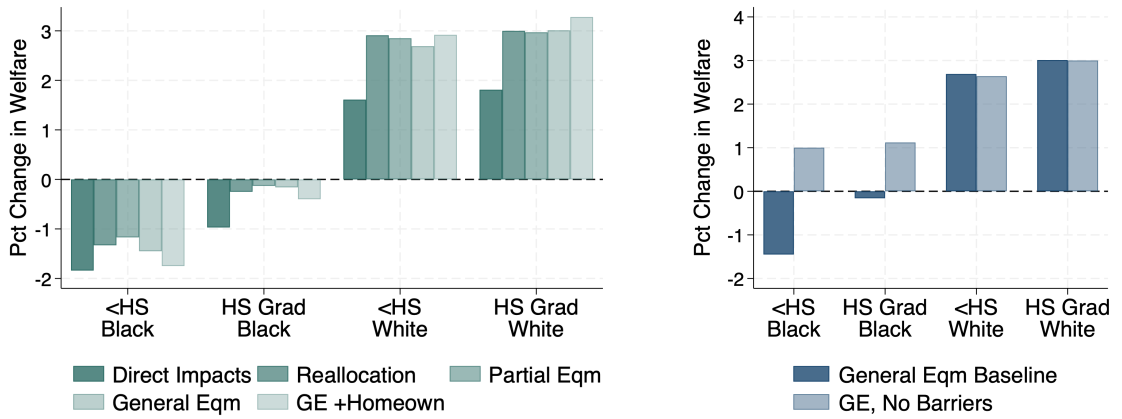
7 Residential Barriers in Welfare Impacts

In this section, I decompose the factors behind the spatial concentration of Black households in central areas. The location-specific barriers that affect the cross-sectional distribution further shape the distributional impacts of the Interstates. I begin with differences in racial composition around the borders of redlining maps where an identification strategy permits clean tests of the presence of residential discrimination. I then discuss the takeaways from this strategy and consequently examine barriers away from the border to study segregation more broadly.

Figure 5: Welfare Changes (%) by Race and Education

(a) Breakdown of Highway Impacts

(b) Highway Impacts without Barriers



Notes: Welfare calculations use Census restricted microdata in 1960. Direct impacts from linear approximation in Section F.1. GE simulation allows firms/wages to respond relative to PE simulation. The general equilibrium simulation with no barriers adds highway impacts to the counterfactual world with barriers removed.

7.1 Evidence from Border Discontinuity

Returning to the model-implied barriers in the location-race-specific wedge, I employ a discontinuity design to test how they are related to the borders of the HOLC maps.

Past research has measured how racial composition sharply shifts across the grades of HOLC maps (Hillier, 2003; Faber, 2014; Aaronson et al., 2021). In Supp. Appendix Figure B.5, percent White drops by a sizable 18 percentage points upon crossing into redlined neighborhoods. Yet instead of solely studying empirical changes in racial composition, I use the previously estimated parameters and model structure to infer the *sources* of segregation. The differences in racial composition at the border are NOT due entirely to discrimination because rental prices are lower in redlined areas, contributing to economic segregation correlated with race, and racial preferences would further reinforce any sorting at the border. I consequently decompose the population changes by race as resulting from various components: prices and commuting access, racial preferences, other SES characteristics, and the discriminatory wedge $(1-\tau^{b}_{igr})$ as the residual.

The border discontinuity design is estimated separately by race in the 1960 Census microdata:

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

In this equation, α_{gr} are education by race fixed effects, D_i^{red} is an indicator for being a redlined neighborhood, and λ_{ilr} are fixed effects for each border l. $DistRED_i$ is the distance to the nearest border between redlined and non-redlined neighborhoods (and is positive if in a redlined one). $\mathbf{F}_r$ and $\mathbf{G}_r$ are polynominal functions of distance. To avoid confounding the effect of social barriers with physical barriers or changes in school districts, I remove areas by railroads, large roads, highways, and school district borders (which come from the National Center for Education Statistics).[30] In estimation, I follow Calonico et al. (2014) to calculate optimal bandwidth.

Y_{igr} corresponds to several outcomes for the factors behind residential choice. As the first outcome, $\log L_{igr}$ is informative of how each race group is distributed across the border. In Table 5 Columns 1 & 5, I find that the combination of Black households living more (a striking 1.43 (0.23) increase in log population) and White households living less (a -0.55 (0.12) decline in log population) in redlined neighborhoods leads to the drop in percentage White entering redlined areas. During this time, Black households were heavily concentrated in redlined areas.

To remove the price and CMA components from residential location $\log L_{igr}$, the next outcome is the amenity term B_{igr}, which is inverted for using the residential choice expression in Eq. (9). In Columns 2 & 6, I find the discontinuity is only slightly reduced for Black households to 1.37 (0.24). As White households also prefer lower prices, the estimate of -0.60 (0.11) is reduced as well. These results show that cheaper rents cannot explain why White households live less in redlined areas or much of the change in Black and White populations over the border.

To remove racial preferences i.e. homophily from location choice, I next invert for the fundamental amenities b_{igr}, which includes the residential wedge for discrimination.[31] When fundamental amenities are the outcome in Columns 3 & 7, the discontinuity remains large for Black households at 1.266 (0.209) and disappears for White households to 0.0031 (0.097). This change from Column 6 to 7 implies that racial preferences fully account for why the White population does not live in redlined areas. Moreover, the insignificant coefficient in Column 7 indicates that discrimination does not affect White residential locations. Yet, racial preferences only explain a portion of the rise in the Black population, leaving a large residual in Column 3.

Importantly, measuring how fundamental amenities look along the border also provides a test of the identification assumption behind the discontinuity design, which is that other neighborhood features (minus prices, CMA, racial composition) should be smooth by the border in the absence of discrimination.[32] As the discontinuity estimate in Column 7 is essentially zero for White households, neighborhoods at the border do not appear to be substantially different, and the identification assumption is satisfied.

[30] 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.

[31] To obtain the most conservative value for the location wedge, when inverting for fundamental amenities, I take the highest estimates for racial preferences for both White and Black households and also take the highest residential elasticity for White households and assign it to Black households. Parameters are listed at the bottom of Table 5.

[32] This identification assumption is distinct from that of Aaronson et al. (2021), which searches for borders where there were no pre-existing racial differences before the maps were drawn in 1932, as they aim to measure the treatment effects of the HOLC maps. The discontinuity estimates of this paper capture discrimination that is not only from the drawing of the HOLC maps.

Adding socioeconomic controls in Columns 4 & 8 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). For Black households, based on these estimates, 65% of the population rise entering redlined areas is in the residual wedge and thus a result of discriminatory barriers.

Additional Results – To further test the identification assumption, in Supp. Appendix E.2.7, I assess if natural amenities change discontinuously along the border. I find that those which are less manipulable, i.e. open water and wetlands, are continuous, which supports the identification assumption.[33] I also conduct additional robustness checks such as decomposing the sources of segregation using controls, rather than the model structure, to reduce the reliance on the structural assumptions and estimated parameters. Finally, I examine how estimates of the discontinuity change over time, for different sample definitions, and for additional variables.

Table 5: Border Discontinuity Decomposition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Black				*White*			
Variables	$\log L_{igB}$	$\theta_B \log B_{igB}$	$\theta_B \log b_{igB}$	+ SES Cont	$\log L_{igW}$	$\theta_W \log B_{igW}$	$\theta_W \log b_{igW}$	+ SES Cont
Border RD	1.425***	1.370***	1.266***	0.914***	-0.546***	-0.603***	0.00305	0.132
	(0.226)	(0.238)	(0.209)	(0.181)	(0.122)	(0.112)	(0.0971)	(0.0937)
Bandwidth (mi)	0.495	0.447	0.509	0.496	0.358	0.398	0.297	0.305
Rounded Obs	N=13000				N=13500			

Notes: Observations are census tracts by redlining-map border by race from the 1960 restricted Census microdata. Dependent variables are residualized on fixed effects for education and border fixed effects. SES Controls: log of pct high school grad, population density, average income, pct bottom/top quintile, and home values. Limited to tracts at least 0.1 miles away from physical barriers of historical large roads, constructed highways in 1960, or railroads, and also at least 0.1 miles away from school district boundaries. The bandwidth is chosen optimally following Calonico et al. (2014) with order of polynomial=1. Observations rounded to 500 for Census disclosure rules. Parameters to invert for dependent variables are $\theta_B = \theta_W = 0.9$, $\theta_B\rho_B = -0.3$, $\theta_W\rho_W = 1.20$, $\beta_{LB} = 0.66$, $\beta_{HB} = 0.78$, $\beta_{LW} = 0.70$, $\beta_{HW} = 0.79$. *** p<0.01, ** p<0.05, * p<0.1

7.2 Interaction with Interstates for Welfare Impacts

Useful conceptual lessons are gleaned from the border design. Specifically, the model-implied barriers appear to be a large determinant of Black residential choices and are correlated with empirical proxies for where discrimination historically occurred.

However, the discontinuity estimate is likely an underestimate of the extent to which Black households are excluded from broad sections of cities because the change in racial composition at the border pales in comparison to the stark segregation during this era. In 1960, 70% of cen-

[33] 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.

sus tracts are more than 99% White, and near the border, neighborhoods are more racially integrated than those in far-flung suburbs. This tradeoff between proper identification and the potential scope of the question is widespread in economics. While the border design allows for a testable identification assumption, the estimates there are a local average treatment effect that overlooks heterogeneity in discrimination further away.

For the final analysis, I remove the residential wedge across all neighborhoods and re-simulate the construction of Interstate highways to measure the new welfare gains and losses. In practice, assuming that housing discrimination does not apply to the White population, eliminating barriers occurs through setting Black fundamental amenities (which contain the wedge) equal to White fundamentals (which should reflect natural amenities). Implicitly, this exercise assumes that the valuation of fundamental, natural amenities is not differential by race.[34] Otherwise, the location-race-residual is overstating the degree of segregation attributable to discrimination.

In this new environment, I display the changes to welfare from Interstate development in Figure 5b. The racial gap in the general equilibrium impacts from highways is greatly diminished by around 54%, so residential barriers determine the majority of inequality from the Interstate system. Black households now experience welfare gains from highways of 1%, versus previously they were facing losses of -1%. This result is explained by the substantial reduction in the spatial concentration of Black families, who now live 94% farther from the CBD and 50% less in redlined neighborhoods, as shown in Supp. Appendix Table A.8.

White households experience similar gains to before of 2.8%, so relaxing residential discrimination does not greatly alter their benefits from Interstate development. This finding notably suggests that policies which assist minority groups do not have to come at great expense to the majority group, especially given the smaller relative size of these populations. All race and education groups in this counterfactual receive large welfare improvements from infrastructure construction.

However, the gap by race in welfare impacts does not fully disappear. Partially, a gap persists because racial segregation is still present from differences in economic status, commuting patterns, and firm locations by race, as well as racial homophily by both Black and White households. Additionally, car usage by the Black population continues to be lower than for the White population, so the commuting benefits are not equalized across groups. Still, the clear takeaway from this counterfactual analysis is that segregation, specifically through forces that cannot be accounted for by economic factors or racial homophily, plays a crucial role in inequality in highway impacts.

[34] The fundamental amenity term is a residual and could contain other location-specific differences by race not yet accounted for that would not be considered discrimination. Examples include differences in social networks or information access.

8 Conclusion

This paper constructs several rich historical datasets and develops a quantitative framework to measure the distributional impacts of the most prominent transportation infrastructure project in the U.S., the Interstate highway system. To understand why there are profoundly unequal effects, I measure how neighborhood discrimination is a central determinant of the spatial concentration of Black families, which then interacts with highway policy to produce disparities across race. Spatial frictions that limit the mobility of minority 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.

While it may seem that Interstate highways and housing discrimination are things of the past, road infrastructure expansions in the modern day encounter the same equity concerns as they have historically.[35] 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 has not disappeared and continues to restrict residential choice for many groups (Bayer et al., 2021). Moreover, the radical transformation of cities brought about by the Interstate highway system has persistent effects, given the permanent nature of large-scale infrastructure.

The findings of this paper do not diminish the immense economic value of building the Interstate highway system. Indeed, every demographic group experiences large welfare gains from its development when given the freedom to live in any neighborhood of their choosing. This study suggests that more policies should improve spatial mobility for the most disadvantaged families, as residential segregation is a pivotal determinant of how equitable any placed-based intervention will be in the distribution of its costs and benefits.

[35] 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.

References

Aaronson, Daniel, Daniel Hartley, and Bhashkar Mazumder, "The Effects of the 1930s HOLC "Redlining" Maps," *American Economic Journal: Economic Policy*, 2021, *13* (4), 355–392.

Adão, Rodrigo, Costas Arkolakis, and Federico Esposito, "General Equilibrium Effects in Space: Theory and Measurement," *National Bureau of Economic Research Working Paper Series*, 2019, *No. 25544.*

Ahlfeldt, Gabriel M, Stephen J Redding, Daniel M Sturm, and Nikolaus Wolf, "The Economics of Density: Evidence From the Berlin Wall," *Econometrica*, 2015, *83* (6), 2127–2189.

Allen, Treb and Costas Arkolakis, "Trade and the Topography of the Spatial Economy *," *The Quarterly Journal of Economics*, 2014, *129* (3), 1085–1140.

_ **and** _ , "The Welfare Effects of Transportation Infrastructure Improvements," *The Review of Economic Studies*, nov 2022, *89* (6), 2911–2957.

Almagro, Milena and Tomas Dominguez-Iino, "Location Sorting and Endogenous Amenities: Evidence from Amsterdam," *Working Paper*, 2020.

Atack, Jeremy, "Historical Geographic Information Systems (GIS) database of Steamboat-Navigated Rivers During the Nineteenth Century in the United States," 2015.

_ , "Historical Geographic Information Systems (GIS) database of U.S. Railroads for 1826-1911," 2016.

_ , "Historical Geographic Information Systems (GIS) database of Nineteenth Century U.S. Canals," 2017.

Bagagli, Sara, "The (Express)Way to Segregation: Evidence from Chicago," 2024.

Balboni, Clare, Gharad Bryan, Melanie Morten, and Bilal Siddiqi, "Transportation, Gentrification, and Urban Mobility: The Inequality Effects of Place-Based Policies," 2020.

Baum-Snow, Nathaniel, "Did Highways Cause Suburbanization?," *The Quarterly Journal of Economics*, 2007.

_ , "Urban Transport Expansions and Changes in the Spatial Structure of US Cities: Implications for Productivity and Welfare," *Review of Economics and Statistics*, 2020.

_ **and Byron F. Lutz**, "School desegregation, school choice, and changes in residential location patterns by race," *American Economic Review*, 2011.

_ **and Lu Han**, "The Microgeography of Housing Supply," *Working Paper*, 2021.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan, "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, 2007, *115* (4), 588–638.

_ **, Kerwin Kofi Charles, and JoonYup Park**, "Separate and Unequal: Race and the Geography of the American Housing Market," *Working Paper*, 2021.

Beall, Jo, Basudeb Guha-Khasnobis, and Ravi Kanbur, *Urbanization and Development: Multidisciplinary Perspectives*, Oxford University Press, 2011.

Becker, Gary S, *The economics of discrimination*, University of Chicago press, 1971.

Borjas, George J, "The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market," *The Quarterly Journal of Economics*, 2003, *118* (4), 1335–1374.

Borusyak, Kirill and Peter Hull, "Non-Random Exposure to Exogenous Shocks," *Working Paper*, 2023.

Boustan, Leah P., "Was postwar suburbanization "White flight"? Evidence from the black migration," *The Quarterly Journal of Economics*, 2010.

Boustan, Leah Platt, "Competition in the Promised Land: Black Migration and Racial Wage Convergence in the North, 1940-1970," *The Journal of Economic History*, 2009, *69* (3), 755–782.

_ , "School Desegregation and Urban Change: Evidence from City Boundaries," *American Economic Journal: Applied Economics*, 2012, *4* (1), 85–108.

Brinkman, Jeffrey and Jeffrey Lin, "Freeway Revolts! The Quality of Life Effects of Highways," *The Review of Economics and Statistics*, 2022, pp. 1–45.

Brooks, Leah and Zachary D. Liscow, "Infrastructure Costs," 2020.

Bunten, Devin Michelle, Ellen Fu, Lyndsey Rolheiser, and Christopher Severen, "The Problem Has Existed over Endless Years: Racialized Difference in Commuting, 1980–2019," *Working Paper*, 2022.

Calonico, Sebastian, Matias D Cattaneo, and Rocío Titiunik, "Robust Data-Driven Inference in the Regression-Discontinuity Design," *The Stata Journal*, 2014, *14* (4), 909–946.

Card, David, "Immigration and Inequality," *American Economic Review*, 2009, *99* (2), 1–21.

Caro, Robert A, *The Power Broker: Robert Moses and the Fall of New York*, [First edition]. New York : Knopf, 1974., 1974.

Census Bureau, "1960 Census of the Population: Supplementary Reports: Race of the Population of the United States, by States: 1960," Technical Report 1961.

Chandra, Amitabh and Eric Thompson, "Does public infrastructure affect economic activity?: Evidence from the rural interstate highway system," *Regional Science and Urban Economics*, 2000, *30* (4), 457–490.

Christensen, Peter and Christopher Timmins, "Sorting or Steering: The Effects of Housing Discrimination on Neighborhood Choice," *Journal of Political Economy*, 2022, *130* (8), 2110–2163.

_ **and** _ , "The Damages and Distortions from Discrimination in the Rental Housing Market*," *The Quarterly Journal of Economics*, nov 2023, *138* (4), 2505–2557.

Combes, Pierre-Philippe, Gilles Duranton, and Laurent Gobillon, "The Production Function for Housing: Evidence from France," *Journal of Political Economy*, 2021, *129* (10), 2766–2816.

Conley, T G, "GMM estimation with cross sectional dependence," *Journal of Econometrics*, 1999, *92* (1), 1–45.

Corey, Michael, Penny Petersen, Kirsten Delegard, Rebecca Gillette, Ryan Mattke, Kevin Ehrman-Solberg, Marguerite Mills, and crowdsourcing community Mapmakers, "U.S. Racial Covenants Series, Hosted by Mapping Prejudice," 2025.

Cullen, Julie Berry and Steven D Levitt, "Crime, Urban Flight, and the Consequences for Cities," *The Review of Economics and Statistics*, 1999, *81* (2), 159–169.

Currie, Janet, John Voorheis, and Reed Walker, "What Caused Racial Disparities in Particulate Exposure to Fall? New Evidence from the Clean Air Act and Satellite-Based Measures of Air Quality," *American Economic Review*, 2022.

Cutler, David M., Edward L. Glaeser, and Jacob L. Vigdor, "The Rise and Decline of the American Ghetto," *Journal of Political Economy*, 1999, *107* (3), 455–506.

Davis, Morris A and François Ortalo-Magné, "Household expenditures, wages, rents," *Review of Economic Dynamics*, 2011, *14* (2), 248–261.

— , **Jesse Gregory, and Daniel Hartley**, "The Long-Run Effects of Low-Income Housing on Neighborhood Composition," 2019.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum, "Global Rebalancing with Gravity: Measuring the Burden of Adjustment," *IMF Staff Papers*, 2008, *55* (3), 511–540.

Diamond, Rebecca, "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Review*, 2016, *106* (3), 479–524.

— **and Cecile Gaubert**, "Spatial Sorting and Inequality," *Working Paper*, 2021.

Dingel, Jonathan and Felix Tintelnot, "Spatial Economics for Granular Settings," *Working Paper*, 2023.

Donaldson, Dave and Richard Hornbeck, "Railroads and American Economic Growth: A "Market Access" Approach," *The Quarterly Journal of Economics*, 2016, *131* (2), 799–858.

Duranton, Gilles and Matthew A. Turner, "Urban Growth and Transportation," *Review of Economic Studies*, 2012, *79* (4), 1407–1440.

— , **Peter M Morrow, and Matthew A Turner**, "Roads and Trade: Evidence from the US," *The Review of Economic Studies*, 2014, *81* (2), 681–724.

Ellison, Glenn, Edward L Glaeser, and William R Kerr, "What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns," *American Economic Review*, 2010, *100* (3), 1195–1213.

Epple, Dennis, Brett Gordon, and Holger Sieg, "A New Approach to Estimating the Production Function for Housing," *American Economic Review*, 2010, *100* (3), 905–924.

ESRI, "USA (Interstate Highways, 1996)," 1996.

— , "US Major Roads (2010)," 2019.

Faber, Benjamin, "Trade Integration, Market Size, and Industrialization: Evidence from China's National Trunk Highway System," *The Review of Economic Studies*, 2014, *81* (3), 1046–1070.

Faber, Jacob W, "We Built This: Consequences of New Deal Era Intervention in America's Racial Geography," *American Sociological Review*, 2020, *85* (5), 739–775.

Fishback, Price V, Jessica LaVoice, Allison Shertzer, and Randall Walsh, "The HOLC Maps: How Race and Poverty Influenced Real Estate Professionals' Evaluation of Lending Risk in the 1930s," *National Bureau of Economic Research Working Paper Series*, 2020, *No. 28146.*

— , **Jonathan Rose, Ken Snowden, and Thomas Storrs**, "New Evidence on Redlining by Federal Housing Programs in the 1930s," *Working Paper*, 2022.

Gibbons, John W and Albert Proctor, "Economic Costs of Traffic Congestion," *Highway Research Board Bulletin*, 1954, (86).

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell, "Long-Run Implications of Investment-Specific Technological Change," *The American Economic Review*, 1997, *87* (3), 342–362.

Head, Keith and Thierry Mayer, "Chapter 3 - Gravity Equations: Workhorse,Toolkit, and Cookbook," in Gita Gopinath, Elhanan Helpman, and Kenneth B T Handbook of International Economics Rogoff, eds., *Handbook of International Economics*, Vol. 4, Elsevier, 2014, pp. 131–195.

Heblich, Stephan, Stephen J Redding, and Daniel M Sturm, "The Making of the Modern Metropolis: Evidence from London*," *The Quarterly Journal of Economics*, 2020, *135* (4), 2059–2133.

Higgs, Robert, "Firm-Specific Evidence on Racial Wage Differentials and Workforce Segregation," *The American Economic Review*, 1977, *67* (2), 236–245.

Hillier, Amy E, "Redlining and the Home Owners' Loan Corporation," *Journal of Urban History*, 2003, *29* (4), 394–420.

Hirsch, Arnold R., *Making the Second Ghetto: Race and Housing in Chicago, 1940-1960*, The University of Chicago Press, 1983.

Holian, Matthew J. and Matthew E. Kahn, "Household carbon emissions from driving and center city quality of life," *Ecological Economics*, 2015, *116*, 362–368.

Holzer, Harry J and Jess Reaser, "Black Applicants, Black Employees, and Urban Labor Market Policy," *Journal of Urban Economics*, 2000, *48* (3), 365–387.

Jackson, Kenneth T, *Crabgrass Frontier: The Suburbanization of the United States*, New York: Oxford University Press, 1985.

Jones-Correa, Michael, "The Origins and Diffusion of Racial Restrictive Covenants," *Political Science Quarterly*, 2000, *115* (4), 541–568.

Katz, Lawrence F and Kevin M Murphy, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 1992, *107* (1), 35–78.

Kline, Patrick and Enrico Moretti, "Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority *," *The Quarterly Journal of Economics*, 2014, *129* (1), 275–331.

Kreindler, Gabriel and Yuhei Miyauchi, "Measuring Commuting and Economic Activity Inside Cities with Cell Phone Records," *Review of Economics and Statistics*, 2022.

Krimmel, Jacob, "Reclaiming Local Control: School Finance Reforms and Housing Supply Restrictions," *Working Paper*, 2022.

Lee, Sanghoon and Jeffrey Lin, "Natural Amenities, Neighbourhood Dynamics, and Persistence in the Spatial Distribution of Income," *The Review of Economic Studies*, 2017, pp. rdx018–rdx018.

Lee, Sun Kyoung, "When Cities Grow: Urban Planning and Segregation in the Prewar US," *Working Paper*, 2022.

Logan, John R, Zengwang Xu, and Brian J Stults, "Interpolating U.S. Decennial Census Tract Data from as Early as 1970 to 2010: A Longitudinal Tract Database," *The Professional Geographer*, 2014, *66* (3), 412–420.

Mahajan, Avichal, "Highways and segregation," *Journal of Urban Economics*, 2024, p. 103574.

Margo, Robert A, *Race and Schooling in the South, 1880-1950: An Economic History*, University of Chicago Press, 2007.

Michaels, Guy, "The Effect of Trade on the Demand for Skill: Evidence from the Interstate Highway System," *The Review of Economics and Statistics*, 2008, *90* (4), 683–701.

Miller, Conrad, "When Work Moves: Job Suburbanization and Black Employment," *The Review of Economics and Statistics*, 2023, *105* (5), 1055–1072.

Monte, Ferdinando, Stephen J Redding, and Esteban Rossi-Hansberg, "Commuting, Migration, and Local Employment Elasticities," *American Economic Review*, 2018, *108* (12), 3855–3890.

Morten, Melanie and Jaqueline Oliveira, "The Effects of Roads on Trade and Migration: Evidence from a Planned Capital City," *Working Paper*, 2018.

Nelson, Robert K., LaDale Winling, Richard Marciano, Nathan Connolly, and Et Al., "Mapping Inequality," in Robert K. Nelson and Edward L. Ayers, eds., *American Panorama*, 2020.

North, Douglass C, "Institutions," *Journal of Economic Perspectives*, 1991, *5* (1), 97–112.

of Minnesota) Manson, Steven (University, Jonathan Schroeder, David Van Riper, and Steven Ruggles, "IPUMS National Historical Geographic Information System: Version 12.0 [Database].," 2017.

Ottaviano, Gianmarco I P and Giovanni Peri, "Rethinking the Effect of Immigration on Wages," *Journal of the European Economic Association*, 2012, *10* (1), 152–197.

Rose, Mark and Raymond A. Mohl, *Interstate: Highway Politics and Policy since 1939*, The University of Tennessee Press, 2012.

Rose, Mark H., *Interstate: Express Highway Politics, 1939-1989*, University of Tennessee Press, 1990.

Rosenthal, Stuart S and William C Strange, "Chapter 49 - Evidence on the Nature and Sources of Agglomeration Economies," in J Vernon Henderson, Jacques-François B T Handbook of Regional Thisse, and Urban Economics, eds., *Cities and Geography*, Vol. 4, Elsevier, 2004, pp. 2119–2171.

Rothstein, Richard, *The Color of Law* 2017.

Rumsey, David, *David Rumsey Map Collection*, San Francisco, California: Cartography Associates, 2020.

Saiz, Albert, "The Geographic Determinants of Housing Supply*," *The Quarterly Journal of Economics*, 2010, *125* (3), 1253–1296.

Severen, Christopher, "Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification," *The Review of Economics and Statistics*, 2021, pp. 1–99.

Silva, J M C Santos and Silvana Tenreyro, "The Log of Gravity," *The Review of Economics and Statistics*, 2006, *88* (4), 641–658.

Song, Jaehee, "Exclusionary Zoning and Transportation," *Working Paper*, 2022.

Taylor, Keeanga-Yamahtta, *Race for Profit*, University of North Carolina Press, 2019.

Tsivanidis, Nick, "Evaluating the Impact of Urban Transit Infrastructure: Evidence from Bogotá's TransMilenio," *Working Paper*, 2023.

Walters, A A, "The Theory and Measurement of Private and Social Cost of Highway Congestion," *Econometrica*, 1961, *29* (4), 676–699.

Wooldridge, Jeffrey M, "Control Function Methods in Applied Econometrics," *The Journal of Human Resources*, 2015, *50* (2), 420–445.

Supplemental Appendix

A Appendix Tables

Table A.1: Change in Home Values over Distance from Central Business District and Distance from Highway (1950-1960, 1960-1970)

Variables	(1) OLS Δ Log Home Value	(2) IV for Log Dist Highway Plans	(3) 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
Observations	10,395	10,395	10,395
KP F-Stat		678.5	469.7

Notes: Observations are tracts from 1950, 1960, and 1970 (IPUMS NHGIS). The first difference is either over 1950 to 1960 or 1960 to 1970, depending on highway construction timing, and stacked into one panel. Limited to <5 miles of the nearest route and 30 miles from the central business district. Fixed effects at the CBSA level. Conley (1 km) standard errors reported. Control are for log distance from rivers, lakes, shores, ports, railroads, canals, and historical large roads, and the gradient (Dist CBD/Dist Highway). Redlined tracts are more than 80% HOLC D. Kleibergen-Paap rk Wald F statistics reported. *** p<0.01, ** p<0.05, * p<0.1

Table A.2: Residential Elasticity and Racial Preferences – Redlined Sample

Variables	(1) $\Delta \log L_{igr}$ (Δ Log Population 1960-1970) OLS	(2) + 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]
$\tilde{\rho}_r = \theta_r \rho_r$: $\Delta \log$ 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
Rounded Obs	56500	56500

Notes: Observations are first differences from 1960 to 1970 for tracts × group from the Census microdata. CBSA fixed effects by group included. Standard errors are cluster-robust by tract. Conley standard errors (1km) reported in brackets. The base controls are changes in log rent and 5 1-mile wide bins for distance from highways built between 1960-1970. SES controls are changes in log of income, pct high school graduate, pct top/bottom income quintile, and home values. Redlining fixed effects included in all specifications. The geographic controls are log distance from the CBD, rivers, lakes, shores, ports, historical railroads, canals, and historical large roads. All specifications include the Borusyak and Hull (2023) control for CMA in large roads. All controls are interacted with group. Observations are rounded to the nearest 500 for Census disclosure. *** p<0.01, ** p<0.05, * p<0.1

Table A.3: 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.4: 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.5: Log Productivity 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.6: 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
$\rho_r = 0, \gamma^A = 0$	-1.44	-0.21	2.79	3.00	-1.05	2.90	2.16	2.78
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 3 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.7: 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 Barriers								
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 4. All values are rounded to four significant digits for Census disclosure.

Table A.8: Changes in Welfare and Equilibrium Outcomes (%)
for Removal of Barriers by Group

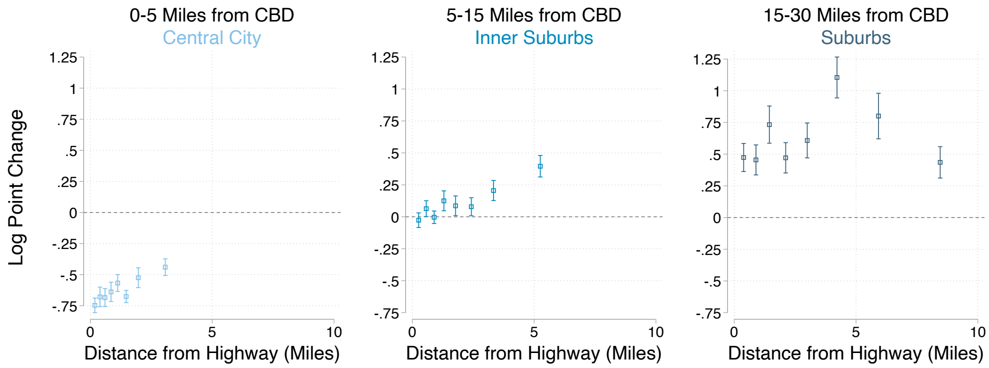
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Race	Black	Black	White	White	By Race		By Educ	
x Educ	<HS	HS+	<HS	HS+	Black	White	<HS	HS+
Welfare Change	—	—	-0.03	-3.27	—	-1.75	—	—
Rent	9.35	11.62	-0.56	-0.33	10.08	-0.44	0.92	0.48
Pct White	136.3	124.0	-5.04	-6.12	132.36	-5.61	16.02	2.75
Pct HOLC D	-52.74	-46.97	12.67	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 simulation removes the location-race-specific wage for Black households, so welfare estimates are not available for them. Parameter values are the same as in Table 4. All values are rounded to four significant digits to meet Census disclosure rules.

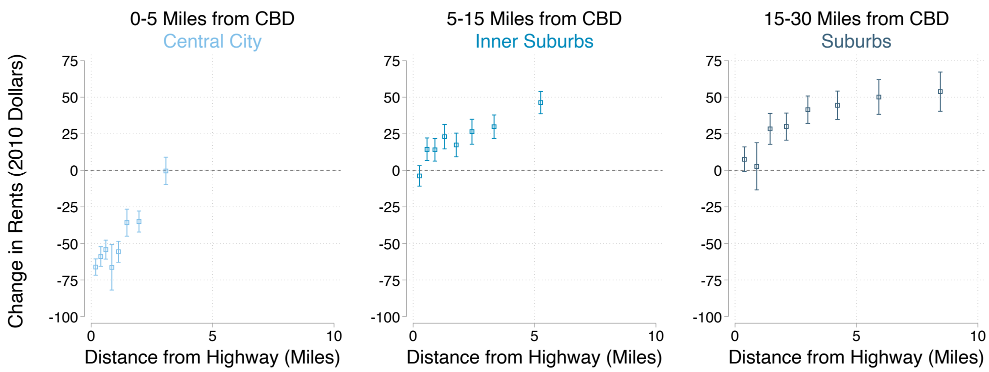
B Appendix Figures

Figure B.1: Changes Over Distance from Central Business District and Distance from Highway (1950-1960, 1960-1970)

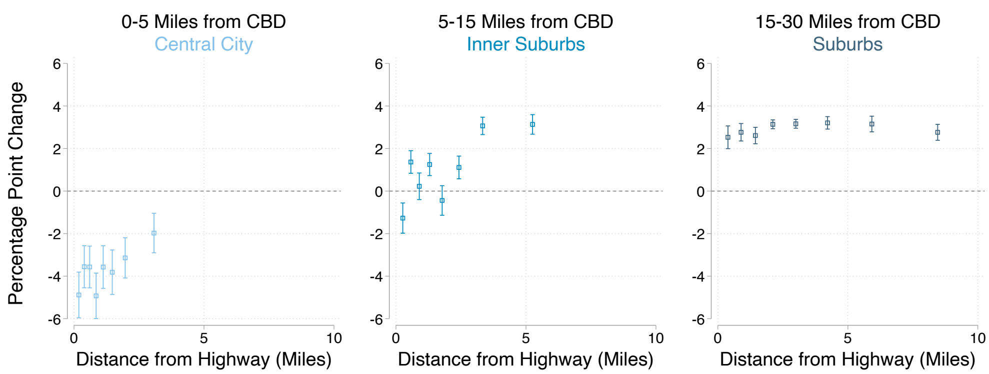
(a) Change in Log Population



(b) Change in Rents

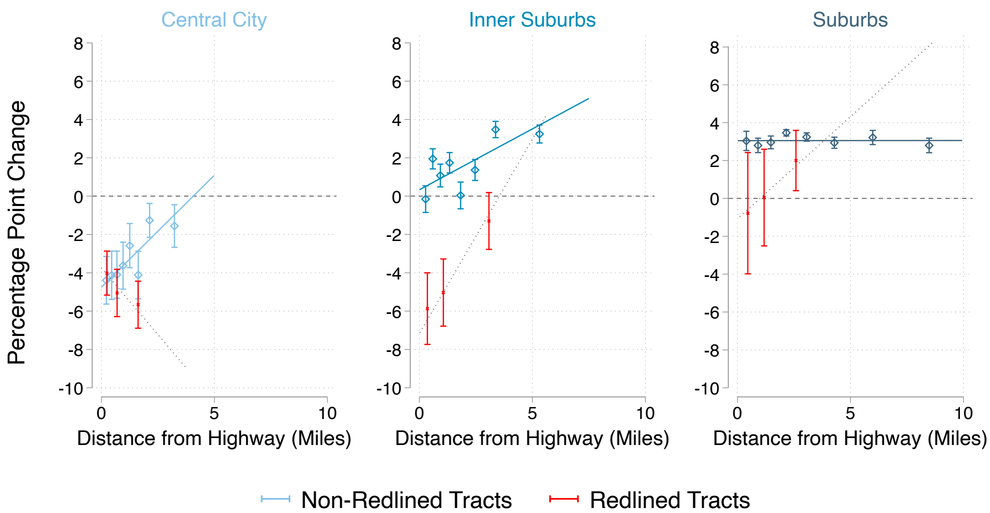


(c) Change in Percentage White



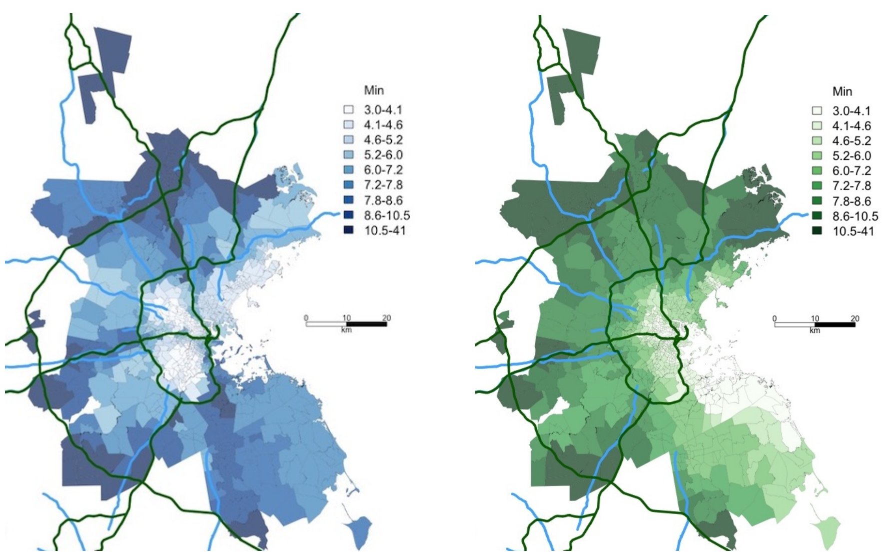
Notes: Unit of observation is census tract. Data comes from 1950, 1960, and 1970 tract-level aggregates retrieved from IPUMS NHGIS. The first difference is either over 1950 to 1960 or 1960 to 1970 and stacked into one panel depending on when highway construction started in the CBSA. All changes over 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.2: 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.3: Commute Time Reductions with Historical Roads as Interstates

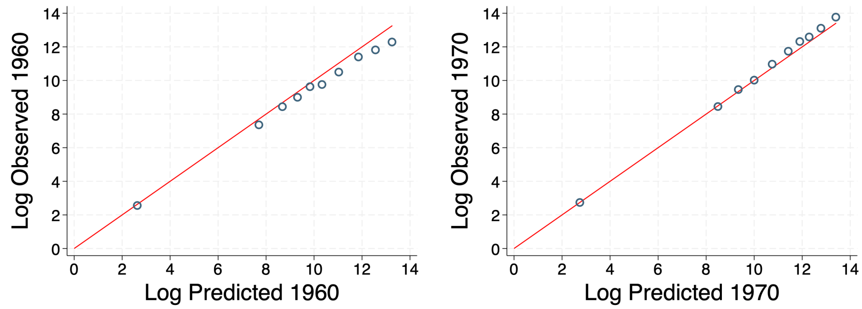


(a) Interstate Roads (b) Historical Large Roads as Interstates

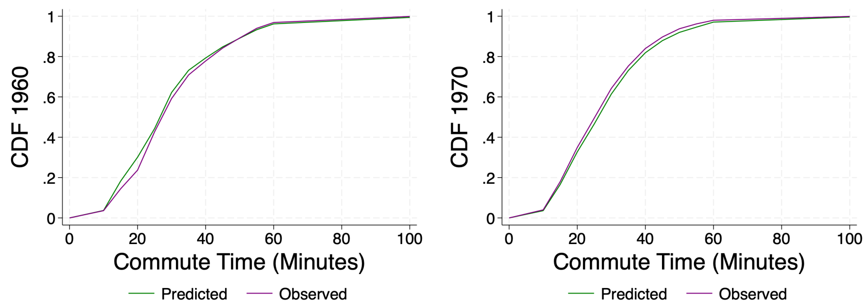
Notes: In Panel (a), commute time changes come from the author's calculations as the difference between commute times for the historical road network and for the entire Interstate network overlayed on the historical road network. In Panel (b) commute time changes come from the author's calculations as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

Figure B.4: Predicted vs. Observed Commute Flows in 1960 and 1970

(a) Linear Fit and Scatter

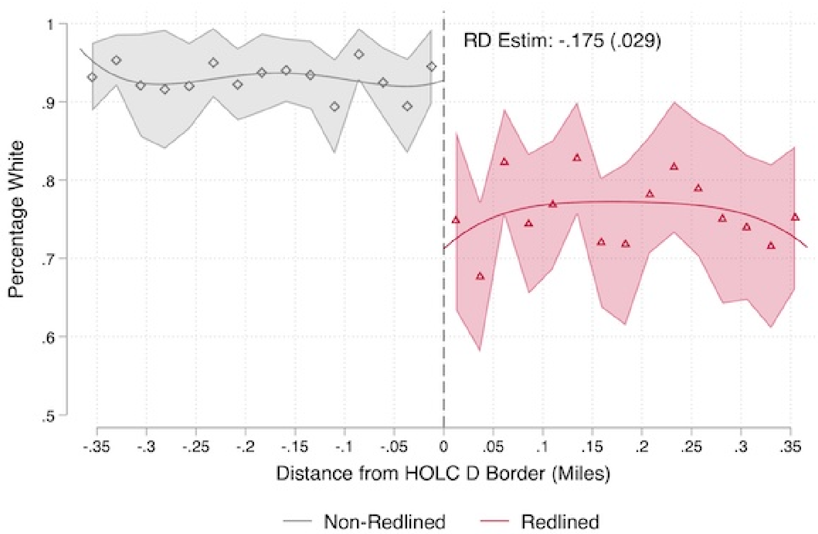


(b) Cumulative Distribution Function



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. 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.5: Border Discontinuity for Percentage White in 1960 at HOLC D Border



Notes: Observations are 1960 census tract–HOLC border pairs (IPUMS NHGIS), comparing non-redlined (left) to redlined (right, ¿80% area is HOLC D). Each side has 15 bins and N=752. The RD uses an Epanechnikov kernel with optimal bandwidth 0.368 and a 4th-order polynomial Calonico et al. (2014). 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 Appendix Table E.24 Panel B with order of polynomial=1, optimal bandwidth=0.368, and the same number of effective observations.

C Descriptive Results

C.1 Instrument Validity

To test for instrument validity, I examine pre-trends 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 Figure 3, 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 C.9. 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.

Table C.9: First-Stage for Highway Placement

	(1)	(2)	(3)	(4)
Variables	Log Dist HW	Log Dist HW	Dist HW = 1 mi	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***	0.0752***	-0.0379***	-0.0422***
	(0.0212)	(0.0241)	(0.00957)	(0.0101)
F-Stat	342.8	156.5	366.3	113.9
R-squared	0.291	0.224	0.251	0.174
Observations	31,627	31,627	31,627	31,627
No. Counties	467	467	467	467

Notes: Unit of observation is census tract. Limited to those <5 miles of the nearest constructed route. CBSA fixed effects included. Standard errors are cluster-robust at the county level. All specifications control for log distance from the central business district, rivers, lakes, shores, ports, historical railroads, canals, and historical large roads. The reported F-stat comes from testing a single coefficient on the excluded instrument. *** p<0.01, ** p<0.05, * p<0.1

C.2 Additional Results on Changes over CMA Improvements

(i) I estimate how the equilibrium outcomes of rents and racial composition respond to CMA in Appendix Table C.10 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 responses to CMA.

(ii) I construct two additional Borusyak and Hull (2023)-proposed CMA controls in Table C.11 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 C.11 Column 4, I do not find substantial heterogeneity within race by education.

Table C.10: 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)	
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

C.3 Instrument for CMA

In Appendix Table C.12, 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 C.9. 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.

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 $\bar{l}_{gr}$

Table C.11: Elasticity of Population to Commuter Market Access – Additional Results

	(1)	(2)	(3)
	$\Delta \log L_{igr}$ (Δ Log Population 1960-1970)		
Variables	+BH (2023) Plans	+BH (2023) Rays	Unscaled CMA CMA
$\Delta \log CMA_{igr}$			
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)
R-squared	0.113	0.113	0.113
CBSA FE	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes
Rounded Obs	N = 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. 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. Column 3 includes the Borusyak and Hull (2023) control for CMA in large roads interacted with race. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. *** p<0.01, ** p<0.05, * p<0.1

Table C.12: First-Stage for Commuter Market Access Improvements

	(1)	(2)	(3)	(4)	(5)
Variables	Δ Log CMA	Δ Log CMA	Δ Log CMA	Δ Log CMA HW	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

that can differ by group.

$$\max_{c_{ij}(o),l_i(o)} \quad \frac{z_i(o)\varepsilon_j(o)B_{igr}}{d_{ijgr}}\left(\frac{c_{ij}(o)}{\beta_{gr}}\right)^{\beta_{gr}}\left(\frac{l_i(o)-\bar{l}_{gr}}{1-\beta_{gr}}\right)^{1-\beta_{gr}}$$
$$\text{s.t.} \quad c_{ij}(o)+Q_i l_i(o)=\frac{w_{jgr}\varepsilon_j(o)}{d_{ijgr}}$$

which leads to the indirect utility function of

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

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

$$\frac{\partial \pi_{igr}}{\partial CMA_{igr}} = \frac{\partial \pi_{n,gr}}{\partial CMA_{igr}}\pi_{igr|n} + \frac{\partial \pi_{igr|n}}{\partial CMA_{igr}}\pi_{n,gr}$$

$$\frac{\partial \pi_{igr}}{\partial CMA_{igr}} = \frac{\lambda_r \pi^2_{igr|n}}{CMA_{igr}}\pi_{n,gr}(1-\pi_{n,gr}) + \frac{\theta_r \pi_{n,gr}}{CMA_{igr}}\pi_{igr|n}(1-\pi_{igr|n})$$

$$\Rightarrow \frac{\partial \pi_{igr}}{\partial CMA_{igr}}\frac{CMA_{igr}}{\pi_{igr}} = \lambda_r \pi_{igr|n}(1-\pi_{n,gr}) + \theta_r(1-\pi_{igr|n})$$

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 $\varepsilon_j(o)$ are likewise distributed Frechet from $F(\varepsilon_j(o)) = \exp(-T_{jgr}\varepsilon_j(o)^{-\phi})$.

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 C.11, 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

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

To achieve a 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 price wedge. The amenity wedge, when no price wedge exists, must satisfy

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

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).[36]

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 Reaser, 2000; Miller, 2023). Moreover, it generalizes the labor aggregate structure of Tsivanidis (2023) 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 Miller (2023). 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

[36]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).

of each group Exp_{igr} so H_{Ri} is determined following

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

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.

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

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

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 Eq. (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 $\{L_{igr}, L_{F\,jgr}, Q_i, \theta_i, w_{jgr},$
$B_{igr}, A_j, U_{gr}\}$ 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

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

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.

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

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

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 construction sector. Demand for capital can be derived 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 < 5 miles of the CBD and $\mu = 0.2$ for neighborhoods ≥ 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.

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

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 E.13, 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.

Table E.13: Housing Price Discrimination in Rents and Home Values in 1960

	Panel A – Log Rent				*Panel B* – Log Home Value			
Variables	(1)	(2) Tract FE	(3) Quality	(4) Tract+Qual	(1)	(2) Tract FE	(3) Quality	(4) Tract+Qual
Black	-0.155***	-0.0250***	-0.0295***	0.0260***	-0.332***	-0.0453***	-0.143***	-0.0146**
	(0.0117)	(0.00719)	(0.00939)	(0.00584)	(0.0175)	(0.0112)	(0.0121)	(0.00675)
Redlined	-0.340***		-0.212***		-0.361***		-0.205***	
	(0.0107)		(0.00804)		(0.0171)		(0.0134)	
Black × Redlined	0.183***	0.0845***	0.0929***	0.0508***	0.142***	0.0602***	0.0967***	0.0509***
	(0.0174)	(0.0103)	(0.0138)	(0.00873)	(0.0319)	(0.0189)	(0.0245)	(0.0123)
Constant	4.272***				9.625***			
	(0.00514)				(0.00567)			
R-squared	0.104	0.433	0.394	0.592	0.078	0.522	0.404	0.658
Rounded Obs	1,729,000	1,729,000	1,729,000	1,729,000	1,562,000	1,562,000	1,562,000	1,562,000

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

E.2.2 Gravity Equation

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

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

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 $\varepsilon_{ijgr,t}$ 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. These times are instrumented using the plans and rays for the post-highway period.

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. 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.

In Table E.14, I find that less-educated groups, both White and Black, tend to have higher elasticities compared to the higher-educated. 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. First stages for the instruments are reported in Supp. Appendix Table E.15, and the estimates from Panel B are the preferred values used for the quantitative analysis. For the Black population, the commuting elasticity rises slightly with PPML estimates in Panel C. For White workers, their elasticities are lowered with the PPML estimator although the observation count only increases a small amount.[37] Overall, the pattern remains quite similar. Lastly, in Panels D and E, 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.

Table E.14: 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 – 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 B – 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 C – Poisson Pseudo Maximum Likelihood			
Log Commute Time	-4.703***	-3.929***	-3.877***	-3.247***
	(0.0819)	(0.0599)	(0.0471)	(0.0359)
	Panel D – 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 E – 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

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 unit (although it represent residence, not workplace). POW by year fixed effects are also included for workplaces at the POW 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. For the IV-PPML estimates, to obtain standard errors, I bootstrap 200 samples with clusters at the Place of Work Zone by Place of Work Zone level. Observation counts are rounded to 500 for Census disclosure. *** p<0.01, ** p<0.05, * p<0.1

[37] 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.

Table E.15: 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

Notes: Observations are POW Zone by POW Zone pairs by year where commuting flows from residential tracts are aggregated up to the POW Zone. Data is the restricted Census microdata in 1960 and 1970. Fixed effects are for POW Zones by year for residences and separately for workplaces. The conditional commuting share is the share of each residence commuting to a workplace. Counts are lower for the Black population as some residences and workplaces have zero Black population. Standard errors are cluster-robust by POW Zone × POW Zone. Observation rounded to the nearest 500 for Census disclosure. The F-stat tests a single coefficient on the excluded instrument and is rounded to four significant digits for Census disclosure. *** p<0.01, ** p<0.05, * p<0.1

E.2.3 Linear prediction of housing consumption share from CEX data

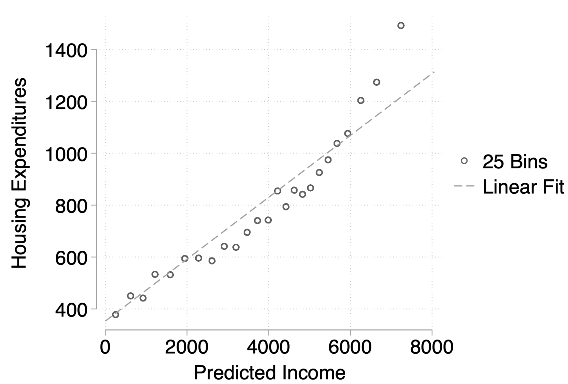
I assign the housing consumption share for each race by education by first estimating a linear function for housing expenditure over income from the Consumer Expenditure Surveys Public-Use Microdata in the year 1980.

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

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.6, the assumption of linearity for the housing consumption Engel curve seems plausible. From this function, I calculate the predicted housing expenditure for each group, given their average income, and set the ratio of predicted housing expenditure to average income as the housing consumption share.

Figure E.6: 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 E.16.

Table E.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 E.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 E.16 and the average level of income of the four race by education groups.

E.2.4 Localized Costs

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

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

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 E.18 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 $k = 0.5, 1.5$.[38]

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 E.19 and are too noisy to measure values precisely. In Table Appendix E.20, 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 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).

Table E.21: 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.

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

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

Table E.18: 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: Observations are the first difference of 1960 to 1970 for census tracts by race and education from the restricted Census microdata. CBSA by race and education fixed effects included. Standard errors are cluster-robust by tract. There are 5 binary indicators for distance from highways built between 1960 and 1970 in 1-mile wide bins. In Column 3, the bins are split further into 0.5-mile wide bins. The geographic controls are log distance from the CBD, rivers, lakes, shores, ports, historical railroads, canals, and historical large roads, all interacted with race and education. Limited to tracts < 10 miles of highway routes. For the placebo test in Column 5, the sample is restricted to > 5 miles of a highway and < 10 miles of historical large roads. The control for distance from historical large roads is dropped since it is now the endogenous variable. All specifications include redlining fixed effects. Observation counts are rounded to the nearest 500 for Census disclosure rules. Parameters used to invert for dependent variables are in Table 5. *** p<0.01, ** p<0.05, * p<0.1

Table E.19: 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: Observations are the first difference of 1960 to 1970 for census tracts by race and education from the restricted Census microdata. CBSA by race and education fixed effects included. Standard errors are cluster-robust by tract. 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. Limited to tracts $<$ 10 miles of planned routes or the Euclidean ray network. Observation counts are rounded to 500 for Census disclosure. Kleibergen-Paap rk Wald and Cragg-Donald Wald F statistics reported. Parameters used to invert for dependent variables are in Table 5. *** p<0.01, ** p<0.05, * p<0.1

Table E.20: 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

E.2.6 Instruments for Estimation of Endogenous Amenities/Preferences

There are two endogenous variables $\{\Delta \log CMA_{igr}, \Delta \log(L_{iW}/L_i)\}$ that require instruments. The instrument for $\Delta \log CMA_{igr}$ uses commute times where the plans or ray network are converted into Interstate highways and scaled wages are fixed to 1960 levels. Specifically, the CMA IV is defined as $CMA^{IV}_{igr} = \frac{1}{\phi}\left(\log \sum_j \omega_{jgr,1960}/d^{IV}_{ijgr}{}^{\phi}\right) - \frac{1}{\phi}\left(\log \sum_j \omega_{jgr,1960}/d_{ijgr,1960}{}^{\phi}\right)$ with commute times in the post period from the planned or ray network. The the instruments for racial composition changes $\Delta \log(L_{iW}/L_i)$ are described below.

Davis Instruments – Instruments following Davis et al. (2019) come from a 3-step process. The first step requires estimating Eq. 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 $CMA^{Plans/Rays}_{igr}$ as well as the CMA instruments in other neighborhoods for additional power $\{CMA^{Plans/Rays}_{igr,3-5}, CMA^{Plans/Rays}_{igr,5-10}, CMA^{Plans/Rays}_{igr,10-15}\}$. The elasticity estimates are presented in Table E.22, 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 $\widehat{L_{iW}/L_i}$ is used for the calculation of racial composition changes in the instrument $\Delta \log(\widehat{L_{iW}/L_i}) = \log(\widehat{L_{iW}/L_i}) - \log(L_{iW,1960}/L_{i,1960})$. The final set of instruments also includes the CMA instruments in other neighborhoods for additional power $\{CMA^{IV}_{igr,3-5}, CMA^{IV}_{igr,5-10}, CMA^{IV}_{igr,10-15}\}$.

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. Specifically, the instruments are $\{CMA^{IV}_{iLB}, CMA^{IV}_{iHB}, CMA^{IV}_{iLW}, CMA^{IV}_{iHW}\}$.

E.2.7 Border Discontinuity

In Appendix Table E.24 Panel, I measure how various natural amenities change at the border. The variables of open water and wetlands, which are less manipulable by human intervention, are continuous, which supports the identification assumption of neighborhood features being similar. However, other variables, such as the amount of tree cover or the extent of urban development, are discontinuous. Still, these other factors may not be in fundamental amenities since they are correlated with prices, racial composition, or the SES controls, which are already residualized out, and the identification assumption is not necessarily violated.

In Appendix Table E.23, 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 at the bottom of Appendix Table E.24. In Panel B, 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. In Panel C, I further display the border discontinuity estimates for control variables used to residualize the fundamental amenities. Lastly, in Panel D,

Table E.22: Elasticity of Population to Commuter Market Access for Residential Parameter 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
Rounded Obs	58000	58000
C-D F-Stat	313.7	259.5
K-P F-stat	26.20	25.97

Notes: Data is tract by group for the first difference 1960-1970 using restricted Census microdata. CBSA fixed effects are interacted with race and education. Standard errors are cluster-robust by tract. Conley (1 km) standard errors in brackets. Controls are changes in log of rent, pct White, and 5 1-mile wide bins for distance from highways (built 1960-1970). Redlining fixed effects included. The geographic controls are log distance from CBD, rivers, lakes, shores, ports, historical railroads, canals, and historical large roads. All controls are interacted with race and education. Observation counts are rounded to the nearest 500 to meet Census disclosure rules. Borusyak and Hull (2023) control for CMA in large roads included. Kleibergen-Paap rk Wald and Cragg-Donald Wald F stats are reported. *** p<0.01, ** p<0.05, * p<0.1

Table E.23: Border Discontinuity Decomposition – Reduced Form Approach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Black				*White*			
Variables	$\log L_{igr}$	Controls 1	Controls 2	Controls 3	$\log L_{igr}$	Controls 1	Controls 2	Controls 3
ψ_r: Border RD	1.425***	1.414***	0.555***	0.489**	-0.546***	-0.556***	-0.101	0.0205
	(0.226)	(0.227)	(0.212)	(0.204)	(0.122)	(0.122)	(0.0855)	(0.0794)
Bandwidth (mi)	0.495	0.488	0.414	0.365	0.358	0.364	0.380	0.397
Rounded Obs	13000	13000	13000	13000	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

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.

Table E.24: Border Discontinuity on Additional Variables

	(1)	(2)	(3)	(4)	(5)
	Panel A – Natural Amenities				
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
	Panel B – 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 C – 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 D – 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

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

F Welfare and Counterfactuals

F.1 Derivation of Direct Impacts to Welfare

This section derives the approximation of changes in welfare from total differentiating Eq. (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 $\{w^0_{jgr}, \theta^0_i\}$. I assume starting values for the endogenous variables that correspond to the observed equilibrium for housing prices and the partially endogenous amenities $\{Q^0_i, B^0_{igr}\}$. From these starting values, I iterate following the equilibrium conditions of the model to reach a new equilibrium $\{Q^1_i, B^1_{igr}\}$.

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

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

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

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

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

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

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

$$\left\| \{Q^0_i, B^0_{igr}\} - \{Q^1_i, B^1_{igr}\} \right\| < \varepsilon$$

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

$$Q^2_i = \lambda Q^1_i + (1-\lambda) Q^0_i$$
$$B^2_{igr} = \lambda B^1_{igr} + (1-\lambda) B^0_{igr}$$

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 $\{w^0_{jgr}, Q^0_i, \theta^0_i, B^0_{igr}, A^0_i\}$. From these starting values, I iterate following the equilibrium conditions of the model to reach a new equilibrium $\{w^1_{jgr}, Q^1_i, \theta^1_i, B^1_{igr}, A^1_j\}$.

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

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

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

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

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

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

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

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

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

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

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

$$W_j = \left(\sum_g \alpha^{\sigma^g}_{jg} \omega^{1-\sigma^g}_{jg}\right)^{\frac{1}{1-\sigma^g}} \quad Y^1_j = \sum_{i \in Tracts_j} Y^1_i$$

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

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

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

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

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 and Arkolakis (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 (2023), 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 and Arkolakis (2022) where spillovers are of an exponential form. I further allow the elasticities to differ by the type of the agent.

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

In this setting, type $\mathscr{N}$ 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 $\mathscr{H}$ 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

$$\begin{aligned} L_{igr} &= \lambda_{gr} \left(B_{igr} Q_i^{\beta_{gr}-1} \Phi_{igr}^{\frac{1}{\phi}} \right)^{\theta_r} \\ L_{Fjgr} &= \lambda_{gr} T_{jgr} w_{jgr}^{\phi} \Phi_{Fjgr} \\ \Phi_{igr} &= \lambda_{gr} \sum_j d_{ijgr}^{-\phi} \frac{L_{Fjgr}}{\Phi_{Fjgr}} \\ \Phi_{Fjgr} &= \lambda_{gr} \sum_i d_{ijgr}^{-\phi} \frac{L_{igr}}{\Phi_{igr}} \\ N_i^{(\sigma_g-1)/\sigma_g} &= \sum_g \alpha_{ig} N_{ig}^{(\sigma_g-1)/\sigma_g} \\ N_{ig}^{(\sigma_r-1)/\sigma_r} &= \sum_r \alpha_{igr} L_{Figr}^{(\sigma_r-1)/\sigma_r} \end{aligned}$$

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

Almost all of the elasticities $\varepsilon_{ijh,jh'}(x_j) = \frac{\partial \log f_{ijh}(x_j)}{\partial \log x_{jh'}}$ are of the form $\varepsilon_{ijh,jh'}(x_j) = \alpha_{hh'}$ 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 and Arkolakis (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 4, $\rho(A) > 1$. 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.26. 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.26. Examples for Baltimore, MA and San Francisco, CA are shown in Figure G.7.

- **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.26, 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.8.

- **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.

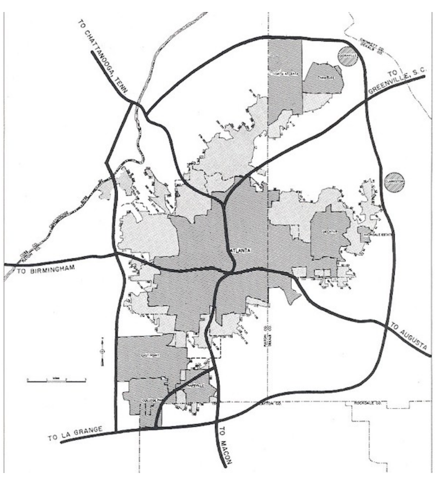
Figure G.7: Historical Roads from Shell Atlases for Baltimore and San Francisco

(a) Baltimore, Maryland

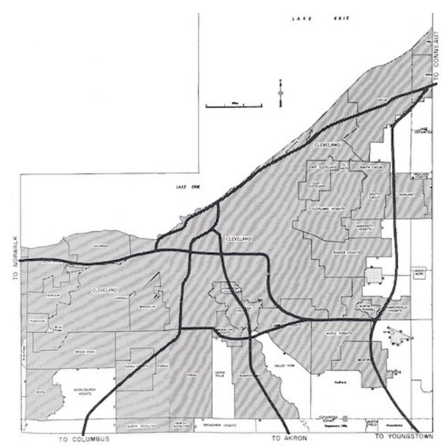
(b) San Francisco, California

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

Figure G.8: 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 Appendix Table G.25. The 1980 Census is the first census survey with commute time data.

Table G.25: 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.

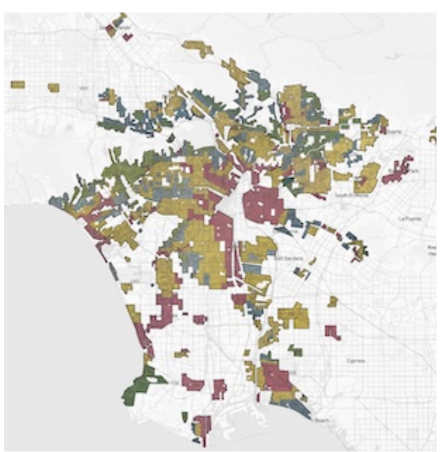
- **HOLC Redlining** – Redlining maps for the Home Owners' Loan Corporation come from a group of digital historians at Mapping Inequality: Redlining in New Deal America (Nelson et al., 2020). Examples for Los Angeles, CA and New York City, NY are in Figure **??**.

  - **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.

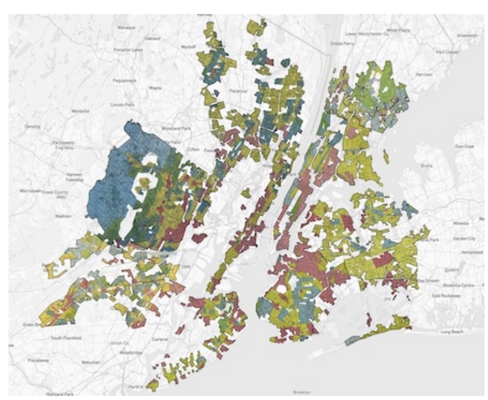
- **School District Borders** – School district boundaries used for the border design are acquired from the National Center for Education Statistics (NCES) for the 1989-1990 school year.

- **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.9: 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.26: Data Availability by Metro Area

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

Table G.26: Data Availability by Metro Area 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 CBSAs because while there are 100 cities in the Yellow Book, not all of them have an associated Metropolitan Statistical Area. Some are in Micropolitan Statistical Areas, and two cities (Dallas and Fort Worth) are combined into one MSA. The HOLC redlining maps are available for more cities, but the table is restricted to the sample of Yellow Book maps. Historical road maps are also available for more cities, but only 71 are digitized in this paper. The Census column indicates which cities are included in the quantitative analysis using Decennial microdata.