The (Express)Way to Segregation: Evidence from Chicago*

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Abstract

How do man-made barriers shape long-term patterns of racial segregation within cities? I exploit expressway construction and document two key channels. First, a disamenity channel: Income differences between Black and white residents drive different responses to changes in neighborhood amenities near expressways. Second, a physical barrier channel: Following expressway construction, racial sorting responds to changes in accessibility to different parts of the city and, in turn, to neighborhoods with distinct demographic compositions. Motivated by these findings, I develop a quantitative spatial urban model with racial preference spillovers and find that mitigating expressways' neighborhood effects would reduce racial segregation by 17%.

Keywords: Racial Segregation, Expressways, Urban Form, Neighborhoods
JEL classification: J15, O18, R23, R42

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1 Introduction

> *"[The Interstate Highway System] was a program which the twenty-first century will almost certainly judge to have had more influence on the shape and development of American cities, the distribution of population within metropolitan areas and across the nation as a whole, the location of industry and various kinds of employment opportunities (and, through all these, immense influence on race relations and the welfare of Black Americans) than any initiative of the middle third of the twentieth century."*
>
> Senator Daniel Moynihan, 1970

Did expressways increase racial segregation in cities? Within two decades, the US built an integrated network of thousands of miles of roads, connecting the country from side to side and dramatically reducing interstate travel times. However, these roads did more than reshape national connectivity—they transformed metropolitan areas, permanently changing the structure of cities and the urban landscape. This paper investigates the long-run effects of these man-made barriers on racial segregation within cities.

I exploit the construction of expressways in Chicago as a source of variation in neighborhoods' quality and connectivity.[1] Expressways are high-traffic and large multilane roads, difficult to cross. Crucially, they were built when the city was already racially mixed. The setting hence allows me to examine the effects of a shock to urban space through both an immediate barrier effect and a longer-term sorting mechanism. As noted in a Washington Post article by Emily Badger and Carla Cameron "Look at racial maps of many American cities, and stark boundaries between neighboring black and white communities frequently denote an impassable railroad or highway, or a historically uncrossable avenue."[2]

I develop an empirical strategy to estimate the effects of expressways on neighborhoods' racial composition across two dimensions.[3] The first considers expressways as a source of permanent reductions in residential amenities in the neighborhoods they cross through (Brinkman and Lin, 2024; Robinson, 1971). By degrading the quality of life through increased pollution, noise, and other disamenities, expressways affect the socio-demographic composition of neighborhoods—reflected in changes in prices and resident populations in areas close to the infrastructure relative to those farther away. The second dimension examines how expressways influence racial sorting through their role as urban barriers. Variation in how the physical layout of expressways affects neighborhood connectedness allows me to characterize their barrier effect. By increasing the physical separation between neighborhoods on opposite sides of the road, expressways affect racial sorting by altering exposure to parts of the city with different racial compositions. I use these two sources of within-city variation—proximity to the road and local changes in accessibility—for identification in both my

[1] Throughout the paper, I refer to expressways as controlled-access roads only (equivalent to interstates).

[2] The Washington Post, July 16, 2015: https://www.washingtonpost.com/news/wonk/wp/2015/07/16/how-railroads-highways-and-other-man-made-lines-racially-divide-americas-cities/

[3] Urban transportation infrastructure also reduces commuting costs, facilitating the separation of workplace and residential locations. Given the decadal frequency and long time horizon of my analysis, granular commuting data are not available in this setting. While what I broadly define as the "disamenity effect" may partly capture the access benefits of expressways, I conduct a series of empirical exercises that are consistent with the role of expressways as local disamenities.

reduced-form and the structural analyses.

I begin by estimating the disamenity effect of expressways using an event-study design. The main results rely on the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). I find that expressways permanently affect the demographic composition, population size, and property values of nearby neighborhoods. On average, the share of Black residents in neighborhoods near expressways increases by 15 percentage points immediately after their opening and by 20 percentage points in the following decades.[4] At the same time, the total residential population in these areas gradually declines, eventually falling by approximately 30% relative to the full sample mean, compared to neighborhoods farther from the expressway.[5] Consistent with the idea that expressways create a negative shock to residential amenities, I also find that neighborhoods closer to expressways exhibit lower house value, land value, and college share (as a proxy for income). These findings are robust to a range of checks, including different choices of treatment and control group bandwidths, the exclusion of certain portions of the city, and alternative empirical specifications.

Next, I measure the impact of the barrier effect of expressways. I define a barrier effect as the increase in the cost of crossing an expressway, measured by travel time. By creating within-city barriers, expressways affect accessibility to different parts of the city, altering the racial composition of areas a neighborhood is exposed to. If expressways create a barrier along racial lines, we may expect neighborhoods to become racially more similar to the areas they are more exposed to—once these urban barriers are in place. I leverage this intuition to test the barrier effect of expressways using a long-difference empirical specification. To estimate how changes in exposure to Black residents affect changes in the racial composition of neighborhoods in Chicago, I construct a novel measure of accessibility to races that captures spatial spillovers from the racial makeup of nearby locations. This metric is a location-specific weighted average of the share of Black residents in each neighborhood. The weights decrease with bilateral travel time between locations and depend on the road network: Higher weights are placed in locations that are more easily accessible, as measured by shorter travel times.[6]

I find that higher exposure to Black areas in the city (i) increases the likelihood that a neighborhood becomes more Black over time and (ii) reduces its valuation in the long run. Both effects are sizable. On the one hand, a one standard deviation increase in exposure to Black areas is associated with a 0.16-0.20 standard deviation increase in the share of Black residents in the neighborhood, depending on the specification. On the other hand, it leads to a 0.24-0.32 standard deviation decrease in land value, which I use as a proxy for neighborhood valuation. The results remain robust to the

[4]I follow the current Associated Press's style, which recommends to capitalize "Black" and not "white" when referring to race, ethnicity, or culture more generally (see https://apnews.com/article/archive-race-and-ethnicity-9105661462).

[5]The change in the racial composition of nearby neighborhoods over time is not simply driven by a drop in total residential population—holding Black population fixed. The results show that these locations experience a change in the racial mix because of both an outflow of the (white) population and an inflow of the Black population.

[6]This summary measure captures, for each origin neighborhood, changes in exposure to Black residents over time. These changes are driven both by sorting and by changes in transportation infrastructure, which alter how accessible other neighborhoods in the city effectively are. An instrumental variable strategy addresses the specific concern that changes in exposure to Black residents may be correlated with unobserved shocks affecting neighborhood composition dynamics. The instrument holds the racial composition of neighborhoods fixed to the pre-period, isolating variation in exposure that is solely due to changes in travel times between locations.

inclusion of a rich set of controls, including proximity to the nearest expressway and a measure capturing changes in exposure to high-income areas in the city. This latter control also partially accounts for broader barrier effects beyond race—for example, reduced access to different sets of amenities in neighborhoods on the other side of the expressway.

A primary concern with the causal interpretation of both sets of results is the potential endogeneity of expressway placement. The decision of where to locate expressways may have been influenced by the socio-demographic characteristics of the areas, as historically argued (Mohl, 2004, 2008; Archer, 2020). I address this concern with a series of checks in the empirical analyses. First, I show that treated and control groups exhibit parallel pre-treatment trends, providing evidence consistent with the key identifying assumption underlying the event-study approach. Second, I complement these results with instrumental variable regressions to address the potentially non-random selection of locations in the treatment group. Using instruments widely used in the literature for the assignment of transportation infrastructures that plausibly satisfy the exclusion restriction (Redding and Turner, 2015), I show that the results remain comparable across specifications. Finally, in estimating the barrier effect of expressways, I document that the results are not driven by locations that may have been intentionally isolated. The finding that higher exposure to Black areas increases the likelihood of a neighborhood becoming more Black remains invariant to (i) excluding historically Black neighborhoods from the analysis and (ii) removing the central areas of the city, where the presence of expressways alongside Black communities was arguably more salient.

The reduced-form analysis shows that expressways influence racial sorting through both disamenity and barrier effects. However, it does not capture the broader general equilibrium effects of these forces on the city's spatial structure. In particular, it cannot quantify how overall segregation patterns would change if the neighborhood effects of expressways were mitigated. In the second part of the paper, I develop a quantitative spatial urban model that incorporates racial preferences in location choices to assess these broader impacts through counterfactual analyses.

The setup adheres to a monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1967) but features an internal city structure following Ahlfeldt et al. (2015).[7] The model provides a unified and tractable framework to quantify how this major road infrastructure shaped residential location decisions and contributed to racial sorting.[8] The city is populated by an endogenous number of residents from one of four socio-demographic groups (race and educational attainment, in a two-by-two classification). Individuals work in the city center and face commuting costs. They choose their residential location alongside the consumption of floorspace and final good to maximize utility. The utility of living in a given area depends on residential amenities, land prices, and idiosyncratic preference shocks. The model produces a type-specific demand system for residential neighborhoods. Expressways enter the model by providing a source of variation in neighborhood quality and accessibility, affecting both amenities and travel times. Total residential amenities depend on location fundamentals, res-

[7]While the monocentric assumption is stylized, it aligns with available data and is broadly supported by commuting patterns in Chicago (see Appendix D.1). A more detailed discussion of this modeling choice and the underlying data constraints appears in Section 6.

[8]The model includes spatial externalities. While these introduce the potential for multiple equilibria, the estimation strategy—following Ahlfeldt et al. (2015)—relies on a mapping from observed data to structural fundamentals that remains unique, ensuring tractability.

idential externalities, and the disamenity of expressways. Residential externalities include both (i) local spillovers—proxied by the share of adults with above-median educational attainment in the neighborhood—and (ii) racial spillovers, which capture racial preferences that extend beyond one's own neighborhood. Using analogous sources of variation of the reduced-form analyses, I estimate the parameters governing residential externalities and the disamenity effects of expressways.

GMM estimation results reveal large and statistically significant racial preference and disamenity parameters. The racial preference parameters show substantial heterogeneity across race-education groups. They point to high degrees of homophily: Both Black and white residents display stronger preferences for living near same-race neighbors, in line with prior findings in the literature on residential choice and neighborhood sorting (Bayer and McMillan, 2005; Bayer et al., 2007; Aliprantis et al., 2024). Residential externalities emerge as an important agglomeration force, particularly with respect to the concentration of same-race residents in surrounding areas. Among white residents, the elasticity of amenities with respect to the concentration of nearby same-race neighbors is notably higher than for different-race neighbors. It ranges from three times as large for low-educated white individuals to six times as large for high-educated white individuals. In contrast, estimates for Black residents suggest strong positive externalities from the presence of same-race residents in the vicinity and potential congestion forces linked to the density of nearby white residents.

In addition, racial externalities are highly localized.[9] Other things equal, racial spillovers decay to near zero after roughly 10 minutes of travel time for Black residents—both high- and low-educated—and after around 20 minutes for white residents across education levels. Finally, the estimated disamenity from proximity to expressways is large across groups, consistent with the reduced-form findings. On average, Black residents attach 22% lower amenities to areas near expressways (attenuating by 95% at 3.8 km from the expressway), while for white residents the reduction is 23.9%.[10]

I use the theoretical framework to run a set of counterfactual experiments evaluating the relationship between urban form and racial sorting. These exercises involve assigning alternative values to location characteristics or model parameters and solving for the model's counterfactual equilibrium. In each case, I fix the reservation utility in the wider economy in the post-period so that the (type-specific) population of Chicago matches its observed 1990 level, which anchors the equilibrium and deals with the possibility of multiple equilibria, following Ahlfeldt et al. (2015). I begin by testing the model's ability to replicate observed outcomes. I analyze whether the observed demographic shifts following expressway construction can be explained by the model's endogenous forces, rather than by changes in location fundamentals. I find that the model captures the changes in neighborhood racial composition well: The correlation between the observed and counterfactual Black shares across census tracts is 0.815.

I then run a counterfactual that removes racial bias. I set the elasticity of amenities with respect to the concentration of different-race residents in the surrounding areas equal to the elasticity of

[9] The estimated rate of spatial decay of racial preferences is 0.674 (s.e. 0.181) for low-educated Black residents and 0.747 (s.e. 0.167) for high-educated Black residents. For low-educated white residents, it is 0.229 (s.e. 0.047) and 0.291 (s.e. 0.048) for high-educated white residents. The average decay rate, weighted by population shares, is 0.342.

[10] The magnitudes are comparable to those found in the literature. Brinkman and Lin (2024) estimate that freeway neighborhoods are associated with an 18.4% reduction in amenities. I calibrate the parameter governing the rate of decay from their work.

amenities with respect to the concentration of one's race. In this benchmark case, the population of Chicago becomes less spatially segregated, with more individuals living in racially mixed neighborhoods. The share of individuals living in neighborhoods that are at least 90% Black falls from 30% to around 5%, while the share living in neighborhoods that are at most 10% Black drops from 50% to below 30%. The population becomes more evenly distributed across the full range of neighborhood compositions.

Finally, I examine the implications of mitigating the neighborhood effects of expressways on racial sorting—while preserving their access benefits. This exercise corresponds to a policy intervention such as placing expressways underground. I simulate the effects of simultaneously removing (i) the disamenity and (ii) the barrier effect of expressways. In the resulting counterfactual, the share of residents living in neighborhoods that are at least 90% Black falls by 10 percentage points. At the same time, close to 20% of the population resides in neighborhoods that are more racially integrated (around 30% Black share)—nearly a seven-fold increase relative to the observed equilibrium. Mitigating the neighborhood effects of expressways is associated with a 16.8% reduction in racial segregation, as measured by the commonly used dissimilarity index.[11]

This research builds on two main strands of the economics literature. The first examines how transportation infrastructure shapes the internal organization of cities, through changes in the spatial distribution of people (Baum-Snow, 2007, 2020; Baum-Snow et al., 2017; Gonzales-Navarro and Turner, 2018).[12] A different literature focuses on the physical layout of such infrastructure to demarcate areas and define neighborhood boundaries. Ananat (2011) and Chyn et al. (forthcoming) use the internal positioning of railroad tracks as an instrument for city-wide racial segregation to study its effects on inequality, poverty, and intergenerational mobility across US cities. Advancing this line of research, this paper—to the best of my knowledge—is the first to provide a long-run analysis of the causal effects of physical barriers on socioeconomic disparities within cities—a link that, until now, remained largely anecdotal.[13] I show that expressways act as urban barriers that alter accessibility and racial exposure. This reshapes residential sorting beyond the traditional channels emphasized in the literature—namely, reductions in transportation and commuting costs (for a review, see Redding and Turner, 2015) and changes in relative amenity values.[14] Related work in quantitative spatial models emphasizes how transportation networks shape urban structure, accessibility, and welfare (Brinkman and Lin, 2024; Weiwu, 2024; Tsivanidis, 2023; Heblich et al., 2020), but typically does not model how transportation-induced changes in urban form alter racial exposure and, in turn, racial sorting within cities.[15]

[11]The index falls from 0.844 to 0.702, meaning that a smaller share of households would need to relocate to achieve a uniform racial distribution across neighborhoods.

[12]A broader literature evaluates the effects of transportation improvements on productivity, trade, and regional output (e.g., Donaldson and Hornbeck, 2016; Duranton et al., 2014; Faber, 2014; for a review, see Redding and Turner, 2015).

[13]In the sociology and urban science literatures, Roberto and Hwang (2017) document the correlation between physical boundaries and residential segregation using 2010 block-level data. Aiello et al. (2025) use contemporary geolocated social network data to show that urban highways reduce social connectedness across neighborhoods in US cities, highlighting the enduring role of past infrastructure on present-day urban social structure.

[14]This latter issue saw a surge in recent urban papers (Brinkman and Lin, 2024; Carter, 2023; Mahajan, 2024; Anderson, 2020; Ahlfeldt et al., 2019).

[15]Weiwu (2024) models how institutional constraints—such as redlining—interact with highways to produce unequal

The second strand of literature studies the causes of racial segregation, including the role of racial preferences in shaping urban spatial structure (Schelling, 1971; Sethi and Somanathan, 2004; Card et al., 2008).[16] Recent contributions incorporate richer heterogeneity in preferences for neighborhood attributes and neighbors' characteristics (Bayer et al., 2007; Bayer et al., 2014; Wong, 2013; Cook, 2023; Gregory et al., 2024).[17] Closely related work estimates racial preferences using models of sorting with quasi-experimental variation in neighborhood composition—such as demolition and displacement (Almagro et al., 2024) or the arrival of different-race neighbors next door versus farther down the block (Bayer et al., 2024)—or through dynamic models of neighborhood change (Davis et al., 2024). I contribute to this literature by estimating the strength and spatial decay of racial preferences, leveraging quasi-random variation in neighborhood composition induced by infrastructure placement.[18] To do so, I develop and estimate a general equilibrium model of urban sorting with spatial racial spillovers. This framework allows me to quantify the intensity and geographic reach of racial preferences, and to simulate the neighborhood effects of expressways on racial sorting in counterfactual scenarios. This paper provides micro-founded support for mechanisms emphasized in recent work modeling the general equilibrium effects of racial clustering across US metro areas, highlighting the role of racial spillovers in shaping segregation patterns (Davis et al., 2025).

The rest of the paper proceeds as follows. Section 2 discusses the relevant setting and the data. Section 3 introduces the empirical analysis. In Section 4, I estimate the disamenity effect of expressways. In Section 5, I estimate the barrier effect of expressways. Section 6 presents the theoretical framework. In Section 7, I describe the estimation procedure and the results. Finally, Section 8 concludes.

2 Background and data

In this section, I describe the historical context, highlighting the most important events that characterize the development of expressways and the dynamics of racial segregation in Chicago. Then, I provide a quick overview of the primary data used in the analyses and their sources.

distributional effects by race. This paper emphasizes how the physical layout of infrastructure reshapes accessibility and racial exposure, and shows that spatial racial preferences extend beyond one's immediate neighborhood.

[16] Well-established economic research examines both the origins and consequences of residential segregation. Some studies document its historical evolution (Cutler et al., 1999) and its emergence in northern US cities, focusing on early (Shertzer and Walsh, 2019) or late periods of the Great Migration (Boustan, 2010; Derenoncourt, 2022). Other foundational work links racial segregation in the US to differences in schooling and labor market outcomes (Kain, 1968; Cutler and Glaeser, 1997; Collins and Margo, 2000). More recent work explores the role of neighborhood effects and social networks on socioeconomic outcomes (Echenique and Fryer, 2007), also leveraging advancements in GIS and GPS technologies (Chetty and Hendren, 2018a; Chetty and Hendren, 2018b; Chetty et al., 2016; Athey et al., 2021).

[17] A growing literature examines the dynamics of neighborhood sorting (including Lee and Lin, 2018; Heblich et al., 2021; Bayer et al., 2016), often emphasizing the role of endogenous amenities (Diamond, 2016; Almagro and Dominguez-Iino, 2025), and the spatial sorting of heterogeneous agents in general equilibrium (Fajgelbaum and Gaubert, 2020; Davis and Dingel, 2020; Redding and Sturm, 2024).

[18] The concept of spatial proximity and the parametrization of racial preferences in this type of framework dates back to Schelling (1971) and has more recently been studied in the context of spatial segregation indices by Echenique and Fryer (2007), Logan and Parman (2017), and Harari (2024). Davis et al. (2025) similarly emphasize spatial spillovers in segregation dynamics across cities.

2.1 Background

The surge in expressway construction in the Chicago Metropolitan Area was driven by the 1956 Interstate Highway Act. The national plan expanded the mileage of a previous plan, commissioned in 1947, to a 41,000-mile interstate system. The 1956 plan required the federal government to pay 90% of construction costs. The plan's purpose was primarily to improve the connection between major metropolitan areas in the US, to serve US national defense, and to connect with major routes in Canada and Mexico. Within metropolitan areas, the 1956 plan also incorporated some highways meant for local commuting. The construction was started after funding approval in 1956, and by 1975, the national system was mostly complete, spanning over 40,000 miles. By 1990, over 43,000 miles were in operation, and virtually the entire plan had been built throughout the country.

Figure 1 shows that the rollout of expressways in the Chicago Metropolitan Area followed the national trend. Each panel of the figure displays a snapshot in time of the completed portions of the expressway network in the respective census year. The first segment was completed in 1951, and by 1970 virtually all roads drawn in the plan were in operation. Only a few segments of suburban ring routes are of more recent construction. In central areas, the expressway network was completely laid out by 1970.

In this paper, I focus exclusively on expressways (interstate highways) due to their distinct physical attributes. Unlike other roads, expressways are controlled-access roadways: All traffic merges via ramps, and roads can cross them only through overpasses or underpasses.[19] In addition to connecting major cities, these multilane roads served the local network in metropolitan areas and contributed to suburban sprawl. Faster commuting times played a crucial role in reshaping the spatial distribution of the population in US metropolitan areas between 1950 and 1990. Baum-Snow (2007) finds that highways account for approximately one-third of the total decline in central city residents relative to the metropolitan population. This pattern of suburbanization, which affected most American cities, also transformed Chicago. In 1950, the Chicago metropolitan area had a population of more than 5.1 million, with 3.6 million residing within city boundaries. By 1990, the city's population had declined to less than 2.8 million (a 22% drop). In contrast, the total metropolitan population grew by more than 50% over this period, reaching eight million in 1990.

The creation of the Interstate Highway System also came with an intertwined history of infrastructure development and racial inequality. As former US Secretary of Transportation Anthony Foxx stated in 2016, these roads were often routed through disadvantaged neighborhoods, where the poorest residents—almost always racial minorities—lived. In some cases, they were even deliberately designed to separate neighborhoods.[20] "It became clear to me only later on that those freeways were there to carry people *through* my neighborhood, but never *to* my neighborhood."[21] Histori-

[19]In contrast, other types of highways (such as US highways, state, and county roads) do have at-grade intersections, including with minor roads. While some segments may be limited-access, most function as free-access roads, allowing private drives to enter and exit directly. See Appendix A.1.1 for further detail.

[20]See for instance the March 28, 2016 Washington Post article on the issue: https://www.washingtonpost.com/local/trafficandcommuting/defeating-the-legacy-of-highways-rammed-through-poor-neighborhoods/2016/03/28.html

[21]Anthony Foxx, before the Center for American Progress (Washington DC, March 30, 2016).

cal accounts document the link between racial configurations and the passage of highways across neighborhoods (Mohl, 2004, 2008; Archer, 2020).

Chicago was no exception. In the late 1940s, city officials estimated that the planned expressways would destroy over 8,100 housing units (Mohl, 2001). Figure A3 shows both sides of Troop Street in 1949, before construction of the Eisenhower Expressway, which runs westward from the Loop. Near the city center, the route primarily cut through Italian and Greek communities and a smaller Black community, forcing many to relocate. A second example is the Dan Ryan Expressway, a north–south route whose alignment was shifted west in 1956. Contemporary accounts suggest this decision may have reflected a desire to reinforce racial separation on the South Side, where the Black population was growing rapidly. The Dan Ryan came to be seen as a zone of division, and many neighborhoods along its path experienced severe deterioration.[22] These examples highlight the possibility that local factors may have influenced some routing decisions. I revisit this issue in the empirical strategy, where I address potential endogeneity in highway placement.

When expressways were laid out, Chicago was home to many minority groups, whose presence had grown significantly since the late 19th century. During the first wave of the Great Migration (1910–1920), more than 50,000 African Americans moved to Chicago from the rural South in search of job opportunities, increasing their share of the city's population to 4.1%. Foreign immigration declined during the Great Depression and World War II, while the Black population continued to grow. By 1944, nearly one in ten Chicago residents was Black.

As foreign-born communities declined in size, Black neighborhoods became increasingly prominent, giving rise to the so-called "Black Metropolis" on the city's South Side. By the late 1940s, over 90% of Chicago's Black population lived in this area (corresponding to the largest purple region in Figure A5 in Appendix A.1.3).[23] In contrast, Hispanic immigration grew steadily only in the second half of the 20th century. In 1960, just about 1.5% of Chicago's total population was Hispanic, but by 1990, this figure reached nearly 20%.[24] Indeed, in population censuses—my primary source of demographic data—Hispanic origin was not separately identified until after 1970.[25]

2.2 Data

The primary data sources are the decennial US census of population and housing covering the period between 1920 and 2010, combined with GIS data. The primary geographic unit used in the analyses is the census tract.[26] To ensure comparability over time, historical census tract boundaries are normalized to 2010 boundaries, following the procedure in Lee and Lin (2018). The geographic extent of

[22] https://www.chicagotribune.com/news/ct-xpm-1998-03-01-9803010173-story.html

[23] With the vast majority of the Black population concentrated in a narrow stretch of land on the South Side, Chicago was already a segregated city before expressways were built, as shown in the figure. However, this area was too small to accommodate the growing number of African Americans migrating to the city. Since then, the Black population has tripled, and the city's spatial structure has changed dramatically.

[24] Today, Chicago is among the most diverse US cities, with its largest racial and ethnic groups making up nearly equal shares of the population: https://fivethirtyeight.com/features/the-most-diverse-cities-are-often-the-most-segregated/

[25] In the following analyses, I distinguish only between Black and non-Black individuals. Due to data limitations, individuals of Hispanic origin, along with other racial and ethnic minorities, are consistently grouped with the white population. While imperfect, this categorization remains sufficient for studying the segregation of one minority group from others.

[26] A census tract typically covers an area of approximately two square kilometers and includes around 6,000 residents.

the metropolitan area is determined by data availability in 1950. This approach results in 1,511 consistent boundary census tracts that partition the Chicago Metropolitan Area between 1950 and 2010. Of these, 780 tracts were already surveyed at the beginning of the 20th century, allowing for data coverage spanning a full century at 10-year intervals (1920–2010). The dataset provides fine-grained spatial information on a wide range of household socio-demographic characteristics and housing attributes. Below, I outline the main variables of interest and the procedure used to construct the time series, grouping them by data source. Summary statistics for 1950 are reported in Table A1 in Appendix A.

Censuses of population and housing The primary demographic of interest is the racial composition of each census tract. Given the long time horizon of the analysis and the changing demography of the period, the type of information available from the decennial censuses allows me to consistently distinguish between two race categories: "Black" and "non-Black."[27] Starting in 1980, race classification in the census became more detailed. For these later periods, I define Black residents as those recorded as "Black, non-Hispanic" (following Logan et al., 2014). Consequently, in the analyses that follow, the complementary category to the share of Black residents is the share of non-Black residents, which includes white individuals, people of Hispanic origin, and other racial and ethnic groups.

Since census tract-level data on (self-reported) household income is available only from 1950 onward, I supplement granular demographic data with an estimate of the share of college graduates, consistently covering the period between 1940 and 2010. This statistic is computed as the share of individuals aged 25 and older who completed at least four years of college.

Related to housing characteristics, I use tract-level data on median house values from the decennial US censuses. These values refer to owner-occupied housing units and are reported in nominal dollars. House value data are available from 1940 for tracts within the city of Chicago and from 1950 onward for the full sample of 1,511 tracts. To ensure comparability over time, I adjust all values to 2010 dollars using the national Consumer Price Index. I also use tract-level counts of housing units, available from 1920 onward, to characterize the housing stock.

Land and road network data I supplement the US population and housing census data with additional sources.

First, to address the limitation that census data do not include information on multi-unit buildings, I use Olcott's Land Value Blue Book, a dataset unique to Chicago. This collection provides estimates of land values for every city block throughout most of the 20th century. The data, digitized and made available by Ahlfeldt and McMillen (2014, 2018), gives spatial coverage at the 300×300-foot

[27] An exception is the 1940 census, which recorded race only as "white" versus "non-white." To ensure consistency, I re-coded the 1940 categories to align with the rest of the time series. Since other non-white racial groups were a small share of the population at that time (Hispanic immigration remained limited before the 1960s), I classify all individuals recorded as "non-white" in 1940 as Black. To validate this assumption, I compared the resulting tract-level shares of Black residents with data from a 1934 population and housing census conducted exclusively in Chicago. The 1934 census classified race as "White," "Negro," and "Other," in line with other census periods. For comparability, I computed the tract-level share of Black residents using the same weighting scheme derived from the 1940 census data. Reassuringly, the correlation between the two measures (from 1934 and 1940) is 98.83%.

grid cell level. For the purposes of my analysis, I extract land values recorded around each census year and compute the median value within each census tract. I then normalize these values to 2010 dollars using the national Consumer Price Index, yielding a tract-level measure of land value that can be compared consistently over time.

Second, contemporaneous transport networks are sourced from the US Census Bureau. From the complete road network of Chicago, I extract expressways that traverse the study area. Starting from the present-day network, I reconstruct historical snapshots of the expressway system at 10-year intervals aligned with census years, capturing temporal variation in infrastructure exposure. The baseline source for expressway opening dates is Baum-Snow (2007). I refine this information by assigning opening years to individual road segments within the city based on state-issued maps from Illinois and Indiana corresponding to each census year.[28] This approach allows me to follow the spatial and temporal rollout of the expressway network across neighborhoods.

Finally, I obtain the 1940 road network from the Urban Transition HGIS Project (Shertzer et al., 2016), which provides a snapshot of the street grid before the introduction of modern expressways.[29]

2.2.1 Sample

The original sample consists of 1,511 census tracts with fixed boundaries (normalized to 2010) covering the area that was part of the Chicago Metropolitan Area in the 1950 census. Of these, 791 tracts fall within the official boundaries of the City of Chicago, while the remaining 720 constitute the suburban area. For the earliest periods, information is only available for the subset of 757 tracts that had already been surveyed by the early 20th century.

Notorious public housing projects, such as Cabrini-Green and the Robert Taylor Homes, were developed by the Chicago Housing Authority as part of mid-20th-century urban renewal efforts. These large high-rise housing developments were predominantly occupied by Black residents. To isolate the neighborhood effects of expressways, the main analyses exclude census tracts that hosted these projects (see Map A4 in Appendix A), and I conduct robustness checks using larger exclusion radii around them. For completeness, I also present results including public housing neighborhoods across the relevant appendix sections. The results remain stable.

3 Overview of the empirical analysis

This section summarizes the empirical strategy used to study the effects of expressways on neighborhood racial composition. The analysis focuses on two key mechanisms. First, expressways create lasting reductions in residential amenities in the neighborhoods they cross, potentially altering neighborhood composition through reductions in property values. Second, expressways act as physical barriers, affecting racial sorting by changing neighborhood connectedness and altering exposure

[28] Digitized copies of official roadway maps are available annually since the 1930s and bi-annually since the mid-1970s from the Illinois Department of Transportation: https://apps.dot.illinois.gov/HistoricalMapViewer/. For Indiana, they are available annually since the 1920s from the Indiana DOT: https://www.in.gov/indot/resources/historic-maps/.

[29] https://s4.ad.brown.edu/Projects/UTP2/ncities.htm

to areas with different racial compositions.

I exploit these two sources of variation—proximity to expressways and changes in accessibility—to identify the disamenity and barrier effects. The disamenity effect is estimated using a difference-in-differences design with multiple time periods, comparing neighborhoods near and far from expressways over time. The barrier effect is estimated using a long-difference empirical design, measuring how changes in exposure to Black residents—based on a travel-time-weighted measure of racial exposure—affect changes in neighborhood racial composition.

4 Disamenity effect of expressways

I employ multi-period difference-in-differences specifications to estimate the dynamic impact of expressway proximity on neighborhood valuation. I compare the average outcomes of census tracts near expressways to those farther away. The estimating equation is of the following form:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{j=-2}^{6} \beta_j D_i \times T_{i,t=t^*+j} + \epsilon_{it} \tag{1}$$

where i is a census tract; t is a census year; Y_{it}, the outcome variable of interest, measures the share of Black residents or total population (depending on the specification) in census tract i at time t; D_i is an indicator variable for being close to the expressway (in the baseline specification, it takes a value equal to 1 if the census tract's centroid is within 1 km from the nearest expressway—corresponding to the largest distance at which both pollution and noise are estimated to reach the benchmark levels of areas with no highways—and 0 if it is more than 3 km away from the closest expressway);[30] $T_{t \geq t^*}$ is an indicator for post-expressway plan period, beginning with the construction phase and continuing into the post-opening years; α_i are census tract fixed effects; γ_t is a set of time fixed effects (further interacted with a set of baseline controls, as stated below each figure). All standard errors are clustered at the census tract level. In robustness checks, I show that the results remain quantitatively similar using alternative choices of the bandwidths defining treatment and control units. The baseline specification leaves a 2 km buffer between treatment and control units to address, in a reduced-form sense, potential spillover treatment effects that could contaminate nearby control locations. I also show that results remain mostly robust to more conservative clustering approaches (see Section 4.2 below for more details).

The coefficients of interest are β_j, which capture the effect of being exposed to treatment since j time periods. Each β_j estimates the difference between treatment and control group outcomes at

[30] Regarding pollution, Karner et al. (2010)—integrating findings from 41 studies on near-road air pollutant dispersion—report that ultrafine particle (UFP) concentrations return to background levels approximately 910 meters from the highway. As for noise, its impact dissipates at a shorter distance than pollution. In an idealized free-field setting (assuming uniform sound propagation), noise follows the inverse square law, decreasing by approximately 6 decibels with each doubling of distance. Under these conditions, highway noise—estimated at around 75 decibels by the Federal Highway Administration—drops to the WHO-recommended ambient noise level of 40 decibels at roughly 320 meters. In real-world settings, reflections and reverberations alter sound propagation, but estimates remain relatively close to this benchmark. According to the US Department of Transportation's transportation noise map (2018), expressway noise in Chicago typically fades around 250 meters from the source. For reference, Figure A8 in Appendix A.3 provides an excerpt of the interactive noise map developed by the Bureau of Transportation Statistics.

event time j. Negative values of j allow us to check for the existence of pre-trends in the dependent variable. All β coefficients are normalized relative to β_{-1}, the decade just before entering into treatment.

The results are computed using the two-way fixed effect estimator proposed by de Chaisemartin and D'Haultfoeuille (2020), which remains valid even when the treatment effect vary across groups or over time, as may be the case in this setting. When treatment effects are heterogeneous, the two-way fixed effects coefficient can be interpreted as a weighted sum of many difference-in-differences comparisons between groups and time periods. However, because the control group in some of these comparisons may also be treated in both periods, some of the weights can be negative. This can be problematic when the average treatment effects differ across groups or periods, as the estimated coefficient may have a different sign than the average treatment effects of the underlying pairwise comparisons. To assess the severity of this issue in my setting, I apply the *twowayfeweights* command from de Chaisemartin and D'Haultfoeuille (2020) to my baseline specification with the full set of controls. I find that 86.1% of the average treatment effects on the treated receive positive weights (78.0% in the specification with no controls), with their weights summing up to 1.041, while 13.9% receive negative weights, summing to -0.041.[31]

The main specifications run regression (1) with a set of baseline variables, each interacted with year-fixed effects. First, I flexibly control for distance to the Central Business District (CBD), a variable likely to affect both the outcomes and treatment status: Black households (and minority groups more generally) initially settled in the central parts of the city, and expressway construction followed a radial pattern centered on the CBD. Second, I include a "city center" fixed effect, which splits the sample into central and suburban areas.[32] This control helps isolate the disamenity effect of expressways.[33] Under the assumption that proximity to expressways within the city does not affect the likelihood of moving to the suburbs, the city fixed effect captures changes in relative residential amenities driven by expressway disamenity effects—net of suburban movements.[34] Third, I control for baseline population density, which likely correlates with both treatment assignment and the primary outcome of interest—Black and minority groups were more likely to live in higher-density areas. Finally, I include a control for baseline neighborhood characteristics using the grades assigned

[31] The command also returns two summary measures of the robustness of the estimated coefficient. The first corresponds to the minimum standard deviation of treatment effects across treated groups and time periods that would be needed for β and the average treatment effect on the treated to have opposite signs. This value is 0.762 (after standardizing the outcome variable). The second measure corresponds to the minimum standard deviation required across treated groups and periods for all average treatment effects to differ in sign from β. The reported value is 3.889 (after standardizing the outcome variable). Reassuringly, both summary measures are large, suggesting that β and the average treatment effects could be of opposite signs only under a high degree of treatment effect heterogeneity across groups or time periods.

[32] Central areas are defined as those within the administrative boundaries of the City of Chicago.

[33] Expressways change the relative amenity of the places they serve in two fundamental ways. The first is the so-called access benefit: expressways increase the relative residential amenity of farther away locations, which are now easier to reach and commute from. The second is the disamenity effect: expressways change the relative amenity of residential neighborhoods by making some places worse than others through increases in pollution, noise, and other disamenities. While these two dimensions are likely to go hand in hand, this paper specifically focuses on the latter.

[34] A potential concern is that households displaced by expressway construction were disproportionately pushed to the suburbs. However, as documented in Valenzuela-Casasempere (2025), individuals displaced by expressway construction were not systematically more likely to relocate farther from the downtown area. On the contrary, available evidence suggests they tended, on average, to move closer to the central business district.

by the Home Owners Loan Corporation (HOLC) in the 1930s (Fishback et al., 2020).[35] Given the history of discrimination against Black residents and European immigrants as they settled in industrialized US cities, minorities tended to concentrate in disadvantaged and economically distressed neighborhoods. HOLC maps reflected these long-lasting inequities.[36] Omitting the neighborhood effects of redlined areas in this context would likely bias the estimated coefficient upwards. In robustness checks (Appendix B), I show that results remain quantitatively similar even when no controls are included (see Figures B1 and B19, for share Black and population as outcomes, respectively).

The empirical specification assumes that, in the absence of expressways, treatment and control group outcomes would have followed similar trends. However, the 1920s were marked by substantial population movements, raising concerns about the validity of this identification assumption in the earliest period. During this time, the city underwent rapid urban expansion, while the Black population remained largely concentrated in the city center. As a result, identifying a reliable comparison group for this period is particularly challenging.[37] In what follows, I omit the year 1920 from the main analysis. However, in Section B.1.9 of Appendix B, I also report results including 1920 and show that the pre-trend in outcomes for this early period disappears once I account for areas that experienced contemporaneous population changes due to factors unrelated to expressways.

4.1 Main results

Following Brinkman and Lin (2024), I first report the effects of expressway proximity on changes in residential population, a measure that reflects shifts in neighborhood quality of life. The estimated coefficients from regression (1) are reported graphically in Figure 2. Event times to the right of the red vertical bar denote post-treatment periods, with event time 1 marking the decade in which the expressway opened to traffic. Event times to the left of the dotted red bar correspond to pre-treatment periods, while the interval between the two bars represents the construction phase—from the first expressway plan to the decade of opening.

The results indicate a persistent decline in residential population in affected areas relative to control units. During the construction phase (before expressways became operational), residential population decreases by an average of 331.52 people (s.e. 118.77), equivalent to about 8% of the full sample mean. After the expressways open, residential population continues to fall by approximately 500 people per decade (about 12% of the sample mean), reaching a cumulative decline of nearly 2,000 people by decade four into treatment. The average treatment effect is estimated at –1,359.84 (s.e. 216.25). Reassuringly, the estimated β coefficients for pre-treatment periods are consistent with the assumption of parallel trends in outcomes between treated and control groups.

Next, I examine the effects of expressway proximity on neighborhood racial composition. The

[35] See Appendix A.2 for background on redlining and the HOLC boundaries in Chicago.

[36] Recent studies have documented long-term consequences of redlining on homeownership, property values, and rents (Aaronson et al., 2021; Krimmel, 2020).

[37] Figure B14 in Appendix B plots the raw average residential population in (eventually) treated versus control areas over time using a binned regression (without controls). Between 1920 and 1930, the population of what would later become the control group doubled before stabilizing at a slower growth rate, raising concerns about its suitability as a counterfactual during this early period.

estimated coefficients from regression (1) on the share of Black residents are plotted in Figure 3. Living near an expressway is associated with a substantial increase in the share of Black residents, all else equal. On average, neighborhoods near expressways experience a 15.43 percentage point increase (s.e. 0.02) in the share of Black residents in the first decade after treatment, and an average increase of roughly 20 percentage points in the following decades relative to the pre-treatment period. The average treatment effect across all post-treatment periods is 15.72 percentage points (s.e. 0.03). The pre-treatment β coefficients are again consistent with the assumption of parallel trends in the outcome variable between treated and control neighborhoods before intervention. During the construction phase, the affected areas already begin to experience both a drop in population and an initial shift in neighborhood demographics, which intensifies in the post-treatment period.

4.2 Robustness checks

I show that the results remain robust and quantitatively similar across a series of checks, including: (i) removing controls; (ii) using a balanced panel (restricting the analysis to observations with full data coverage); (iii) weighting observations by baseline population; (iv) varying treatment and control group bandwidths; (v) excluding portions of the city; (vi) using alternative clustering levels for standard errors; (vii) employing alternative empirical specifications; and (viii) applying the semi-parametric difference-in-differences estimator of Callaway and Sant'Anna (2020). In addition, I present a set of IV regressions designed to address potential non-random selection into treatment. The estimated effects are consistent with the event study results.

These robustness exercises are described in detail in Appendix B and summarized here. First, I report results for changes in both the share of Black residents and residential population without controls, showing that the estimates remain quantitatively similar. Second, I restrict the analysis to a balanced panel of 760 observations per period. These tracts correspond to areas within the City of Chicago that were enumerated at the beginning of the study period, fully encompassing the city's most historically significant sites. Results remain virtually unchanged. Third, to ensure that findings are not driven by low-population or non-representative tracts, I weight observations by baseline population density. The results remain robust.

Fourth, I show that the results do not significantly vary with the choice of bandwidths used to define treated and control units. In the baseline specification, I conservatively account for potential spatial spillovers by imposing a 2 km buffer between treated tracts—defined as those with centroids within 1 km of the nearest expressway—and control tracts, whose centroids lie more than 3 km away. This yields nearly equal-sized groups (388 treated and 454 control tracts at baseline), but at the cost of excluding approximately 40% of sample units—those with centroids located between 1 and 3 km of an expressway. Appendix B confirms that the results are robust to alternative definitions of treated and control units. When I reduce the buffer zone—and in particular when I allow control tracts to lie closer to expressways—the estimated coefficients attenuate somewhat but remain highly statistically significant. These findings suggest that the empirical design effectively captures the impact of expressways on neighborhood racial composition and demographic changes.

Fifth, I provide additional evidence that the main results are not driven by areas undergoing notable changes during this period. Restricting the sample to tracts within the City of Chicago yields similar estimates. The findings also hold after excluding the area that historically housed the vast majority of the Black population (i.e., the so-called Black Belt), confirming that results are not driven by these locations. In the baseline specification, I exclude census tracts where large public housing projects were developed. To account for potential spillover effects in nearby neighborhoods, I run robustness checks that additionally exclude tracts located within a certain radius (500 meters or 1 km) of a public housing site. For completeness, I also report results including the areas where these projects were located. In all cases, the results remain stable.

Sixth, I test the robustness of the results to alternative conservative clustering approaches that account for spatial correlation in the errors. For the city sample, I show that the results remain largely robust under a coarse clustering strategy, partitioning the city into 25 grid cells of 6×6 km. As an additional check, I cluster standard errors at an even broader regional level—north, west, and south sides of the city—despite this yielding only three clusters. Even in this setting, the estimates remain statistically different from zero. For the full metropolitan sample, I partition the city into 60 grid cells of 8×8 km and cluster standard errors accordingly. While this increases the standard errors, the main results remain robust.

Seventh, I further examine the negative relationship between proximity to expressways and the share of Black residents using a distance-based regression. I divide the continuous distance variable into five approximately equal-sized bins (Appendix B.3). In both city and suburban areas, the share of Black residents declines with distance from the expressway. In the city, the share of Black residents increases by 9.6 to 33.5 percentage points (from the farthest to the closest bin) relative to suburban areas more than 4 km away from the nearest expressway (the omitted category). In the suburbs, magnitudes are smaller, but the negative relationship remains evident (Figure B31).

Finally, I show that the estimated causal effects of expressway proximity are robust to using the Callaway and Sant'Anna (2020) estimator (Appendix B.4). Like the estimator by de Chaisemartin and D'Haultfoeuille (2020), this method produces unbiased estimates in settings with multiple time periods and variation in treatment timing. In two-by-two designs, it estimates group-specific average treatment effects across all periods while imposing a weaker parallel trends assumption.

4.2.1 IV results

The identification assumption for estimating regression (1) is that, in the absence of expressways, census tracts in the treatment and control groups would have followed similar trends, conditional on controls. Under this assumption, the estimated β coefficients capture deviations from parallel trends in outcomes attributable to the expressway rollout. The richness of the temporal data in my empirical setting allows me to test for pre-trends in outcome evolution between treated and untreated units before treatment—thus providing empirical support for the parallel trends assumption, which is necessary for valid identification in my preferred specification.

As an additional robustness check, I also estimate a set of instrumental variables (IV) regressions, a standard approach in the literature to address concerns about the potential non-random selection of locations into treatment. The results remain consistent across specifications. In Appendix B.5, I report

IV results based on instruments widely used in the literature to predict transportation improvements within cities and that plausibly satisfy the exclusion restriction (Redding and Turner, 2015).

Several instruments can be employed to predict expressway routes in this setting. One approach relies on a straight-line instrument, which isolates variation arising from the fact that expressways were primarily designed as long-distance road infrastructures to connect cities nationwide, rather than to facilitate metropolitan development (Baum-Snow, 2007). The instrument is constructed using straight lines from Chicago to the cities targeted by the 1947 Interstate Highway System plan. Expressways were thus more likely to be built through neighborhoods that happened to lie along those routes. A second set of instruments exploit historical transportation networks. I use proximity to the 1898 railroad network as an instrument for the current location of expressways. Identification relies on the assumption that historical routes are unlikely to be correlated with contemporary changes in neighborhood characteristics, conditional on baseline controls. Instrument relevance is supported by the fact that expressways often followed pre-existing rail corridors due to lower right-of-way costs. Finally, unique to this context, I use proximity to proposed routes from the 1909 Burnham Plan as an instrument for actual expressway proximity. Since the plan predates the Great Migration, it is plausibly uncorrelated with more recent shifts in neighborhood demographics.

The IV results are reported in Appendix B.5. In the preferred specification combining all instruments (column 6), each additional kilometer from the nearest expressway is associated with a 0.04 percentage point decrease in the share of Black residents, holding all else constant. These estimates are quantitatively similar to the event study results.[38] The IV estimates are slightly larger in magnitude than the corresponding OLS estimates from the two-by-two design (also reported in the same table), suggesting that the observed changes in neighborhood composition near expressways may be somewhat understated. The larger IV estimates imply that expressways were more likely to be allocated to growing neighborhoods, amplifying their effects, rather than to areas already in decline—a pattern also found in Brinkman and Lin (2024). While suggestive, these results help alleviate concerns about negative selection in expressway placement, hinting that expressways were on average not primarily routed through locations expected to decline.

4.3 Effects by wave of expressway construction

A potential concern may arise regarding the non-random timing of expressway construction, specifically, whether local factors influenced the decision about which segments to build first. However, two considerations suggest that this issue is unlikely to pose a serious threat to identification in this setting: (i) census data are available at 10-year intervals, so selection concerns would only apply over longer time horizons; and (ii) 97% of eventually treated units were connected to the expressway network within just two consecutive census waves, i.e., with only a single decade separating treatment groups. Additionally, all expressways near the city center were completed within the first two decades (Figure 1). Only a few suburban ring routes were constructed later, between 1971 and 2010.

[38]The average distance to the nearest expressway in the control group of the event study (census tracts with centroids more than 3 km away) is 5.3 km, compared to 0.5 km in the treatment group (tracts within 1 km). Based on the IV estimates, the implied difference in Black share between treated and control units is $(5.3 - 0.5) \times 0.04 = 0.192$, or 19.2 percentage points. The baseline event study reports a similar average treatment effect of 15.7 percentage points.

Because nearly all treated units entered treatment in either 1960 or 1970, I estimate separate leads and lags regressions for each group. This specification allows for the estimation of treatment effects by census year within each treatment group, capturing potential heterogeneity in the effects of expressway construction depending on the timing of entry.

The results are reported in Appendix B.6. To improve precision, I weight observations by baseline population density. Figure B36, panels (a) and (b), plot the estimated average treatment effects on the share of Black residents for units treated in 1960 and 1970, respectively, relative to never-treated (control) units. The results reveal meaningful differences in the effects of expressway proximity between the two groups—heterogeneity that is masked in the pooled event study estimates.

In census tracts treated in 1960, the share of Black residents increased by approximately seven percentage points relative to 1940 levels already in the decade before expressways opened to traffic, suggesting that demographic change began during the construction phase. This trend continued: By 1960, the share of Black residents in these tracts had risen more than 20 percentage points relative to 1940, eventually stabilizing at a 40 percentage point increase in subsequent years. Appendix Figure B37, panel (a), shows a systematic population decline in these neighborhoods relative to pre-expressway periods, but with no evidence of anticipation effects. Taken together, the findings suggest that non-Black residents began leaving these neighborhoods during the construction phase, with their places increasingly occupied by incoming Black residents.

The results for 1970-treated tracts, however, tell a different story. The share of Black residents declined consistently following expressway construction, dropping by four percentage points as early as 1960—during the construction phase. This demographic shift was accompanied by a substantial population loss of over 700 residents (19% of the full sample mean) already in 1960, before these expressways became operational. These findings align with those of Brinkman and Lin (2024), which shows that, starting in the mid-1960s, expressways were increasingly routed through Black neighborhoods, and Carter (2023), which documents patterns of displacement in Detroit.

Taken together, the evidence suggests that by 1970, expressways were more likely to cut through densely populated neighborhoods, contributing to greater displacement and disproportionately affecting Black communities. In contrast, expressways constructed in 1960 did not exhibit the same pattern: Population decline occurred only after expressways became operational, not before. These results highlight that the effects of expressways on neighborhood composition varied over time—initially driven by demographic shifts, and later by more direct displacement. They are consistent with expressways introducing local disamenities that reduced the desirability of nearby areas, contributing to neighborhood deterioration. The findings suggest that expressways have persistent and reinforcing effects on neighborhood valuation—and, in turn, on long-run residential population trends.

4.4 Additional evidence

Appendix B.7 reports additional results, summarized here.

First, I document changes over time in the number of housing units following expressway construction. In event time 0 (when construction was ongoing), affected locations saw an average reduction of 139.01 housing units (s.e. 29.57) relative to control group locations. The number of housing units continued to decline in subsequent decades, stabilizing at a reduction of approximately 600 units (44.6% of the full sample mean). While part of this drop is likely mechanical—reflecting the physical displacement of buildings—the sustained decline suggests reduced investment in these areas relative to comparable locations far from expressways.

To further assess whether the population decline reflects worsening neighborhood conditions and falling property values, I examine the effects of expressway proximity on house and land values.[39] In addition, to better understand changes in neighborhood composition, I analyze the effect of expressways on the share of college graduates. This additional set of results aligns with findings from Brinkman and Lin (2024).

Figure B42 plots the estimated β coefficients from a regression using average house value (in real terms) as the outcome. In the first decade after expressways opened to traffic, self-reported house values remained stable relative to the pre-treatment period. One decade later, however, house values declined by an average of $24,072.40 (s.e. 4,871.94), equivalent to 16.25% of the full sample mean. The estimates also suggest a mean reversion in later decades, with the average treatment effect equal to -$14,359.72 (s.e. 4,627.94). When comparing raw means between eventually treated and never treated units (Figure B43), separately for suburban and the central areas, the mean reversion observed in the event study appears to be driven by the 2000 housing bubble and the subsequent subprime mortgage crisis. House values declined sharply between the 2000 and 2010 census periods, especially among control units in both central and suburban areas.

Figure B44 plots the estimated β coefficients for land value. Since Olcott's land value data covers only the most central part of the Chicago metropolitan area, the analysis is restricted to census tracts within the City of Chicago. The results are relatively noisy. In general, locations that received the expressway were on an upward trend in land values before construction, a trend that was entirely offset once expressways became operational. On average (albeit suggestively), land value declined by around 0.2 log points in the first decades of treatment, before becoming statistically indistinguishable from zero by decade four. As with house values, the estimated coefficients suggest a mean reversion effect, which here appears to begin as early as the second decade after treatment. A comparison of raw means between treated and untreated tracts (Figure B45) suggests that this mean reversion may reflect the post-2000 housing boom—and potentially to gentrifying central neighborhoods.

Finally, I further explore the effects of expressway construction on neighborhood demographics, using the share of college graduates as the outcome of interest. I consider college share as a proxy for income, since self-reported income was only included in census records starting in 1950.[40] Results are reported in Figure B46. The estimated average treatment effect of expressway proximity on the share of college graduates corresponds to a reduction of 0.03 percentage points (s.e. 0.01), equivalent to 17.6% of the full sample mean. As with house values, the effect emerges gradually over time, becoming apparent only in the second decade after treatment.

[39] The sample correlation between average real house value and (log) land value is 0.58. Appendix Figure A9 plots binned scatterplots of their relationship.

[40] The two measures are highly correlated, with a sample correlation of 0.77. Besides being already available since 1940, college share is less prone to measurement error. Appendix Figure A10 shows binned scatterplots of their relationship.

4.5 Discussion of the disamenity effect of expressways

The first empirical design of the paper isolates the dynamic impact of expressway proximity on racial composition and neighborhood valuation. The results show that, on average, expressways are associated with persistent increases in the Black share of nearby neighborhoods, long-run population decline, and reductions in house values, land values, and college share—consistent with a negative amenity shock.

I conclude the section by briefly addressing a few remaining confounding factors. One possible source of the observed declines in population and housing units is the physical displacement required to construct expressways. To assess how much of this decline can be attributed to the physical space needed for road construction, I compare neighborhoods treated in the earliest wave (1956–1960) to those treated later (1961–1970), before construction began in the latter group. This comparison assumes that, conditional on controls, the two groups are roughly comparable in terms of exposure to construction-related disruptions, apart from timing. The results (Appendix B.8) suggest that mechanical displacement accounts for only part of the persistent population decline observed in treated neighborhoods: Estimated losses are around 298 residents and 85 housing units per tract, implying the displacement of approximately 3.5 individuals per demolished unit—consistent with the average household size reported in the 1950 census (mean of 3.4). While suggestive and somewhat noisy due to sample size, these effects indicate that most of the long-run decline is not explained by physical demolition alone. Reassuringly, the estimated differences disappear once the later-treated areas also begin construction, as expected if the comparison captures displacement timing rather than underlying differences between locations.

Beyond physical demolition, two alternative explanations for population decline near central freeways are worth considering. First, increased demand for commercial space could displace residents from the center. Brinkman and Lin (2024) use travel survey data from Chicago and Detroit to identify historical job locations and find little evidence that central freeways attracted jobs, suggesting commercial demand is unlikely to explain the decline. Second, population losses might reflect households following employment to the suburbs. However, Glaeser and Kahn (2001) argue that job decentralization largely followed suburban population growth—driven by residential preferences and rising car ownership—rather than caused it. Together, this evidence suggests that employment-related mechanisms were unlikely to be the primary drivers of residential decline near expressways, reinforcing the interpretation that local disamenities played a central role.

5 Barrier effect of expressways

In this section, I examine the presence of a barrier effect of expressways. I define the barrier effect as an increase in the cost of crossing an expressway. These higher costs affect accessibility between different parts of the city, characterized by distinct racial compositions. To the extent that expressways create within-city barriers, I test whether neighborhoods become racially more similar to the areas they are more exposed to—once these urban barriers are in place.

The hypothesis to test is based on the intuition that the barrier effect of expressways manifests itself by increasing racial divergence between areas on opposite sides of the road while reinforcing similarity between neighborhoods on the same side. In an ideal experiment, within each pair of census tracts cut by an expressway, the tract experiencing the largest increase in exposure to Black residents should become increasingly more Black over time, relative to the census tract on the opposite side of the road. The identification assumption required to causally estimate the barrier effect is that, in the absence of expressways, census tracts located on either side of a planned expressway would have evolved similarly.

I leverage this intuition and test for the barrier effect of expressways by running a long-difference empirical specification where I estimate the effect of changes in exposure to Black residents on the change in the racial composition of neighborhoods in Chicago. Areas experiencing the largest increase in exposure to Black residents are expected to exhibit greater increase in their own Black population share over time.

To measure the change in exposure to Black residents, I compute a novel metric of accessibility, defined as a location-specific weighted average of the share of Black residents in each neighborhood. The weights are a decreasing function of bilateral travel time between each origin location and all other neighborhoods in the city. The weights depend on the development of the underlying road network—in particular, the construction of expressways—and assign higher values to locations that are more easily accessible. As a result, this summary measure captures, for each origin neighborhood, changes in exposure to Black residents over time, driven both by residential sorting and by changes in transportation infrastructure that affect how accessible other neighborhoods in the city are.

The estimating equation in first differences is the following:

$$\Delta y_i = \beta_s \Delta S_i + \beta_d Dist.\, expressway_i + Region\ FE + \gamma_c' Controls_i + \epsilon_i \tag{2}$$

where $\Delta y_i = y_{i,1990} - y_{i,1950}$ measures the change in outcome (share of Black households, land value) between 1950 and 1990 (in the baseline specification);[41] $\Delta S_i = \sum_{j \neq i} e^{-\rho \tau_{ij\, post}} share\ Black_{j\, post} - \sum_{j \neq i} e^{-\rho \tau_{ij\, pre}} share\ Black_{j\, pre}$ captures the change in exposure to Black residents, induced by both sorting and changes in transportation infrastructure; $Dist.\, expressway$ represents the distance (in km) between the centroid of each census tract and the nearest expressway.[42] Region fixed effects for being in the north, west, or south of the city are always included. Baseline control variables are added sequentially, as stated below each table, to partially account for changes in observables that might be correlated with neighborhood dynamics. Standard errors are clustered at the census tract level unless indicated differently.[43]

[41] To examine how the effects evolve over time, I replicate the long-difference specification using outcomes in 1980 and 2000. The results (Appendix C.3 and C.4) remain consistent: Exposure to Black neighborhoods continues to be a strong predictor of neighborhood change, while the effect of proximity to expressways appears relatively stronger in the earlier decades.

[42] Based on the previous reduced-form results, this variable accounts for the disamenity effect of expressways and the identification of the coefficient of interest β_d relies only on the residual variation in the predicted change in exposure. The sample correlation between distance to the nearest expressway and change in exposure to Black areas is -0.28.

[43] To allow for arbitrary spatial correlation, I also report baseline results (i) clustering standard errors at a grid level that partitions the city into 25 equally sized squares; (ii) using Conley (1999) standard errors with a 3 km cutoff (results, not reported here, remain similar at different cutoff values, such as 5 km and 10 km).

A concern in estimating regression (2) is that the change in exposure to Black residents (ΔS) is likely correlated with unobserved shocks to neighborhood residential amenities, which are captured in the error term. The variable is indeed constructed as a weighted average of exposure to Black areas, where weights are a function of the bilateral travel times between any pair of locations, and contains information on the racial composition of the neighborhoods in the city in both periods.[44,45] I instrument for the change in exposure to Black areas by holding the racial composition fixed to the baseline period, thereby isolating variation that is solely due to changes in travel time between locations. Formally, the instrument is constructed as: $\Delta SMA_i = \sum_{j \neq i} share\ Black_{j\ pre} (e^{-\rho \tau_{ij\ post}} - e^{-\rho \tau_{ij\ pre}})$.

In the baseline specification reported in the main text, I calibrate the rate of spatial decay of the weights (ρ) from the literature. I set $\rho = 0.019$ following the estimated elasticity of consumption travel cost with respect to travel times in Miyauchi et al. (2021). To isolate the barrier effect, I also set the cost of crossing the expressway network to be infinitely high, capturing the idea that infrastructure may create discontinuities beyond physical distance—echoing the widely recognized notion of being on the "wrong side of the tracks."[46] In the Appendix, I explore the sensitivity of the results to the choice of the decay parameter. I report additional results where I increase the parameter ρ to values that effectively set the weights used to compute changes in exposure to Black residents virtually zero beyond distances of 10 km and 20 km ($\rho = 0.5$ and $\rho = 0.25$, respectively). These exposure measures can thus be interpreted as iso-areas, i.e., network-based equivalents of buffer zones. The local exposure measure is a weighted average of the racial composition of neighborhoods within a given distance (10 or 20 km, depending on the specification) from the origin location, when traveling on the road network.

Figure 4, panels (a) and (b), display the change over time in exposure to Black residents (ΔS) and the instrumental variable (ΔSMA), respectively. Census tracts are grouped into deciles based on the value of the respective variable, with darker colors representing higher values. The maps reveal two key patterns. First, both variables exhibit substantial independent variation with distance from the expressway network: Being closer to the road does not necessarily result in larger changes in either variable. Second, they show a high degree of spatial correlation, reflecting the unequal distribution

[44] Bilateral travel times are computed as shortest-path distance between each census-tract pair over the period-specific road network, assuming a constant travel speed of 20 km/h. This value corresponds to the average travel speed across socio-demographic groups and time periods. Results remain broadly consistent when using alternative travel speeds (e.g., 15 km/h or 30 km/h).

[45] To address the correlation between initial residential choices and local unobserved shocks, I exclude the location itself when calculating its predicted change in exposure.

[46] The idea that the relationship between inequality and social networks in cities is mediated by physical space goes far back in the social sciences (Wachs and Kumagai, 1973). Ananat (2011) formalizes the idea that infrastructure can also act as a mechanism for social and economic separation, showing that cities more subdivided by railroads became significantly more segregated during the Great Migration—interpreting infrastructure as a technology for producing segregation. Additional evidence supports this interpretation in contemporary settings. Roberto and Korver-Glenn (2021) extend this perspective, combining spatial and ethnographic analysis in Houston, Texas, to show that physical barriers—such as highways and railroad tracks—not only coincide with greater racial segregation but are also experienced by residents as symbolic dividers. Aiello et al. (2025) use Twitter connections to show a strong negative correlation between the number of highways separating tracts and the volume of social ties. Tóth et al. (2021) find that geographic features such as highways or rivers can amplify economic inequality by shaping local social networks. While these present-day effects may partly reflect the long-lasting influence of the infrastructure itself—shaping a form of "experienced segregation" (Athey et al., 2021), that is, a sense of social disconnection rooted in where people go and whom they encounter in daily life—they nonetheless highlight the prominent role of physical barriers in structuring urban communities.

of racial groups across different parts of the city. The IV takes its highest values in the south and its lowest values in the north, consistent with the broader racial geography of Chicago.

To address the concern that the IV may be capturing spatially clustered features within the city, I conduct the following robustness checks. First, I always include city-side fixed effects, ensuring that identifying variation comes exclusively from within the city's north, west, and south sides. Second, I introduce a control variable that captures changes in exposure to high-income areas. This measure is computed as the weighted average of the share of college graduates in each location (serving as a proxy for neighborhood income levels), similar to the measure of exposure to Black residents.[47] The inclusion of this control accounts for the possibility that changes in neighborhood accessibility may affect not only exposure to Black areas in the city but also access to different sets of residential amenities (e.g., parks or restaurants), correlated with resident income—accounting for broader barrier effects beyond race.[48] Finally, as mentioned above, I replicate the results using more localized exposure measures by adjusting the weights so that locations beyond 10 or 20 km from each origin effectively receive near-zero weights. These localized exposure measures exhibit lower spatial correlation, mitigating concerns that the findings may be influenced by broader citywide segregation patterns.

5.1 Results

Table 1 presents the estimated coefficients from regression (2), where the outcome variable is the change in the share of Black residents. Fixed effects for being in the north, west, or south of the city are always included.

OLS results are reported in columns (1) to (7). Column (1) shows the sample correlation between the (standardized) change in exposure to Black residents and the (standardized) change in the share of Black residents in the origin neighborhood. The estimated coefficient is large and statistically significant at the 1% level: A one standard deviation increase in exposure to Black residents is associated with an average 0.50 standard deviation increase (s.e. 0.053) in the share of Black residents in the neighborhood. In column (2), I include distance to the nearest expressway (in km) as an additional regressor. The estimated coefficient for exposure to Black residents remains stable.[49]

Columns (3) to (5) sequentially introduce additional controls to partially account for changes in observables that might correlate with changes in neighborhood composition. In column (3), I control for basic census tract characteristics: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to the water. Column (4) extends the set of controls to capture historical conditions.[50] In column (5) I further control for changes in exposure to high-income areas

[47] The weights used are the same as those applied in computing exposure to Black residents.

[48] This ensures that the estimated effects of exposure to Black residents are not confounded by changes in access to higher-income neighborhoods and their amenities.

[49] For reference, the adjusted R^2 rises from 0.1285 to 0.2269 when adding the exposure measure to a baseline specification with distance to the expressway and region fixed effects. This suggests that changes in exposure to Black neighborhoods explain substantial variation beyond what is captured by proximity to expressways and broad regional differences. Without region fixed effects, the R^2 of a regression of changes in the share of Black residents on expressway proximity increases from 0.0145 to 0.2267 after including the exposure measure.

[50] The complete set of historical controls includes distance to railroads in 1898, HOLC grade, the share of Black residents

in the city (ΔY).[51] The point estimate remains largely stable after the inclusion of additional controls. The estimated coefficient for distance to the expressway reveals a strong negative relationship between the share of Black residents in a neighborhood and distance from the road: The share of Black residents decreases by approximately 0.2 standard deviations for every additional kilometer from the expressway, on average, holding all else fixed.

In columns (8) to (11), I instrument for the actual change in exposure to Black residents using a measure that holds the racial geography fixed at its 1950 distribution and captures changes in accessibility induced by modifications to the road network. This isolates the variation in exposure that is driven solely by the construction of expressways, net of residential sorting. The coefficient captures the causal effect of infrastructure-induced changes in exposure to Black residents on neighborhood racial composition. The estimated coefficient remains large and statistically significant at the 1% level ($\beta = 0.158$, s.e. = 0.069). As expected, the point estimate is lower than in the OLS specification, confirming that the OLS estimates were largely inflated by sorting effects. In column (11), I additionally instrument for the change in exposure to high-income neighborhoods in the city using an instrumental variable (ΔYMA) constructed analogously to ΔSMA.[52] Both the point estimates for the change in exposure to Black residents and the point estimate for distance to the expressway remain stable and highly statistically different from zero. Notably, the estimated coefficient for the change in exposure to wealthy areas (ΔY) is not statistically different from zero in the estimated regressions.

Next, Table 2 presents the estimated coefficients from regression (2), where the outcome variable is the change in land value—used as a proxy for neighborhood valuation—between 1950 and 1990. On average, an increase in exposure to Black residents reduces land value by approximately 0.3 standard deviations (s.e. 0.051) in the regression with the full sets of controls in column (5). After accounting for sorting effects, the results remain largely stable in the IV specifications, though smaller in magnitude (around -0.25, s.e. = 0.065, in column 11). In addition, the results show that the estimated coefficient for distance to the expressway is, on average, positive, but statistically different from zero only in the IV specifications. Point estimates above zero are consistent with the idea that expressways generate disamenity effects within cities.

As an extension, I replicate the long-difference specification using post-period outcomes in 1980 and 2000 to assess whether the estimated effects persist over time. Since I observe the road network only as of 1940 (pre-period) and 2019 (post-period), the exposure weights are held fixed as in the main specification, while the changes in sorting and outcomes reflect neighborhoods' evolution over time. The results, reported in Appendix C.3 and C.4, are broadly consistent: Both exposure to Black neighborhoods and proximity to expressways remain significant predictors of changes in neighborhood racial composition and valuation. However, over time, the relative importance of proximity to expressways declines relative to exposure to Black areas in explaining changes in both Black share and land value.

in 1920, and the change in population density between 1920 and 1940.

[51] Similar to ΔS, the variable is constructed as $\Delta Y_i = \sum_{j \neq i} e^{-\rho \tau_{ij\,post}} c_{j\,post} - \sum_{j \neq i} e^{-\rho \tau_{ij\,pre}} c_{jpre}$ where c_j is the share of college graduates in neighborhood j.

[52] $\Delta YMA_i = \sum_{j \neq i} c_{j\,pre} (e^{-\rho \tau_{ij\,post}} - e^{-\rho \tau_{ij\,pre}})$, where c_j is the share of college graduates living in neighborhood j. This instrument holds sorting fixed to the pre-period and isolates variation in exposure to high-income areas induced solely by changes in travel times.

To summarize, the barrier-effect estimation yields four main takeaways. First, a higher exposure to Black residents increases the likelihood that a neighborhood becomes more Black over time and decreases its valuation in the long run. Second, changes in exposure to high-income areas do not appear to affect a neighborhood's racial composition, after controlling for distance to the expressway and changes in exposure to Black residents. Third, both the disamenity and the barrier effect of expressways affect the racial distribution within the city. Fourth, land value appears to be more responsive to changes in neighborhood composition induced by the barrier effect than to the disamenity effect of expressways.

5.1.1 Reduced-form effects

In the main specification, I show that the estimated coefficients from OLS are inflated due to sorting effects, as expected. The IV estimates are substantially smaller, since they account for this source of endogeneity. Here, I present reduced-form effects of infrastructure-induced changes in potential exposure to Black residents. I regress the change in neighborhood racial composition directly on measures of infrastructure-induced change in access to the 1950 Black population distribution.[53] This approach holds the racial geography fixed to the pre-expressway period and captures the effect of changes in accessibility—driven by expressway construction—on subsequent changes in neighborhood demographic composition. The estimated coefficient reflects what would be expected if accessibility to other parts of the city changed over time while the racial composition of all other neighborhoods remained constant. In this sense, the variation can be interpreted as the immediate effect of introducing an uncrossable barrier in the city before residents adjust their location decisions.

The results are presented in columns (1)–(3) of Table C1 in Appendix C.2. A one standard deviation increase in infrastructure-induced exposure to Black residents is associated with a 0.09–0.14 standard deviation increase in the neighborhood's Black population share, on average. While assuming infinitely high crossing costs helps isolate the barrier effect in a reduced-form setup, I also estimate results under a high—but not infinite—cost of crossing. Columns (4)–(6) report estimates based on exposure measures computed with a 10-minute crossing penalty.[54] When the exposure measure assumes an uncrossable barrier, I find that a 10 percentage point increase in potential exposure—roughly a doubling of average pre-highway exposure to Black areas—is associated with a 5.1 percentage point increase in Black share (column 3, with the full set of controls). This amounts to about 13% of a standard deviation and 17% of the average demographic shift over the period. In contrast, when the exposure measure is based on the 10-minute crossing penalty, a 10 percentage point increase in potential exposure is associated with a 1.1 percentage point increase in Black share (column 6, with the full set of controls), i.e., about 4% of the average change.

[53] The estimating equation is of the following form: $\Delta ShareBlack_i = \beta_{RF}\Delta SMA_i + \gamma_c' Controls_i + \epsilon_i$, where, as before, $\Delta SMA_i = \sum_{j \neq i} share\ Black_{j\,pre}(e^{-\rho\tau_{ij\,post}} - e^{-\rho\tau_{ij\,pre}})$.

[54] That is, whenever the shortest route between any two census tracts crosses an expressway, I add 10 minutes to the total travel time between the two. While the two exposure measures are highly correlated (correlation = 0.78), their distributions differ. Unsurprisingly, the exposure measure based on the 10-minute crossing penalty exhibits less variation than the one based on the uncrossable barrier, with standard deviations equal to 0.009 and 0.112, respectively.

5.2 Robustness checks

I conduct several robustness checks. First, I allow for arbitrary spatial correlation of errors across census tracts within the same grid cell or within a certain distance from each other. Second, I restrict the sample to census tracts that had fewer than 20% Black residents at the beginning of the century (95% of the data) to address concerns that a few historically Black neighborhoods might be driving the results. Third, I rerun the analysis using only census tracts located more than 5 km from the central business district (this exercise removes 12% of the data). The results remain robust to all these specifications. Fourth, in Appendix C, I report results using more localized exposure measures and show that the main findings still hold. Finally, I provide additional evidence using house value and college share as alternative outcomes. Below, I describe these robustness checks in more detail.

The remaining columns in Table 1 and Table 2 report the results of the robustness checks. Columns (6) and (7) present the results for the specification with the full set of controls, accounting for potential spatial correlation of errors. Columns (6) display the standard errors under the assumption that errors are spatially correlated within grid cells (for this exercise, I partitioned the city into 25 squares). In columns (7), I use Conley (1999) standard errors to allow for arbitrary spatial correlation of errors across tracts within 3 km of each other (results remain similar when using alternative cutoffs, e.g., 5 km and 10 km). The point estimates of interest remain highly statistically different from zero.

Columns (9) in Tables 1 and 2 present the results after removing the 5% of the sample that historically had a high concentration of Black residents. This exercise addresses concerns that the main results may be driven by a few census tracts that were already predominantly Black at the beginning of the twentieth century. At that time, the city was highly segregated, with Black neighborhoods concentrated in the south (and, to a lower extent, in the west). Reassuringly, the point estimates in both tables remain stable.

Columns (10) report the estimated coefficients after removing census tracts within 5 km of the central business district. This exercise helps account for the potential effects of gentrification in downtown areas and, more broadly, demonstrates that the results are not solely driven by central areas, which may have undergone recent redevelopments. The results become slightly stronger in the regression where the share of Black residents is the outcome, consistent with the idea that gentrification may influence the racial composition of neighborhoods in the city center. Similarly, the results for land value become stronger in absolute terms, suggesting that gentrification may partially offset negative neighborhood effects.

Appendix Sections C.5 and C.6 report results using the local exposure measures described above, with 20 km and 10 km cutoffs, respectively. The maps at the beginning of each section display changes in the regressor of interest (ΔS) and the IV. In all cases, the maps exhibit greater spatial variation than those relative to the primary analysis. This is because the weights for both types of local measures are set so that only areas within a certain (network-based) distance from each origin location receive high weights.

The increased spatial variation helps alleviate concerns that both the IV and the endogenous regressor may capture unobserved characteristics shared among geographically clustered units, which could influence neighborhood dynamics. At the same time, however, these variables are also more susceptible to bias from local unobservable characteristics. In the OLS specifications, the correlation between exposure to Black residents and the change in the neighborhood's Black share is even stronger. On average, across specifications, a one standard deviation increase in exposure to Black residents is associated with a high 0.8 standard deviation increase in outcome. Comparing these results to the even larger point estimates using a 10 km cutoff suggests that the racial composition of nearby neighborhoods strongly influences the racial mix of an area. However, it is reassuring to observe that when sorting is held fixed to the pre-expressway period in the IV regressions, the point estimates drop substantially and become closer to those in the baseline specification. The estimated coefficients after instrumenting for the change in exposure to Black neighborhoods drop to approximately 0.2-0.3 standard deviations. In addition, the estimated effects of instrumented localized changes in exposure to Black residents on land value are qualitatively in line with the main results. However, the point estimates from the IV regression in the last column become strongly attenuated after instrumenting for changes in exposure to high-income areas in both the 20 km and 10 km cutoff specifications.

Finally, in Appendix C.7, I estimate the barrier effect on two additional outcomes of neighborhood change: house value and college share. Both outcomes respond strongly to changes in exposure to high-income areas in the city but remain unaffected by changes in exposure to Black areas once exposure to high-income neighborhoods is accounted for.

5.3 Discussion of the barrier effect of expressways

The second empirical design evaluates the barrier effect of expressways. I find that higher exposure to Black areas increases the likelihood that a neighborhood becomes more Black over time. The effect is sizable: depending on the specification, a one standard deviation increase in exposure to Black residents is associated with a 0.16-0.20 standard deviation increase (in the IV specifications) in the share of Black residents living in the neighborhood, on average. The results remain stable after including a rich set of controls, such as distance to the nearest expressway and a measure of changes in exposure to high-income areas. Next, I estimate the barrier effect of expressways on changes in land value between 1950 and 1990, using land value as a proxy for neighborhood valuation. An increase in exposure to Black residents reduces land value by 0.24-0.32 standard deviations in the long run. Taken together, these findings indicate that both the disamenity and the barrier effect of expressways affect racial sorting within the city. However, land value appears to respond more strongly to changes in neighborhood composition induced by the barrier than to the disamenity of expressway proximity.

6 A quantitative spatial urban model with racial preferences

To assess the overall impact of expressways on racial segregation in Chicago, I develop a quantitative spatial urban model that incorporates racial preferences in location choices. The setup adheres to a monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1967) but features an internal city structure following Ahlfeldt et al. (2015).[55] The model provides a unified and tractable framework to quantify how this major road infrastructure shaped residential location decisions and contributed to racial sorting. I consider a city embedded within a wider economy. The city consists of discrete locations indexed by $j = 1, ..., J$. For simplicity, the time subscript is omitted, but all expressions hold in each period. Land K_j is allocated exclusively to residential use and is supplied by a competitive floorspace sector. The city is populated by an endogenous number of residents N^o, from one of four socio-demographic groups, indexed by $o \in WH, WL, BH, BL$—a two-by-two classification based on race (B Black, W white) and educational attainment (H high-educated, L low-educated). Agents are perfectly mobile within the city and the wider economy. The outside option of living outside the city provides a reservation level of utility $\bar{U}^o$ for type o. Individuals decide whether to move to the city before observing idiosyncratic utility draws for city locations. Conditional on moving, they observe the realization of idiosyncratic utility and choose the residential location that maximizes their utility. Locations differ in residential amenities, residential land availability, and access to the transport infrastructure, which determines travel times between locations.

6.1 Preferences

The city is populated by an endogenous number of residents in each period, N^o, belonging to one of four socio-demographic groups $o \in \{WH, WL, BH, BL\}$. Individuals derive utility from residential amenities, a consumption index, and an idiosyncratic preference shock for each location, capturing unobserved tastes for particular neighborhoods.

The utility of individual ω of type o living in j is given by:

$$U(\omega)^o_j = B^o_j C(\omega)^o_j z(\omega)_j \tag{3}$$

Residential amenities B^o_j capture features that make a location desirable, and are allowed to vary by type to reflect heterogeneity in preferences across race and education. The consumption index $C^o_j(\omega)$ is defined over a composite of the consumption good $c^o_j(\omega)$ (chosen as the numeraire) and residential land $L^o_j(\omega)$, and takes a Cobb-Douglas form:[56]

[55] Heblich et al. (2020) develop a method to recover historical commuting and workplace distributions using post-period commuting flows and contemporaneous residence and employment data, under the assumption that employment-to-population ratios are stable across locations over time. While this assumption appears feasible in their context, applying it here would require considerably stronger assumptions—namely, that these ratios remain constant across demographic groups, neighborhoods, and over a long historical horizon. In addition, data availability is limited. The earliest US commuting data come from the 1960 Census (already after the first wave of expressway construction) and report only aggregate residence-to-workplace flows at the city or county level, without any demographic breakdown. Since the data used for estimation cover only census tracts within the city of Chicago, and there is no observed variation in workplace locations across tracts in 1960, I adopt a monocentric structure as a tractable modeling choice consistent with the available data. This assumption is further supported by 2000 Census Transportation Planning Package (CTPP) data, which show that, for each group, at least 50% of jobs are located within 5 km of the CBD and 90% within 16 km (see Appendix D.1 Figure D1). These shares are even higher among the (city-wide) above-median earnings groups: for the non-Black population, 55% of jobs are located within 2 km of the CBD, while for the Black above-median earnings group, nearly 50% are located within 4 km. Notably, across all groups, the highest concentration of employment appears near the CBD. Beyond 5 km, the cumulative employment distributions increase smoothly with distance, suggesting that employment is not heavily decentralized into a series of distinct polycentric hubs.

[56] I assume a common expenditure share α across types in the baseline model, though this assumption can be relaxed to

$$C(\omega)^o_j = \left(\frac{c(\omega)^o_j}{\alpha}\right)^{\alpha}\left(\frac{L(\omega)^o_j}{1-\alpha}\right)^{1-\alpha} \tag{4}$$

Individual heterogeneity is modeled as in structural urban models following McFadden (1974). For each worker ω of type o living in j, the idiosyncratic component of utility ($z(\omega)_j$) is drawn from a common independent Fréchet distribution:

$$F(z(\omega)_j) = e^{-T_j(z(\omega)_j)^{-\epsilon}} \tag{5}$$

where the scale parameter $T_j > 0$ determines the average utility from living in j and the shape parameter $\epsilon > 1$ controls the dispersion of the idiosyncratic utility.[57]

After observing their idiosyncratic preferences, individuals choose where to live to maximize their utility, taking as given amenities, land prices, and the location decisions of others. As a result, different types sort endogenously into residential locations according to amenities, commuting costs, and idiosyncratic preferences.

I assume that all individuals work in the Central Business District (C) and supply one unit of labor in exchange for a type-specific wage w^o. All jobs are located in the city center. Labor is used to produce a final good that is exclusively traded in external markets, and the full revenues are shared between absentee entrepreneurs.[58] Commuting to the Central Business District is costly and depends on the mode of transportation, which differs by education level (denoted by the subscript H for highly educated and L for low-educated individuals). The effective wage of a household of type o residing in j is equivalent to $\frac{w^o}{d^{H,L}_{jC}}$. The iceberg commuting cost $d^{H,L}_{jC} = e^{\kappa\tau^{H,L}_{jC}}$ increases with the travel time (τ_{jC}) between the location of residence (j) and employment (C).[59] Finally, the parameter κ controls the size of the commuting costs.

The indirect utility from living in location j can be expressed in terms of the common component of amenities, the effective wage, floorspace prices, and the idiosyncratic utility shock:

$$u(\omega)^o_j = \frac{B^o_j w^o R^{\alpha-1}_j z(\omega)_j}{d^{H,L}_{jC}} \tag{6}$$

Since $z_j(\omega)$ is Fréchet distributed, the indirect utility also follows a Fréchet distribution. As a

allow for type-specific expenditure shares.

[57]In principle, I could allow idiosyncratic preference distributions to vary by type, both in terms of the average idiosyncratic preferences for amenities in a given location (the scale parameter T_j) and the variance of preferences across locations (captured by the shape parameter ϵ). This would introduce an additional source of heterogeneity in the model. For example, if different types exhibit varying degrees of dispersion in their preferences, they may respond differently to the same commuting cost shock. A group with less dispersed idiosyncratic preferences would be less affected by a change in commuting costs, as their location choices are more rigid. In practice, I assume a common Fréchet distribution for all types, as is standard in the literature. Estimating type-specific parameters would require detailed commuting flow data by type, which are not available in this historical context.

[58]I assume firms do not occupy land, and that all land is allocated to residential use, consistent with the lack of spatially detailed employment and land use data.

[59]Travel time is measured in minutes and depends on the underlying transport network.

result, the probability that an individual ω of type o chooses location j is given by:

$$\begin{aligned}\pi_j^o &= P(u(\omega)_j^o \geq max\, u(\omega)_j^o \ \ \forall j) \\ &= \frac{T_j(R_j^{1-\alpha})^{-\epsilon}(B_j^o)^{\epsilon}(w^o/d_{jC}^{H,L})^{\epsilon}}{\sum_s T_s(R_s^{1-\alpha})^{-\epsilon}(B_s^o)^{\epsilon}(w^o/d_{sC}^{H,L})^{\epsilon}} = \frac{\Phi_j^o}{\Phi^o}\end{aligned} \tag{7}$$

Because of the idiosyncratic utility component, individuals of the same type may choose different residential locations even when facing identical prices and location characteristics. The probability that a type-o individual lives in j increases with amenities B_j^o, the average idiosyncratic utility level T_j, and the effective wage, and decreases with floorspace prices R_j and commuting costs $d_{jC}^{H,L}$. Note that the denominator Φ^o is type-specific but not location-specific: it corresponds to the expected utility of living in the city for a type-o individual.

To illustrate how different types sort across locations, consider the ratio of the probabilities that individuals of type o and m choose location j:

$$\begin{aligned}\frac{\pi_j^o}{\pi_j^m} &= \frac{T_j(R_j^{1-\alpha})^{-\epsilon}(B_j^o)^{\epsilon}(w^o/d_{jC}^{H,L})^{\epsilon}/\Phi^o}{T_j(R_j^{1-\alpha})^{-\epsilon}(B_j^m)^{\epsilon}(w^m/d_{jC}^{H,L})^{\epsilon}/\Phi^m} \\ &= \left(\frac{B_j^o}{B_j^m}\right)^{\epsilon}\left(\frac{w^o/d_{jC}^{H,L}}{w^m/d_{jC}^{H,L}}\right)^{\epsilon}\left(\frac{\Phi^o}{\Phi^m}\right)^{-1}\end{aligned} \tag{8}$$

That is, a worker of type o is more likely to live in j than a worker of type m if they place a higher value on residential amenities, have a higher effective wage, or face a lower utility from the outside option. When the two types share the same education level, commuting costs are identical and any (effective) wage differences are constant across locations. As a result, only differences in amenity valuation drive spatial variation in the relative probabilities of types o and m residing in location j—as captured by the first term on the right-hand side of the expression.

Since employment is fixed in the Central Business District, there is no uncertainty in wages: A type-o individual's income upon choosing location j is simply w^o.[60] Thus, variation in effective wages across space arises solely from commuting costs, with net earnings being higher in locations closer to the center.

Finally, population mobility implies that the expected utility of a type-o individual from moving to the city must equal the reservation utility in the wider economy, $\bar{U}^o$:

$$\mathbb{E}[u^o] = \gamma\left[\sum_s T_s(R_s^{1-\alpha})^{-\epsilon}(B_s^o)^{\epsilon}(w^o/d_{sC}^{H,L})^{\epsilon}\right]^{1/\epsilon} = \bar{U}^o \tag{9}$$

where the expectation is taken over the distribution of the idiosyncratic component of utility; $\gamma = \Gamma(\frac{\epsilon-1}{\epsilon})$ and $\Gamma(.)$ is the Gamma function.[61]

[60] The expected worker income conditional on living in j is indeed simply equal to $\mathbb{E}(w^o|j) = w^o$.

[61] A further implication of assuming a Fréchet distribution for idiosyncratic utility is that residence locations with more attractive features draw more residents on the extensive margin. High amenities in a location increase the utility of a

6.2 Land market clearing

Residential land market clearing requires that the demand for residential land $D(L_j)$ equals the supply of residential land $S(L_j)$ in each location. Following a standard approach in the literature, I assume that residential floorspace L is supplied by a competitive construction sector that uses land K and capital M as inputs. The production function takes the Cobb-Douglas form $L_j = M_j^{\mu} K_j^{1-\mu}$ (as in Combes et al., 2014; Epple et al., 2010; Ahlfeldt et al., 2015). Since the price of capital is constant across locations, the relationship between floorspace and land can be summarized as $L_j = S(L_j) = \phi_j K_j^{1-\mu}$, where $\phi_j = M_j^{\mu}$ captures the density of development (Ahlfeldt et al., 2015).

From the households' maximization problem, the demand for residential land in location j is:

$$D(L_j) = \mathbb{E}[L_j] N_j = \frac{(1-\alpha)\bar{W}_j N_j}{R_j} \tag{10}$$

where $\bar{W}_j = (1/N_j) \sum_o (w^o / d_{jC}^{H,L}) N_j^o$ is the average effective wage in location j, accounting for type-specific wages and commuting costs.

Land market clearing is equal to:

$$\phi_j = \frac{(1-\alpha)\bar{W}_j N_j}{R_j K_j^{1-\mu}} \tag{11}$$

In estimation, the term ϕ_j (unobserved density of development) is a structural residual that guarantees that floorspace market clearing exactly holds in each location, given observed data and recovered amenities.

6.3 Equilibrium with total amenities

An equilibrium of the model is characterized by the assignment of type-specific residents to neighborhoods and a vector of floorspace prices such that the land market clears in each location, and no individual has an incentive to relocate. Given the model's parameters $\{\alpha, \epsilon, \kappa, \eta, \mu\}$, the vectors of exogenous location characteristics $\{T, B, K, \tau^{H,L}\}$, the reservation level of utility $\bar{U}^o$, and wage w^o for each type $o \in \{WH, WL, BH, BL\}$, the general equilibrium of the model can be referenced by the vector of floorspace prices $\{R_j\}$, the vector of residence probabilities $\{\pi_j^o\}$, and the type-specific population scalars N^o.

Equilibrium is pinned down by a system of nine equations: four population mobility conditions (one per type), four residence choice probabilities (one per type), and the land market clearing condition. Ahlfeldt et al. (2015) provide a proof of existence and uniqueness of equilibrium under the assumption of exogenous location characteristics. I recover total amenities B_j by inverting the model's equilibrium conditions, specifically the residence choice probabilities. In the next section, I give structure to the recovered amenities B_j, decomposing them into exogenous attributes and en-

resident with a given idiosyncratic realization of z, raising the likelihood that the location is chosen. At the same time, they also induce individuals with lower realizations of z to choose the location, which lowers the average idiosyncratic utility among residents. With a Fréchet distribution, these two forces exactly offset each other in expectation, so the expected utility of choosing a location remains unchanged.

dogenous components. I then estimate the model with endogenous amenities by jointly recovering the structural parameters and unobserved fundamentals through an iterative procedure, conditional on initial conditions and calibrated parameters. Further details are provided in Appendix D.4.

7 Estimation

The estimation proceeds in three steps. First, I calibrate the necessary components of the model, including commuting elasticity and wages. Second, I invert the model in both periods to recover the amenity levels that rationalize the observed spatial distribution of the population as an equilibrium outcome. Third, I exploit the quasi-experimental variation induced by expressway construction to estimate the parameters of interest—namely, racial preference and disamenity parameters—that best fit changes in the spatial distribution of population within the city, subject to orthogonality conditions.

Before outlining each step in detail, I first describe the data used for estimation.

7.1 Data

The quantitative analysis requires three key data components: residence by type, floorspace prices, and travel times between locations. I collect this information for the city of Chicago for periods before and after expressway construction, using data from around the 1940 and 1990 census years.

For neighborhood demographics, the two main sources are the 1934 Special Census of Chicago and the 1990 Census of Population and Housing.[62] Unlike the federal censuses conducted around that time, the 1934 census reports tract-level data on race by educational attainment. This offers a major advantage for the analysis, as it provides reliable, disaggregated information on education by race prior to expressway construction. I classify individuals by race (Black vs. non-Black) and by education (above vs. below the city-wide median in each period).[63] The data are normalized to 2010 census tract boundaries, yielding a consistent panel of 791 tracts covering the city.

To measure floorspace prices, I use land value data from the 1940 and 1990 editions of Olcott's Land Value Blue Book (Ahlfeldt and McMillen, 2014, 2018). After excluding tracts with missing land value data, the final sample consists of 767 tracts.[64]

Finally, I compute commuting times between all tract pairs based on the shortest travel path over the relevant road network. For 1940, I use road data from the Urban Transition HGIS Project (Shertzer et al., 2016);[65] for 1990, I use contemporary road data from the US Census Bureau. Travel times, measured in minutes, reflect the transport infrastructure available in each period and vary by education group based on differences in transport mode.[66]

[62] The 1934 census was conducted by the Chicago Census Commission (not the US Census Bureau) to assess, in the words of then-Mayor Kelly, "exactly what had been the effects of the depression upon changes of residences, occupancy of dwellings, housing needs, health of the people, etc." (Newcomb and Lang, 1934).

[63] In 1934, the median corresponds to completing grades 5-8; in 1990, to completing high school.

[64] The 1990 sample includes 766 tracts, as one central tract was lost due to redevelopment of Midway Airport in the 1960s.

[65] https://s4.ad.brown.edu/Projects/UTP2/ncities.htm

[66] Highly educated individuals are assumed to commute by car in both periods. In 1940, low-educated individuals are assigned bus travel. In 1990, they are assumed to commute by bus with 0.75 probability and by car with 0.25 probability. These modal shares are based on national survey data from the 2001 National Household Travel Survey (Hu and Reuscher,

7.2 Step 1: Calibrate commuting elasticity and wages

If data on both residence and workplace locations were available, the commuting elasticity could be recovered from the commuting choice probability—analogous to the residential choice probability in Equation (7)—using a gravity equation framework.[67] As discussed in the model setup, workplace location was not recorded at a sufficiently granular level in this historical setting and is therefore assumed to be the same central location for all individuals. As a result, the vector of distances from each residence location to the Central Business District, d_{jC}, varies only at the origin level and is thus collinear with origin fixed effects. This precludes consistent estimation of the commuting elasticity in a gravity-type framework. I therefore calibrate the relevant parameters using values from the literature. I set the Fréchet dispersion parameter to $\epsilon = 6$, the central value found in the literature (Miyauchi et al., 2021), and the spatial decay parameter for commuting costs to $\kappa = 0.01$ (Ahlfeldt et al., 2015).

In quantitative spatial urban models with data on both residence and workplace location decisions (e.g., Ahlfeldt et al., 2015), unobserved workplace-specific wages are typically recovered by exploiting the model's recursive structure, after estimating commuting elasticities. Wages are then inferred from the commuting market clearing condition.[68] Since I lack the data necessary to recover wages, I instead calibrate them using national-level wage data by group, adjusted for the distribution of race by educational attainment observed in the city.[69]

7.3 Step 2: Recover overall amenities

Starting from the expression for the residential choice probabilities in Equation (7), I multiply both sides by the total number of residents of type o, denoted N^o, and use the identity $\pi_j^o N^o = N_j^o$ to obtain:

$$N_j^o = \frac{T_j (R_j^{1-\alpha})^{-\epsilon} (B_j^o)^{\epsilon} (w^o / d_{jC}^{H,L})^{\epsilon}}{\sum_s T_s (R_s^{1-\alpha})^{-\epsilon} (B_s^o)^{\epsilon} (w^o / d_{sC}^{H,L})^{\epsilon}} N^o \tag{12}$$

Since T_j enters the model isomorphically—that is, it cannot be separately identified from overall residential amenities in the data—I define the composite amenity term $\tilde{B}_j^o = T_j^{\frac{1}{\epsilon}} B_j^o$. To simplify the exposition, I also define $W_j^o = (w^o / d_{jC}^{H,L})^{\epsilon}$, so that:

$$N_j^o = \frac{(R_j^{1-\alpha})^{-\epsilon} (\tilde{B}_j^o)^{\epsilon} W_j^o}{\sum_s (R_s^{1-\alpha})^{-\epsilon} (\tilde{B}_s^o)^{\epsilon} W_s^o} N^o \tag{13}$$

The model can then be calibrated to recover unique adjusted location fundamentals $\tilde{B}j^o$, given

2004), which reports that roughly three-quarters of low-income households do not own a car. Further details are provided in Appendix D.2.1.

[67] This corresponds to a regression of commute flows on commute times and origin and destination fixed effects.

[68] This condition ensures that the number of workers in a location equals the total number of commuting residents who choose to work there, aggregated over all residence locations.

[69] The calibrated wages (all in $2010) for the pre-period are: $12,605 for high-educated Black; $11,020 for low-educated Black; $17,738 for high-educated white; and $12,197 for low-educated white. In the post-period: $30,766 for high-educated Black; $12,790 for low-educated Black; $38,924 for high-educated white; and $17,153 for low-educated white. For details, see Appendix D.2.2.

known values of the model's parameters α, ϵ, κ and observed data $R_j, N_j^o, \tau_{jC}^{H,L}$. That is, there is a unique mapping from the model's parameters and the data to the overall residential location characteristics (up to a normalization). Dividing both sides by the geometric mean of N_j^o and using the fact that constant terms cancel out, I obtain:[70]

$$\frac{N_j^o}{\bar{N}^o} = \left(\frac{R_j}{\bar{R}}\right)^{-(1-\alpha)\epsilon} \left(\frac{\tilde{B}_j^o}{\bar{\tilde{B}}^o}\right)^{\epsilon} \frac{W_j^o}{\bar{W}^o} \tag{14}$$

Inverting the system gives the following closed-form solution for overall residential amenities as a function of data, model parameters, and calibrated values:

$$\frac{\tilde{B}_j^o}{\bar{\tilde{B}}^o} = \left(\frac{N_j^o}{\bar{N}^o}\right)^{\frac{1}{\epsilon}} \left(\frac{R_j}{\bar{R}}\right)^{1-\alpha} \left(\frac{W_j^o}{\bar{W}^o}\right)^{-1/\epsilon} \tag{15}$$

Maps showing the distribution of recovered overall amenities by type—i.e., the left-hand side of Equation (15)—after inverting the model in each period are provided in Appendix D.3. Darker colors correspond to higher amenity levels. Total recovered amenities consist of both an exogenous component (related to the physical attributes of each location) and an endogenous component (reflecting sorting and residential choice), as discussed in more detail in the next section. As a result, amenity values tend to be higher near the lakeshore and lower near industrial corridors. At the same time, there is substantial heterogeneity across time and demographic groups. By 1990, the spatial distribution of amenities reveals strong polarization, with the white population increasingly concentrated in northern neighborhoods and the Black population residing predominantly in the south.[71]

7.4 Step 3: Structural estimation

Before outlining the structural estimation procedure, I specify how total residential amenities depend on location fundamentals, the disamenity of expressways, and the demographic composition of neighborhoods. First, location fundamentals ($\tilde{b}_j^o$) capture physical characteristics that affect the desirability of a location—such as proximity to the lakeshore or green space. Second, residential amenities are affected by proximity to expressways. Following Brinkman and Lin (2024), I model the disamenity of expressways as a function of distance to the nearest segment. The disamenity term is defined as:

$$E_j^o \equiv 1 - g^o e^{-\eta dist_j} \tag{16}$$

where $dist_j$ is the distance from location j to the closest expressway; g^o governs the size of the disamenity, and η its spatial attenuation.[72]

[70] Denote the geometric mean of a variable X by $\bar{X}$, then: $\bar{X} = (\Pi_{s=1}^{S} X_s)^{\frac{1}{s}}$. It is useful to note that the geometric mean of a product equals the product of the geometric means of its terms. Following Ahlfeldt et al.(2015), I normalize adjusted residential amenities so that their geometric mean equals one for each type o: $\bar{\tilde{B}}_j^o = (\Pi \tilde{B}_s^o)^{1/S} = 1$.

[71] For instance, in 1940, amenities were high for high-educated white residents along most of the southern shore. By 1990, however, only the area around the University of Chicago campus remains a high-amenity location for this group.

[72] g^o is allowed to vary by type, while η is fixed, as it captures how quickly disamenities like pollution and noise decay

Third, I introduce residential externalities, imposing structure on how the demographic composition of surrounding neighborhoods affects amenities in a given location. Specifically, I model racial preferences as:

$$\Omega_j^o = \left(\sum_{i\neq j} e^{-\rho^o \tau_{ji}^{H,L}} \frac{N_i^B}{K_i}\right)^{\lambda_B^o} \left(\sum_{i\neq j} e^{-\rho^o \tau_{ji}^{H,L}} \frac{N_i^W}{K_i}\right)^{\lambda_W^o} \tag{17}$$

Amenities in each location are thus a power function of the distance-weighted racial composition of all other neighborhoods, where $\tau_{ji}^{H,L}$ denotes travel time between locations j and i. ρ^o is the spatial decay rate of racial preferences, and λ_B^o, λ_W^o are the elasticities of amenities with respect to the concentration of nearby Black and white residents, respectively.

Fourth, I include a term capturing local educational spillovers, defined as the share of adults in location j with above-median education:

$$H_j = \frac{N_j^H}{N_j} \tag{18}$$

This variable proxies for endogenous amenities correlated with education and income—such as safety, school quality, and public good provision.[73]

Putting all components together, the composite amenity term is:

$$\tilde{B}_j^o = \tilde{b}_j^o H_j E_j^o \Omega_j^o \tag{19}$$

Substituting into Equation (15), I obtain an expression for location fundamentals:

$$\frac{\tilde{b}_j^o}{\bar{\tilde{b}}^o} = \left(\frac{N_j^o}{\bar{N}^o}\right)^{\frac{1}{\epsilon}} \left(\frac{R_j}{\bar{R}}\right)^{1-\alpha} \left(\frac{W_j^o}{\bar{W}^o}\right)^{-1/\epsilon} \left(\frac{H_j}{\bar{H}}\right)^{-1} \left(\frac{E_j^o}{\bar{E}^o}\right)^{-1} \left(\frac{\Omega_j^o}{\bar{\Omega}^o}\right)^{-1} \tag{20}$$

The left-hand side represents structural residuals (residential fundamentals) expressed relative to their geometric mean. As is clear from the equation, they are a function of observed data and model parameters only. I solve for these residential fundamentals across all locations, before and after the shock induced by expressway construction. Denoting the change over time by Δ, and following Ahlfeldt et al. (2015), I assume that these location fundamentals consist of a time-invariant fixed component $\tilde{b}j^{oF}$ and a time-varying stochastic shock $\tilde{b}_{jt}^{oV}$. Using a first-difference estimator, the time-invariant fixed effects are differenced out. Taking logs of both sides (and making time explicit with the subscript t) yields:

$$\Delta \ln\left(\frac{\tilde{b}_{jt}^{oV}}{\bar{\tilde{b}}_t^{oV}}\right) = \frac{1}{\epsilon}\Delta \ln\left(\frac{N_{jt}^o}{\bar{N}_t^o}\right) + (1-\alpha)\Delta \ln\left(\frac{R_{jt}}{\bar{R}_t}\right) - \frac{1}{\epsilon}\Delta \ln\left(\frac{W_{jt}^o}{\bar{W}_t^o}\right) - \Delta \ln\left(\frac{H_{jt}}{\bar{H}_t}\right) - \Delta \ln\left(\frac{E_{jt}^o}{\bar{E}_t^o}\right) - \Delta \ln\left(\frac{\Omega_{jt}^o}{\bar{\Omega}_t^o}\right) \tag{21}$$

These structural residuals correspond to double-differenced adjusted residential fundamentals. The first difference is over time (pre- versus post-period), while the second is across locations within the city, implemented by dividing each term by its geometric mean in each period prior to taking

in space—assumed to depend on environmental factors.

[73] Fogli et al. (2025) use the share of college graduates. Here, I use the share of adults with above-median education, an endogenous variable in the model.

logs. This normalization removes city-wide, period-specific shocks—such as changes in reservation utility—and ensures that results are invariant to the units in which amenities are measured. By construction, the mean change in log fundamentals is equal to zero. Although the presence of spatial externalities introduces the possibility of multiple equilibria in the model, this does not affect identification. Following Ahlfeldt et al. (2015), the inversion from observed data and parameters to structural fundamentals is uniquely defined. As a result, the estimation remains tractable, and the structural residuals are well identified, regardless of equilibrium multiplicity.

The parameters of interest are those governing the disamenity of expressways, g^o, and those governing racial preferences, $\lambda_B^o, \lambda_W^o, \rho^o$.

7.4.1 Moment conditions

To estimate the parameters of interest, I exploit sources of variation analogous to those used in the reduced-form analysis. The first set of moment conditions imposes that changes in adjusted residential fundamentals from Equation (21) are uncorrelated with exogenous changes in exposure to Black areas induced by the construction of urban barriers. To measure this, I construct percentile-based distance bins from the centroid of the so-called Black Belt—historically the area of highest African American concentration in the city—and interact these bins with an indicator for whether a census tract is separated from the Black Belt by an expressway. The second set of moment conditions, used to identify the disamenity parameters, imposes orthogonality between changes in adjusted residential fundamentals and distance to the expressway network. To capture the idea that locations closer to the CBD experience greater net disamenity from proximity to expressways—since access benefits are relatively lower—I further interact expressway distance bins with distance bins from the CBD. Formally, the two sets of moment conditions are:

$$\begin{aligned} \mathbb{E}[\mathbb{I}bb_k \times \mathbb{I}Barrier \times \Delta \ln(\tilde{b}^o_{jt} / \bar{\tilde{b}}^o_t)] = 0 \\ \mathbb{E}[\mathbb{I}cbd_{k'} \times \mathbb{I}exp_{k''} \times \Delta \ln(\tilde{b}^o_{jt} / \bar{\tilde{b}}^o_t)] = 0 \end{aligned} \tag{22}$$

where $\mathbb{I}bb_k$ for $k \in 1, \ldots, K_{\mathbb{I}bb}$ are indicator variables for distance bins from the centroid of the Black Belt; $\mathbb{I}Barrier$ is an indicator for whether a tract is separated from the Black Belt by an expressway; $\mathbb{I}cbd_{k'}$ for $k' \in 1, \ldots, K'\mathbb{I}cbd$ are indicator variables for distance bins from the CBD; and $\mathbb{I}expk''$ are indicator variables for distance to the expressway network. Distance bins for all three dimensions—Black Belt, CBD, and expressways—are constructed based on percentiles of distance, using 20 bins for the Black Belt, 4 bins for the CBD, and 3 bins for expressways.[74]

Following the construction of expressways, residential patterns in the city may change for two reasons. First, through forces captured in the model: For example, expressways increase the effective

[74] The number of bins is chosen to reflect a trade-off between flexibility and statistical precision. For each dimension, distance bins are based on percentiles of the relevant distance measure, ensuring an approximately balanced number of observations within each dimension. The choice of 4 bins for the CBD reflects the smoother decline of amenities with distance to the CBD (see Appendix Figure D6, panel a), whereas the steeper decline of amenities with distance from the Black Belt motivates using a larger number of bins (panel b). Expressway effects are expected to be more localized and non-linear; accordingly, 3 bins are used for distance to the expressway network within each CBD-distance bin, capturing potential non-linearities in amenity responses to expressway proximity (panel c).

distance between locations situated on opposite sides of the road, and—consistent with the reduced-form results—neighborhood demographics are expected to respond. Second, residential fundamentals may evolve for reasons unrelated to expressway construction. The moment conditions impose restrictions on how residential fundamentals can change—specifically, that changes should average to zero within each distance-bin interaction.

7.4.2 Identification

I estimate the parameters of interest using the Generalized Method of Moments (GMM) applied to the moment conditions described above, separately by group.[75] Additional details on the estimation procedure are provided in Appendix D.6. These moment conditions allow me to simultaneously identify the model's unknown parameters and recover the unobserved residential fundamentals (structural residuals). Equation (20) provides closed-form solutions for the structural residuals, which are functions of observed data and model parameters only. In principle, the moment conditions do not guarantee unique identification of the parameters: Multiple local minima could correspond to different combinations of parameters and fundamentals consistent with the observed data. However, in practice, the objective function appears to be well-behaved over the parameter space.[76]

Although the construction of expressways constitutes a single historical shock, the framework allows for separate identification of type-specific racial preference parameters and disamenity parameters via GMM estimation. Identification relies on exploiting variation in residential sorting and neighborhood amenities induced by the expressway network: Road-induced changes in exposure to Black areas, interacted with distance bins from the Black Belt, affect residential externalities (racial sorting), while distance to expressways, interacted with distance bins from the CBD, affect neighborhood quality of life.[77] Identification requires these sources of variation to be plausibly orthogonal to unobserved shifts in residential fundamentals.

In the model, changes in neighborhood amenities are attributed either to demographic composition (through residential externalities) or to disamenity effects from expressways. Any residual variation is absorbed into adjusted residential fundamentals. If key parameters, such as racial preference elasticities, are mis-specified, the model may incorrectly attribute sorting dynamics to changes in fundamentals rather than to endogenous racial sorting. Such misattribution would systematically

[75]While a joint estimation of the full system across types is in principle feasible, it would require solving a high-dimensional nonlinear GMM problem and interpreting 16 group-specific parameters estimated under a shared moment structure. Because joint estimation minimizes a single objective function, the link between each parameter and its identifying variation is less clear. I therefore apply the two sets of moment conditions in equation (22) separately by group, to retain a more transparent mapping between the identifying variation and the parameters of interest.

[76]Instead of plotting the objective function over the high-dimensional parameter space, I assess convergence behavior by randomly varying initial starting values across broad admissible ranges. The estimation converges to the same solution in the vast majority of cases (100% for white residents, 90% for Black residents). See Appendix D.6.1 for details.

[77]While the effects of distance to the expressway network on racial sorting have been extensively documented in the reduced-form analysis, the role of proximity to the Black Belt has been only implicitly assessed through the variation exploited by separation from historically Black areas via expressways. Appendix D.6.2 documents broader spatial patterns of racial change around the Black Belt. Changes in Black population share between 1950 and 1990 exhibit an inverse-U relationship with distance from the Black Belt, even after controlling for distance to the CBD. This pattern supports the empirical relevance of proximity to the Black Belt in shaping racial sorting dynamics, consistent with the sources of variation used for identification.

violate the orthogonality conditions required for valid estimation. I examine the change over time in recovered location fundamentals across space and demographic groups in Appendix D.6.3, Figure D8, which presents type-specific maps of changes in fundamentals. This visual check supports the identification strategy and confirms that observed changes in recovered location fundamentals are modest and do not systematically align with patterns of demographic sorting, which would have suggested a misspecification.[78]

In Appendix D.6.4, I examine the sensitivity of the estimated parameters to the moment conditions, following Andrews et al. (2017). These sensitivity measures capture how much each parameter estimate would change in response to small perturbations in individual moments, providing insight into the sources of identification within the model. The results are consistent with the economic interpretation of the parameters and the structure of the moment conditions. The disamenity parameters g are most sensitive to moments related to proximity to the expressway network, as expected. The type-specific spatial decay parameter ρ exhibits broader spatial sensitivity, consistent with its role in capturing distance-related variation in racial externalities. Moments involving both exposure to the Black Belt and proximity to expressways contribute to its identification. The elasticity parameters λ_W and λ_B display relatively uniform sensitivity across moment conditions, consistent with their identification from broad spatial variation in sorting.

7.4.3 GMM estimation results

Table 3 reports the efficient GMM estimation results. The estimates reveal large and statistically significant racial preference and disamenity parameters. To clarify their interpretation and relative magnitudes, I discuss the main results in order below.

First, the racial preference parameters exhibit substantial heterogeneity across types, particularly between Black and white individuals.[79] The estimates point to high degrees of homophily: Both Black and white residents display stronger preferences for living near same-race neighbors, in line with prior findings in the literature on residential choice and neighborhood sorting (Bayer and McMillan, 2005; Bayer et al., 2007; Aliprantis et al., 2024). Residential externalities emerge as an important agglomeration force, especially with respect to the concentration of same-race individuals in nearby tracts. Among white individuals, the estimated elasticity of amenities with respect to the concentration of same-race neighbors is markedly higher than for different-race neighbors—3.3 times larger for white low-educated individuals and six times larger for white high-educated individuals. For Black residents, the estimates suggest strong positive externalities from the presence of same-race neighbors and potential congestion forces linked to the density of nearby white residents.

Second, residential externalities are highly localized and appear more spatially concentrated for

[78] The maps also display neighborhoods where changes in residential fundamentals could not be recovered because the relevant demographic group was absent in at least one period. In such cases, the model imposes that the location has zero residential fundamentals for that group in the corresponding period. Tracts where a group was present in only one year reflect spatial entry or exit patterns.

[79] The estimated racial preference elasticities reflect structural preferences over neighborhood racial composition but cannot distinguish between homophily, anticipated discrimination, or other mechanisms influencing sorting behavior. As in related models (e.g., Bayer et al., 2014), these parameters reflect the revealed influence of racial composition on residential choice, regardless of the underlying cause.

Black individuals than for white individuals, based on separate estimations of the same structural model by group. The rate of spatial decay of racial preferences is estimated at $\rho = 0.674$ (s.e. 0.181) for low-educated and $\rho = 0.747$ (s.e. 0.167) for high-educated Black individuals. For white individuals, the estimates are lower: $\rho = 0.229$ (s.e. 0.047) for low-educated and $\rho = 0.291$ (s.e. 0.048) for high-educated. The population-share-weighted average rate of decay is $\rho_{whgt} = 0.342$.[80] To illustrate magnitudes, and holding other factors constant, residential externalities for Black residents decay to near-zero after roughly 10 minutes of travel time, while for white residents, they persist for approximately 20 minutes. Figure 5 illustrates the implied proportional reductions in externalities with travel time (Table D4 in Appendix D reports the same results alongside the corresponding utility losses due to increased commuting time).[81]

Third, the estimated disamenity from proximity to expressways appears quite large for all groups, consistent with the reduced-form findings. Black residents attach amenities that are, on average, 22% lower in neighborhoods near expressways, while for white residents, the reduction is 23.9%. These disamenities attenuate by 95% at a distance of 3.8 km from the expressway, in line with values recently reported in the literature.[82]

7.4.4 Over-identification checks

A limited number of over-identification checks can be conducted in this setting due to constraints in data availability. I examine how the model's predictions correlate with external variables not used in the estimation.

First, I focus on the number of housing units. In the structural estimation, I recover a measure of adjusted density of development—the ratio of residential floor space to land area—a structural residual that ensures demand for floor space equals supply in each location.[83] To the extent that development density should be higher in more residentially dense areas, I investigate how the model-derived density measure correlates with the reported number of housing units from the census. I find a positive relationship (sample correlation of 0.698 in 1940 and 0.318 in 1990) between the (model-derived) density of development and the number of housing units reported in the census for the relevant year. Regression results are reported in the top panel of Table D5 in Appendix D.6. On average, a 1% increase in the number of housing units corresponds to a 0.77% increase (s.e. 0.06) in the model-derived density measure in 1940 and a 0.52% increase (s.e. 0.14) in 1990.

Second, I use contemporary information on zoning regulations to check how the density of development measure correlates with the share of land designated for residential use in each location.

[80] To the best of my knowledge, this is the first estimate of this kind, making it difficult to benchmark directly. Nonetheless, it falls within the broad range of related estimates in the literature. For comparison, Ahlfeldt et al. (2015) estimate a residential externality parameter of 0.76, while Miyauchi et al. (2021) estimate the elasticity of consumption travel cost with respect to travel time at 0.019.

[81] Put differently, the estimated decay parameters imply that racial composition in nearby neighborhoods matters most within a short spatial range. Residential externalities decay by 95% after approximately 1.2 km for low-educated Black individuals and 1.7 km for high-educated Black individuals. For white individuals, the corresponding distances are longer—around 3.8 km (low-educated) and 4.4 km (high-educated)—reflecting slower preference decay.

[82] Brinkman and Lin (2024) report that freeway neighborhoods are associated with an 18.4% reduction in amenities.

[83] Figure D13 in Appendix D.6 reports the maps of the deciles of the distribution of this structural residual in 1940 and 1990. It is reassuring to observe that the two distributions are similar over time.

While the model-derived density of development (the ratio of residential floor space to land area) can exceed 1—due to multistory construction for instance—the zoning data provide only the share of land permitted for residential use (as opposed to commercial, industrial, or open space use). I find a strong and positive log-linear relationship (sample correlation of 0.462 in 1990) between $\log(\phi)$ and the share of land zoned for residential use.[84] Regression results are reported in the bottom panel of Table D5. Overall, the strength of these results supports the model's predictions. I find that a 1% increase in the share of land zoned for residential use is associated, on average, with a 0.02% increase in the model-derived density of development.

7.5 Counterfactual exercises

I use the model to run a series of counterfactual exercises that serve both validation and explanatory purposes. These involve altering selected location characteristics or model parameters and solving for the corresponding counterfactual equilibrium. I begin by assessing the model's fit: I examine the extent to which the observed effects of expressway construction on neighborhood demographic changes can be replicated by the model's endogenous forces, rather than by shifts in location fundamentals over time. I then evaluate the consequences of eliminating racial preferences to isolate their role in driving sorting patterns in a benchmark scenario. Finally, I use the model to quantify the role of expressway-related disamenity and barrier effects in shaping segregation and residential sorting patterns across neighborhoods.

In the first counterfactual, I simulate the shock induced by expressway construction using the estimated parameters, while holding location fundamentals (i.e., residential fundamentals $\tilde{b}_j^o$ and density of development ϕ_j) fixed to their pre-period values. I use the values of the endogenous variables from the observed 1990 equilibrium as the initial guess for the counterfactual equilibrium. To address the possibility of multiple equilibria, I follow Ahlfeldt et al. (2015) and select the counterfactual equilibrium closest to the observed one. I further set the reservation utility in the wider economy so that the total population (for each type) matches its 1990 value. The correlation between the model-predicted and actual 1990 share of Black residents across tracts is 0.815. The model thus replicates the demographic pattern of racial sorting in 1990 well. A binned scatter plot comparing predicted and observed values is shown in Figure D14 in Appendix D.7.[85]

The counterfactual treatment effects on racial sorting for the remaining counterfactual exercises are reported in Figure 6, which plots the distribution of population in Chicago by neighborhood racial composition. Each counterfactual distribution is shown alongside the observed equilibrium in 1990 (yellow dots). Chicago in 1990 was highly segregated: 50% of the population lived in neighborhoods

[84] This second over-identification check is conducted exclusively for 1990 because zoning information is available only for the present period.

[85] The model predicts the distribution of racial composition across neighborhoods closely. It slightly underestimates the Black share in the most heavily Black areas, suggesting that additional mechanisms—such as mobility frictions or the lasting effects of redlining—may contribute to the persistence of segregation beyond what is captured by fundamentals and estimated preferences. Notably, the model does not tend to overpredict segregation in neighborhoods with low observed Black shares, which is consistent with the idea that these forces may help sustain existing patterns rather than create segregation where it would not otherwise emerge. Given the model's strong overall fit, however, these omitted forces likely account for a relatively small share of the total observed change in neighborhood demographics.

that were at most 10% Black, and another 30% lived in neighborhoods that were at least 90% Black.

In the second counterfactual, I examine the implications of removing racial bias. I set the elasticity of amenities with respect to the concentration of different-race residents in the surrounding areas equal to that for same-race neighbors.[86] That is, I assume that the elasticity of amenities from having an extra resident of a different race is equivalent to the estimated elasticity from having an additional neighbor of the same race. In this benchmark scenario, the city becomes substantially more integrated. The share of residents living in neighborhoods that are at least 90% Black falls to around 5%, while the share living in neighborhoods that are at most 10% Black declines from 50% to below 30%. The population is more evenly distributed across the full range of neighborhood compositions.

Next, I examine the neighborhood effects of expressways. I conduct a counterfactual that removes both the disamenity ($g^o = 0$) and the barrier effect of expressways. To set the barrier effect to zero, I follow Brinkman and Lin (2024). I define pairwise travel time as $\tau_{ji} = \tau^*_{ji} + c_{ji}$, where τ^*_{ji} is travel time in the absence of an expressway, and c_{ji} captures the cost of crossing it. Based on their estimates, I set $c_{ji} = 2$ minutes for trips under 5 km that cross an expressway. I find that the counterfactual share of Chicago residents living in neighborhoods that are at least 90% Black falls by 10 percentage points. At the same time, close to 20% of the population lives in perfectly integrated neighborhoods (characterized by around 30% Black share)—nearly a seven-fold increase relative to the observed equilibrium. Removing the disamenity alone doubles the population living within 1 km of an expressway—offsetting the effects identified in the reduced-form analysis—and increases the population within 2 km by 50%, with larger increases near the city center.

Finally, I compute how segregated Chicago would be in the absence of expressway-related neighborhood effects. The index of dissimilarity falls from 0.844 in the observed equilibrium to 0.702 when both disamenity and barrier effects are removed.[87] This corresponds to a 16.8% reduction in segregation—a substantial shift, given that the dissimilarity index measures the share of Black residents who would need to relocate to achieve full spatial integration across the city.

8 Conclusion

This paper deepens our understanding of how urban structures and spatial design shape the allocation of people within cities. While anecdotal evidence on the link between physical barriers and socio-economic disparities is abundant, to the best of my knowledge, this is the first work to systematically examine that link, providing both a setting and an empirical strategy to plausibly identify causal effects.

I show that expressways influence racial sorting through two distinct channels. First, they act as local disamenities that affect residential location decisions by altering neighborhood desirability. Since Black households are, on average, poorer than white households, they are more likely to live near expressways due to lower housing costs. Second, expressways function as physical barriers that

[86] For Black types, I set $\lambda^*_W = \lambda_B$; for white types, I set $\lambda^*_B = \lambda_W$, where the asterisk denotes the counterfactual value.

[87] First proposed by Duncan and Duncan (1955), the index of dissimilarity is a widely used measure of spatial segregation (for an application, see Cutler et al., 1999). It is defined as $D = (1/2)\sum_i \left| \frac{Black_i}{Black_{total}} - \frac{non\text{-}Black_i}{non\text{-}Black_{total}} \right|$.

affect accessibility to different parts of the city, altering the racial composition of areas a neighborhood is exposed to. I show that higher exposure to Black neighborhoods (i) increases the likelihood that a neighborhood becomes more Black over time and (ii) reduces its valuation in the long run. This suggests a second sorting channel, driven by individual preferences over the racial composition of surrounding neighborhoods.

Motivated by these findings, I develop a quantitative spatial urban model with racial preferences for residential locations. The framework builds on the canonical monocentric city model of Alonso (1964), Muth (1969), and Mills (1967), and incorporates an internal city structure following Ahlfeldt et al. (2015). Using sources of variation analogous to those in the reduced-form analysis, I estimate racial preference parameters and simulate counterfactual scenarios. Mitigating the neighborhood effects of expressways in Chicago would lead to a 16.8% reduction in racial segregation. While my counterfactuals focus on expressways, the underlying mechanism may apply more broadly. Similar barrier effects can arise from other types of infrastructure, such as at-grade rail lines. Placing such infrastructure underground could help reduce spatial fragmentation and promote greater integration across neighborhoods.

These results highlight the long-lasting and often unintended neighborhood consequences of transportation infrastructure—still a defining feature of many urban landscapes—and speak to ongoing debates in urban policy and planning. Future research could examine the extent to which these long-run effects are shaped by institutional changes—for example, shifts in school, police, or administrative boundaries—made in response to the construction of urban barriers. In addition, the growing availability of GPS-based mobility data opens opportunities to better understand how urban form affects access to consumption, services, and experiences within cities.

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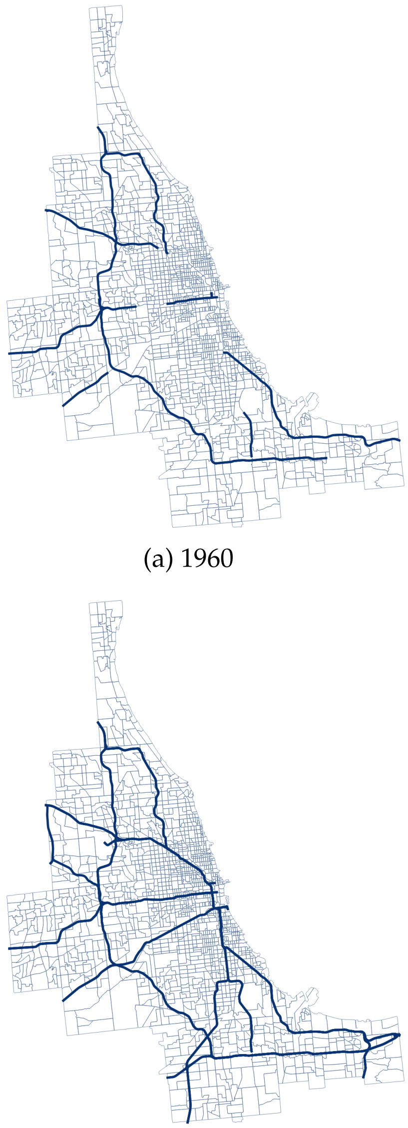
Figures

Figure 1: Timeline of expressway construction, 1950-2010

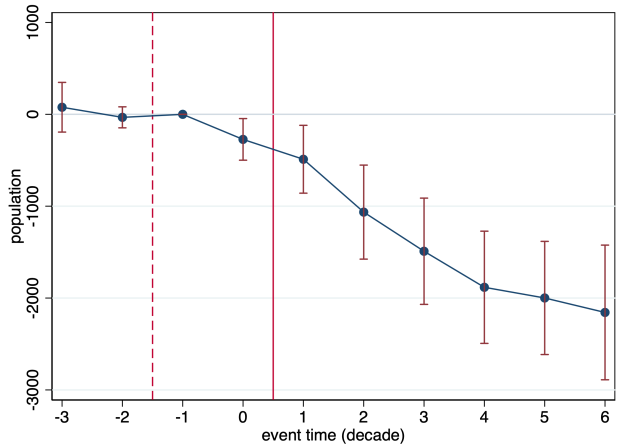


(a) 1960 (b) 1970 (c) 1980

(d) 1990 (e) 2000 (f) 2010

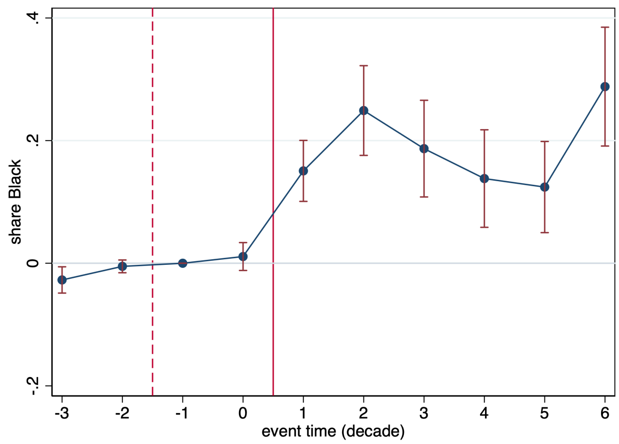
The maps show the rollout of the expressway network within the boundaries of the Chicago Metropolitan Area. The geographic extent of the city is determined by data availability in 1950. Polygons are the 1,511 consistent-boundary census tracts that constitute the units of analysis.

Figure 2: Effect of proximity to expressways on residential population



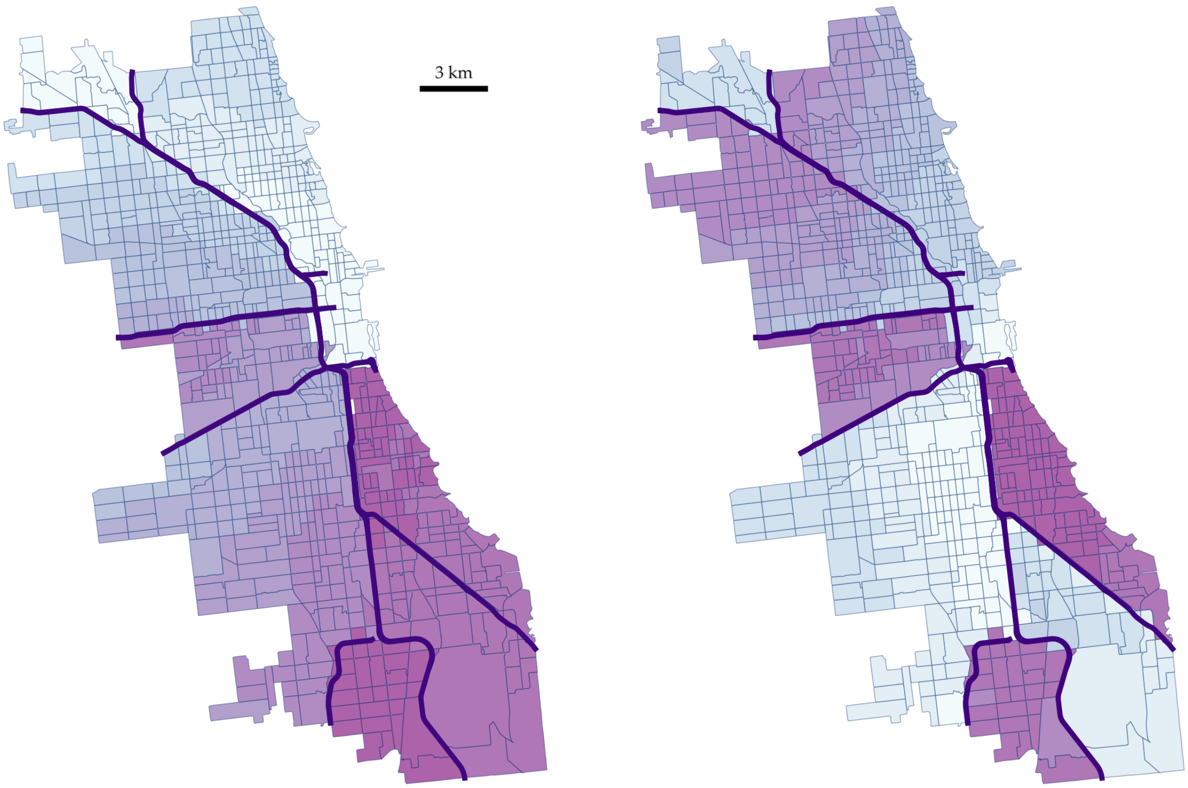
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is residential population. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds to the decade in which the expressway is found to be in operation. A census tract belongs to the treatment group if its centroid lies within 1 km from the closest expressway; it is part of the control group if its centroid is farther than 3 km from the closest expressway. Event times to the right of the solid red vertical bar correspond to post-treatment periods. Event times to the left of the dotted red vertical bar correspond to pre-treatment periods. Event times in between correspond to the periods between expressways were first planned and the year in which they were in operation. The full set of controls includes: Dist. to CBD $\times$ Year FE, Quadratic Dist. to CBD $\times$ Year FE, HOLC Grade $\times$ Year FE, 1940 Pop.D. $\times$ Year FE, City $\times$ Year FE. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

Figure 3: Effect of proximity to expressways on share of Black residents



Note: The figure plots the β coefficients estimated from regression (1) using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds to the decade in which the expressway is found to be in operation. A census tract belongs to the treatment group if its centroid lies within 1 km from the closest expressway; it is part of the control group if its centroid is farther than 3 km from the closest expressway. Event times to the right of the solid red vertical bar correspond to post-treatment periods. Event times to the left of the dotted red vertical bar correspond to pre-treatment periods. Event times in between correspond to the periods between expressways were first planned and the year in which they were in operation. The full set of controls includes: Dist. to CBD $\times$ Year FE, Quadratic Dist. to CBD $\times$ Year FE, HOLC Grade $\times$ Year FE, 1940 Pop.D. $\times$ Year FE, City $\times$ Year FE. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

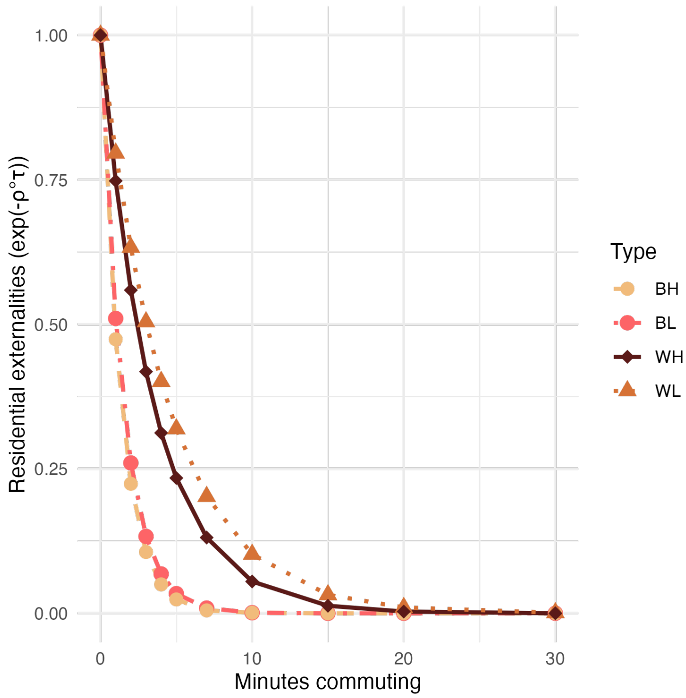
Figure 4: Change in exposure to Black residents and its IV, 1950-1990



(a) Change in exposure to Black residents (ΔS) (b) Instrument (ΔSMA)

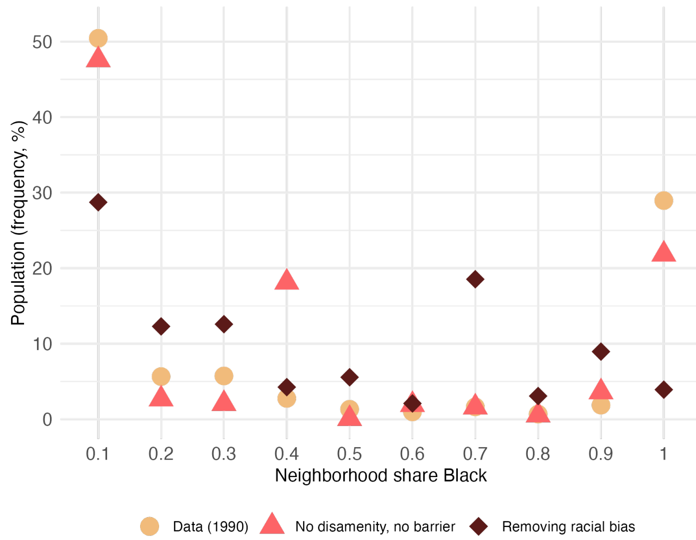
Note: Panel (a) shows the overall change in exposure to Black residents, ΔS_i, for each neighborhood in the city. This change reflects both the spatial resorting of residents between 1950 and 1990 and the impact of expressway development. Panel (b) displays the baseline instrument for ΔS_i, which isolates variation driven solely by changes in travel times due to expressway construction. To capture the barrier effect, the cost of crossing the expressway network is set to infinity. Census tracts are grouped into deciles based on their change in exposure, with darker colors indicating larger increases. Purple lines denote the expressway routes as of 1990.

Figure 5: Spatial decay of racial preference ρ^o



Note: The figure plots the estimated decay in racial spillovers with travel time (in minutes), $e^{-\rho^o \tau}$, separately for each type. The decay parameters are estimated via GMM and equal $\rho^{BL} = 0.674$, $\rho^{BH} = 0.747$, $\rho^{WL} = 0.229$, and $\rho^{WH} = 0.291$. Full numerical values and additional interpretation are reported in Table D4 in Appendix D.6.5.

Figure 6: Counterfactual racial distributions



Note: The figure plots the distribution of the population in Chicago by neighborhood racial composition. Yellow dots show the observed equilibrium in 1990. In the first scenario (pink triangles), I remove both the disamenity and the barrier effect of expressways by setting the amenity penalty from living near an expressway to zero ($g^o = 0$) and eliminating the added crossing cost for short trips (see main text for details). In the second scenario (maroon diamonds), I remove racial bias in residential preferences by setting the amenity elasticity with respect to different-race neighbors equal to that for same-race neighbors (i.e., $\lambda_W^* = \lambda_B$ for Black types, and $\lambda_B^* = \lambda_W$ for white types). In 1990, 50% of Chicago's population lived in neighborhoods that were at most 10% Black, and 30% lived in neighborhoods that were at least 90% Black. Under both counterfactuals, segregation decreases substantially: fewer people reside in highly segregated neighborhoods, and more live in racially mixed areas.

Tables

Table 1: Dep variable: Δ share Black (standardized)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS All	(6) Grid city se	(7) Conley se	(8) IV All	(9) IV Subs 1	(10) IV Subs 2	(11) IV Δ YMA
ΔS (std)	0.496***	0.500***	0.335***	0.395***	0.411***	0.411***	0.411***	0.158**	0.170**	0.203***	0.156**
	(0.053)	(0.052)	(0.054)	(0.050)	(0.052)	(0.123)	(0.085)	(0.069)	(0.068)	(0.070)	(0.069)
Dist expressway (km)		0.011	-0.179***	-0.204***	-0.202***	-0.202***	-0.202***	-0.231***	-0.233***	-0.241***	-0.231***
		(0.018)	(0.020)	(0.021)	(0.021)	(0.059)	(0.031)	(0.022)	(0.022)	(0.023)	(0.022)
ΔY (std)					0.091*	0.091	0.091	0.033	0.039	-0.079	0.038
					(0.050)	(0.122)	(0.091)	(0.051)	(0.052)	(0.060)	(0.058)
Observations	764	764	764	727	727	727	727	727	722	648	727
Adjusted R^2	0.224	0.223	0.397	0.470	0.471	0.471	0.470				
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Historical Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat								1265	1249	1055	573.4

Note: The table reports estimation results from regression (2) on the change in the share of Black residents. The main regressor of interest is ΔS (standardized), which captures the change in exposure to Black neighborhoods in the city. Additional controls include: distance to the nearest expressway (in km); ΔY, the change in exposure to high-income neighborhoods (standardized); and region fixed effects for the North, West, and South sides of the city. Tract-level controls include a quadratic polynomial in distance to the central business district (CBD), land area, and distance to water. Historical controls include distance to railroads in 1898, HOLC grade, the share of Black residents in 1920, and the change in population density between 1920 and 1940. Census tracts with public housing projects are excluded from the sample. Column (6) reports standard errors allowing for spatial correlation across tracts within 25 grid cells partitioning the city. Column (7) reports Conley (1999) standard errors, allowing for arbitrary spatial correlation of errors within 3 km. Columns (8)–(11) report IV estimates, instrumenting for the change in exposure to Black residents using a measure that holds the racial distribution fixed at the pre-period. Column (9) excludes the 5% of tracts in the full sample that had more than 20% Black residents in 1920. Column (10) excludes the 12% of tracts in the full sample located within 5 km of the CBD. Column (11) adds an instrument for the change in exposure to high-income neighborhoods, ΔY, using a variable (ΔYMA) constructed analogously to ΔSMA. Details on the construction of the exposure measures are provided in the main text. Standard errors are clustered at the census tract level unless otherwise noted. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Dep variable: Δ land value, log (standardized)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS All	(6) Grid city se	(7) Conley se	(8) IV All	(9) IV Subs 1	(10) IV Subs 2	(11) IV Δ YMA
ΔS (std)	-0.354***	-0.399***	-0.353***	-0.342***	-0.333***	-0.333**	-0.333**	-0.235***	-0.299***	-0.323***	-0.250***
	(0.045)	(0.045)	(0.050)	(0.051)	(0.051)	(0.137)	(0.074)	(0.064)	(0.061)	(0.064)	(0.065)
Dist expressway (km)		-0.130***	0.028	0.042	0.044	0.044	0.044	0.057**	0.052*	0.085***	0.056**
		(0.024)	(0.027)	(0.027)	(0.027)	(0.084)	(0.064)	(0.027)	(0.027)	(0.026)	(0.027)
ΔY (std)					0.057	0.057	0.057	0.077	0.046	0.292***	0.125*
					(0.061)	(0.119)	(0.108)	(0.061)	(0.059)	(0.060)	(0.065)
Observations	742	742	742	720	720	720	720	720	715	641	720
Adjusted R^2	0.284	0.320	0.436	0.436	0.436	0.436	0.435				
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Historical Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat								1341	1283	1104	559.3

The table reports the estimation results from regression (2) on the change in land value. The main regressor of interest is ΔS (standardized), which captures the change in exposure to Black neighborhoods in the city. Additional controls include: distance to the nearest expressway (in km); ΔY, the change in exposure to high-income neighborhoods (standardized); and region fixed effects for the North, West, and South sides of the city. Tract-level controls include a quadratic polynomial in distance to the central business district (CBD), land area, and distance to water. Historical controls include distance to railroads in 1898, HOLC grade, and the change in population density between 1920 and 1940. Census tracts with public housing projects are excluded from the sample. Column (6) reports standard errors allowing for spatial correlation across tracts within 25 grid cells partitioning the city. Column (7) reports Conley (1999) standard errors, allowing for arbitrary spatial correlation of errors within 3 km. Columns (8)–(11) report IV estimates, instrumenting for the change in exposure to Black residents using a measure that holds the racial distribution fixed at the pre-period. Column (9) excludes the 5% of tracts in the full sample that had more than 20% Black residents in 1920. Column (10) excludes the 12% of tracts in the full sample located within 5 km of the CBD. Column (11) adds an instrument for the change in exposure to high-income neighborhoods, ΔY, using a variable (ΔYMA) constructed analogously to ΔSMA. Details on the construction of the exposure measures are provided in the main text. Standard errors are clustered at the census tract level unless otherwise noted. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: GMM estimation results

	BL	BH	WL	WH
Elasticity λ_B^o	0.154	0.180	0.075	0.044
	(0.015)	(0.015)	(0.014)	(0.009)
Elasticity λ_W^o	-0.146	-0.124	0.251	0.268
	(0.042)	(0.040)	(0.030)	(0.017)
Spatial decay of racial pref. ρ^o	0.674	0.747	0.229	0.291
	(0.181)	(0.167)	(0.047)	(0.048)
Size of disamenity g^o	0.215	0.229	0.263	0.204
	(0.101)	(0.099)	(0.057)	(0.044)

Note: The table reports GMM estimates of the racial preference parameters (λ_B^o, λ_W^o), the spatial decay parameter of racial preferences (ρ^o), and the size of the expressway disamenity (g^o) for each socio-demographic group. Groups: BL = Black low-educated, BH = Black high-educated, WL = white low-educated, WH = white high-educated. Cluster-robust standard errors are reported in parentheses.