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

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Abstract

How do man-made barriers shape racial segregation within cities? I study the long-run effects of the construction of expressways in Chicago in the 1950s on racial segregation. These multilane roads (i) produce a local shock to residential amenities, and (ii) divide the areas they cross through, creating local barriers to the interaction of nearby communities. I find that expressways affect within-city racial segregation through two main channels. First, a price or disamenity channel: Racial segregation increases because of income differences between Black and white residents, which on average lead the two groups to react differently to changes in house prices induced by proximity to expressways. Second, a physical barrier channel: Racial sorting appears to be affected by expressway-induced changes in accessibility to different portions of the city and, in turn, to neighborhoods with different demographic compositions. Motivated by these findings, I build a structural urban model to study the link between urban barriers and racial preferences in shaping the allocation of people across space. The model is used to estimate racial preference parameters and to undertake counterfactual experiments to inform current public policies targeting the social issues of transport infrastructures in US cities.

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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 urban centers? Within less than 20 years, the US became nationally connected by an integrated network of thousands of miles of roads, spanning from east to west, north to south. These roads serve major metropolitan areas, dramatically reducing the traveling times of inter-state journeys. At the same time, within metropolitan areas, such concrete strips permanently changed the structure of cities and the urban landscape. This paper presents a long-run analysis of the effects of man-made barriers on residential racial segregation within cities.[1]

I exploit the construction of expressways in the city of Chicago as a source of variation in neighborhoods' quality and connectivity.[2] Expressways are heavily trafficked and large multilane roads, difficult to cross. In addition, they were built when the city was already racially mixed. The setting hence allows us to examine the effects of a shock on urban spaces through the lenses of both an immediate barrier effect and an eventual sorting mechanism. As written by Emily Badger and Carla Cameron in their Washington Post article (dated July 16, 2015): "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."[3]

I develop an empirical strategy that allows us to causally estimate the effects of expressways on neighborhoods' racial composition along two dimensions.[4] The first considers the expressways to create permanent reductions in residential amenities in the neighborhoods they cross through (Brinkman and Lin, 2022; Robinson, 1971). By making some places worse than others due to increases in pollution, noise, and other disamenities in nearby locations, expressways affect the socio-demographic composition of the neighborhoods through a decrease in the quality of life of impacted areas – reflected by changes in prices and resident population in close as opposed to farther away locations. The second effect on racial sorting starts from the phenomenon mentioned above, that racial segregation in US cities tends to occur along man-made barriers. The variation in accessibility induced by the creation of urban barriers within a city allows us to characterize the barrier effect of

[1] 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).

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

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

[4] These urban transportation infrastructures also reduce commuting costs, facilitating a separation between workplace and residential locations. Given the decadal frequency and long-time horizon of my analysis, I do not observe commuting patterns in this setting. While it might be that what I generally define as "disamenity effect" embeds in part the "access benefits effect" of expressways (leading to decentralization), I perform a series of empirical exercises that are consistent with the role of expressways as local disamenities – despite access benefits effects may also be at play.

expressways. By increasing the physical separation between locations on opposite sides of the road, expressways affect racial sorting by altering neighborhoods' exposure to parts of the city characterized by different racial configurations. I use these two sources of within-city variation (distance to the road and local changes in accessibility) as identification strategies in the reduced form and structural analyses.

I begin by empirically estimating the disamenity and barrier effects of expressways. The first set of results documents that, over time, expressways permanently affect the demographic composition, the size of the population, and the valuation of neighborhoods nearby. On average, expressways lead to an increase of 15 percentage points in the share of Black residents living in nearby neighborhoods immediately after their opening and 20 percentage points in the following decades. At the same time, the total residential population permanently drops. Areas near expressways lose approximately 30% of the full sample mean in the post-treatment period, as opposed to comparable unaffected locations.[5] Consistent with the idea that expressways create a negative shock to residential amenities, I also find that neighborhoods closer to expressways tend to exhibit lower house value, land value, and college share (as a proxy for income). The main results use de Chaisemartin and D'Haultfoeuille (2020) two-way fixed effects estimator and fulfill the assumptions for identification of causal effects.[6] They hold strong to a host of robustness checks, which include different choices of treatment and control group bandwidth, the removal 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 the degree of accessibility to different parts of the city – altering the racial mix of the areas a neighborhood is exposed to. If expressways create a barrier along the racial dimension, 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 and test for the barrier effect of expressways by running a long-difference empirical specification. To estimate the effect of changes in exposure to Black residents on the change in the racial composition of the neighborhoods in Chicago, I build a measure of accessibility to races that draws inspiration from the market access literature. It is constructed as a location-specific weighted average of the share of Black residents living in each neighborhood. The weights are a decreasing function of the bilateral travel time between each pair of locations and depend on the road network: higher weights are placed in locations that are more easily accessible.[7]

I find that higher exposure to Black areas in the city (i) increases the likelihood that a neighbor-

[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] In the baseline analyses, census tracts in the treatment groups are those within 1 km from the closest expressway; census tracts in the control group are those further than 3 km away.

[7] This summary measure captures, for each origin neighborhood, the change in the degree of exposure to Black residents over time induced both by sorting and by changes in transportation infrastructure, which affect how accessible the other neighborhoods in the city effectively are. In estimation, I employ an instrumental variable strategy to address the concern that the variable that measures the change in exposure to Black residents is likely correlated with unobserved shocks affecting the dynamic of neighborhood composition. I instrument for the change in exposure to Black residents holding the racial composition fixed to the pre-period. Hence, the instrument isolates variation in exposure to Black residents only due to changes in the travel time between locations.

hood 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 living in the neighborhood. On the other hand, it reduces land value (used as a proxy for neighborhoods' valuation) by an average of 0.24-0.32 standard deviations. The results remain stable to the inclusion of a rich set of controls, including distance to the closest expressway and a measure that captures changes in exposure to rich areas in the city.[8]

A primary concern with the causal interpretation of these 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 outlined above. First, in estimating the disamenity effects of expressways, I show that the assumptions for identification to be valid are fulfilled. The estimated coefficients in the pre-periods are consistent with the assumption of parallel trends in outcomes between the treated and control groups. Second, I complement these results by addressing the possibly non-random selection of locations in the treatment group, running a set of instrumental variable regressions. 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 might have been purposely isolated. The finding that higher exposure to Black areas increases the likelihood of a neighborhood becoming more Black remains invariant to (i) removing historically Black neighborhoods from the analysis and (ii) removing the central areas of the city, where the relation between the location of expressways and Black communities was arguably more salient.

To quantify the overall impact of expressways on racial segregation in Chicago, I then build a quantitative spatial urban model with racial preferences for location choices. The setup adheres to a monocentric city model but features an internal city structure following Ahlfeldt et al. (2015).[9] I assume the city is populated by an endogenous number of residents of either one of four types (two-by-two race by educational attainment categories). Individuals work in the center of the city, and commuting is costly. They choose the location of residence and consumption of the final good and floorspace to maximize utility. The utility of living in a given area depends on residential amenities, land prices, and idiosyncratic shocks. Hence, the model produces a heterogeneous type-specific demand system for residential neighborhoods. Expressways enter the model by providing a source of variation in the quality and accessibility of neighborhoods in the city, affecting amenities and commuting times. Total residential amenities depend on location fundamentals, neighborhood demographics (residential externalities), and the disamenity of expressways. Using analogous sources of variation of the reduced-form analyses, I structurally estimate the parameters governing residential externalities and the disamenity parameters.

GMM estimation results show large and statistically significant racial preferences and disamenity

[8] I also perform a set of robustness checks to establish that the results are not driven by potentially concerning locations for identification (e.g., historically Black neighborhoods, or downtown area).

[9] The canonical monocentric city model was initially formalized in Alonso (1964), Muth (1969), and Mills (1967).

parameters. The racial preference parameters have high degrees of heterogeneity by type, particularly when comparing Black and white individuals. The estimates are consistent with Black and white residents exhibiting higher utility for living close to same-race neighbors. Residential externalities appear to be an important agglomeration force, particularly in relation to the concentration of same-race residents in the vicinity. For white individuals, the estimated elasticity of amenities with respect to the concentration of nearby residents is notably higher for same-race neighbors compared to different-race neighbors, ranging between three and six times as large.[10] Conversely, estimates for Black residents align with substantial agglomeration forces linked to the density of same-race residents in the surrounding neighborhoods while suggesting congestion forces concerning the density of white residents nearby.

In addition, residential externalities are highly localized – and appear more localized for Black households than white households.[11] Other things equal, residential externalities fall to zero after around 10 minutes of travel time for Black residents and after around 20 minutes for white residents. For both Black and white groups, the rate of spatial decay of racial preferences goes towards zero faster among the highly educated types. Finally, the size of the disamenity on average appears larger for white residents (attaching 23.9% lower amenities in proximity to the expressway) than for Black residents (22% inferior amenities), attenuating by 95% at 3.8 km from the expressway.[12]

I use the theoretical framework to run counterfactual experiments to evaluate the relation between urban forms and racial sorting. These exercises consist of assuming alternative values of location characteristics or model parameters and solving for the model's counterfactual equilibrium. In all these counterfactuals, I choose the reservation level of utility in the wider economy in the post-period to ensure that the total (type-specific) population in Chicago is equal to its value in 1990. I begin by using counterfactuals to provide further evidence of the model's fit. I analyze the extent to which the effects of the construction of expressways on neighborhood demographics can be explained by the endogenous forces of the model rather than by changes in location fundamentals over time. I find that the model with endogenous forces is able to explain the observed changes in neighborhoods' demographics well (the correlation between the distribution of the share of Black in the observed equilibrium and its counterfactual value is 0.815).

I then run a counterfactual where I study the implications of removing the 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 amenities with respect to the concentration of one's race. I find that the counterfactual population of Chicago lives in more integrated neighborhoods. The share of

[10]Specifically, for white low-educated individuals, the estimate is 3.3 times larger, while for white high-educated individuals, it is 6.1 times larger.

[11]The rate of spatial decay of racial preferences is equal to 0.674 (s.e. 0.181) for low-educated Black individuals and to 0.747 (s.e. 0.167) for high-educated Black individuals. For low-educated white residents, it equals 0.229 (s.e. 0.047) and 0.291 (s.e. 0.048) for high-educated white residents. The average value of the rate of spatial decay of racial preferences, weighted by the population shares, is 0.342. To the best of my knowledge, this is the first estimate of this sort, making it difficult to benchmark its value. Nevertheless, it is reassuring to observe that it falls within the range of the most pertinent estimates found in the literature. The residential externalities parameter is equal to 0.76 in Ahlfeldt et al. (2015). The elasticity of consumption travel cost with travel times is estimated at 0.019 in Miyauchi et al. (2022).

[12]The magnitudes are comparable to the values recently found in the literature. Brinkman and Lin (2022) find freeway neighborhoods having 18.4% lower amenities, attenuating by 95% at 3.8 km from the expressway (I calibrate the parameter that governs the rate of decay from their work).

individuals living in neighborhoods with 90% or more Black share drops from 30% in the observed equilibrium to around 5%, while the share of residents living in a neighborhood with at most 10% Black share drops from 50% to less than 30%. The population appears more evenly distributed across all neighborhood configurations.

Finally, I conduct an additional counterfactual analysis, examining the implications of mitigating the neighborhood effects of expressways on racial sorting – while maintaining their access benefits. The exercise would hence correspond to a policy intervention that places the expressways underground. I investigate the counterfactual treatment effects of simultaneously removing (i) the disamenity and (ii) the barrier effect of expressways. I find that the distribution of races in the counterfactual equilibrium is characterized by a drop of 10 percentage points in the share of residents of Chicago living in a neighborhood with 90% or more Black individuals. At the same time, almost 20% of Chicago's total population would end up residing in integrated neighborhoods (characterized by around 30% Black share) – nearly a seven-fold increase relative to the observed equilibrium. Mitigating the neighborhood effects of expressways is associated with a reduction of 16.8% in racial segregation as measured with the dissimilarity index (moving from 0.844 in the observed equilibrium to 0.702 in the counterfactual equilibrium).

This research builds on three main strands of the economics literature. The first looks at the effects of investments in transportation infrastructure within cities, including Baum-Snow (2007), Baum-Snow et al. (2017), and Gonzales-Navarro and Turner (2018) on population and property prices; Tsivanidis (2022), Baum-Snow (2020), and Heblich et al. (2020) on city structure and welfare.[13] Close to this paper, Brinkman and Lin (2022) evaluate the local adverse effects of freeways on population and welfare in US cities. While their paper is the first to provide evidence of an increase in the cost of travel across highways using travel diary microdata, I fill a gap in this literature by emphasizing the role of expressways as urban barriers. By affecting the level of accessibility to different areas in the city, I show that this feature affects the spatial distribution of people across neighborhoods, on top of more traditional channels studied 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]

The second related literature looks at the causes and consequences of residential segregation. Many influential works explore the link between segregation in the US to schooling and labor market outcomes (Kain, 1968; Cutler and Glaeser, 1997; Cutler et al., 1999; Collins and Margo, 2000; Ananat, 2011). Others investigate the emergence of segregation in northern US cities, focusing on early (e.g., Shertzer and Walsh, 2019) or late periods of the Great Migration (Boustan, 2010; Derenoncourt, 2022;

[13] A large body of works looks at the impact of transportation infrastructure on various outcomes (Redding and Turner, 2015). For instance, long-distance transportation infrastructures (mainly railroads and highways) have been shown to affect land value (Donaldson and Hornbeck, 2016), regional output (Chandra and Thompson, 2000; Jedwab and Moradi, 2016; Ahlfeldt and Feddersen, 2018; Banerjee et al., 2020), trade (Donaldson, 2018; Faber, 2014; Duranton et al., 2014), urban development (Duranton and Turner, 2012; Baum-Snow et al., 2020), migration (Morten and Oliveira, 2023), the spatial sorting of heterogeneous residents and workers (Fretz et al., 2022; Weiwu, 2023), firms and labor markets (Gibbons et al, 2019; Michaels, 2008).

[14] This latter issue saw a surge in recent urban papers (Brinkman and Lin, 2022, Carter, 2023; Ahlfeldt et al., 2019; Anderson, 2020; Mahajan, 2023).

Shi et al., 2022).[15] To the best of my knowledge, this is the first paper to provide a long-run analysis of the causal effects of physical barriers on socioeconomic disparities within cities – a link that was, until this research, an anecdotal observation.[16]

Finally, this work speaks to the literature studying the dynamics of neighborhood sorting (Lee and Lin, 2018; Heblich et al., 2020; Heblich et al., 2021; Bayer et al., 2016), and to the growing literature on the spatial sorting of heterogeneous agents (Fajgelbaum and Gaubert, 2020; Davis and Dingel, 2020; Redding and Sturm, 2023; Davis et al., 2023; Gechter and Tsivanidis, 2023).[17] This paper makes two main contributions to this strand of the literature. First, I create a novel measure of exposure to races in the city that builds on the market access literature. This metric allows us to estimate the intensity of spatial proximity and the strength of racial preferences when space matters.[18] Second, I model the geography of Chicago in a general equilibrium framework to estimate racial preference parameters and undertake counterfactual experiments to inform of the continuous neighborhood effects of expressways.

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.

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 former national plan, commissioned in 1947, to a 41-thousand-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

[15] A growing strand of this literature examines the importance of neighborhood effects and social networks on socioeconomic outcomes (Echenique and Fryer, 2007; Cutler et al., 2008), also thanks to advancements in GIS and GPS technologies (Chetty and Hendren, 2018a; Chetty and Hendren, 2018b; Chetty et al., 2016; Athey et al., 2020).

[16] In the sociology literature, a paper by Roberto and Hwang (2017) explores the correlation between physical boundaries and residential segregation, using 2010 block-level data in a cross-section of US cities.

[17] Closely related is also the literature evaluating the dynamics of segregation and tipping points (Schelling, 1971; Card et al., 2008; Dorn, 2008; Logan and Parman, 2017; Caetano and Maheshri, 2019; Gregory et al., 2022; Sethi and Somanathan, 2004; Christensen and Timmins, 2023).

[18] The concept of spatial proximity and the parametrization of racial preferences in this type of framework dates back to Schelling (1971) and has recently been studied by Logan and Parman (2017). In both works, the notion of segregation is based on next-door neighbors. A key contribution is estimating the parameter that governs the rate at which racial preferences decay spatially.

Canada and Mexico. Within metropolitan areas, the 1956 plan also incorporated some highways that were 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.

For this project, I only consider expressways (interstates) among the various types of highways due to their distinct physical attributes. Expressways are controlled-access roadways only, which implies that exits and entrances are limited. All traffic merges on or off ramps that connect them to highways, secondary, or tertiary roads. Therefore, any route crosses an expressway only through overpasses or underpasses.[19]

Serving the local network in metropolitan areas – in addition to connecting major cities – these multilane roads fostered suburban sprawl. Faster commuting times had a crucial role in influencing changes in the spatial distribution of the population in US metropolitan areas between 1950 and 1990. Baum-Snow (2007) finds that highways can explain about a third of the total change in central city residents relative to residents in the entire metropolitan area. The pattern of suburbanization that affected most American cities also affected Chicago. In 1950, more than 5.1 million people lived in the Chicago Metropolitan Area, with 3.6 million living within city boundaries. In 1990, the population living in the city shrank to less than 2.8 million (totaling a 22% drop). In contrast, the total metropolitan population increased by more than 50% over this period, reaching 8 million in 1990.

The creation of the Interstate highway system also came with an intertwined history of infrastructure and racial inequality. As the former US Secretary of Transportation (under President Obama's second term) Anthony Foxx declared in 2016, in most American cities, these roads were often routed in degraded neighborhoods where the poorest residents were living – almost always racial minorities – and sometimes they were intentionally meant 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] Historical accounts document the link between racial configurations and the passage of highways across neighborhoods (Mohl, 2004; 2008; Archer, 2020).

Chicago was not spared. In the late 1940s, city officials estimated that the planned expressways would destroy over 8,100 housing units (Mohl, 2001). Figure A3 shows two sides of Troop Street in 1949, when the Eisenhower Expressway – which runs westwards from the Chicago Loop – was built.

[19] Other highways instead do have intersections, even with minor roads. While they can be limited-access roads in some portions of their routes, in most parts, they are free-access roads, with private drives exiting and entering. For more details, see Appendix A.1.1.

[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).

Close to the center, the road passed mostly through the Italian and Greek communities, forced to relocate to the Northwest Side and the suburbs. The small Black community instead moved further west. Another notable example is the Dan Ryan Expressway, which runs north-south. In 1956, it was shifted west, arguably to isolate the growing Black community living on the South side of Chicago. Long considered as "lifeline of the South Side", the Dan Ryan Expressway indeed created a zone of demarcation, as many neighborhoods deteriorated along the route.[22] As these examples show, the allocation of expressways within the urban space was likely not random. On the contrary, local factors arguably played a role in determining the precise arrangement of these roads, as is generally the case in the assignment of transportation infrastructure to various locations (Redding and Turner, 2015).[23]

When expressways were laid out, Chicago was populated by many minority groups that gained importance in size in the late 19th century. During the first wave of the Great Migration, between 1910 and 1920, more than 50,000 African Americans moved to Chicago from the rural south, attracted by job opportunities – increasing the city-wide share to 4.1%. During the Great Depression and World War II, foreign immigration decreased, while the percentage of the Black population kept growing: in 1944, almost 1 in 10 residents was Black.

While the foreign-born communities grew smaller, Black neighborhoods assumed increasing importance, and the so-called "Black Metropolis" emerged in the city's south side. In the late 1940s, over 90% of the total Black population living in Chicago was residing there (corresponding to the largest purple area in Figure A5 in Appendix A.1.3).[24] Hispanic immigration instead grew steadily only in the second half of the 20th century. In 1960, only about 1.5% of the total population in the city of Chicago was recorded as Hispanic. By 1990, it reached almost 20%.[25]

In population censuses – my primary source of demographic data – Hispanic origin as a racial breakdown appears only after 1970. In the following analyses, I only distinguish between Black and non-Black individuals; nevertheless, there is a sufficient categorization when studying the segregation of one minority group from others. Given the data limitation, people of Hispanic origin are, together with other racial minorities, consistently grouped with the white population.

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 analysis is the census tract.[26] For comparability over time, historic census tract boundaries have been normalized to 2010 boundaries (the procedure follows closely Lee and Lin, 2018). The geographic extent

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

[23] Given this endogeneity concern, in the empirical strategy I lay out the assumptions for my identification to be valid.

[24] With the vast majority of Black population living in the narrow tongue of land on the South Side, Chicago was a segregated city already before expressways were built, as it can be seen from the figure. Nevertheless, the area was too small to accommodate the growing number of African Americans who migrated to the city. Since then, the Black population has increased threefold, and the spatial arrangement of people within the city has dramatically changed.

[25] Today, Chicago is one of the most diverse US cities, since its majority races are split into nearly equal shares within the city: https://fivethirtyeight.com/features/the-most-diverse-cities-are-often-the-most-segregated/

[26] A census tract covers an area of approximately 2 square km and has around 6,000 residents.

of the metropolitan area is determined by data availability in 1950. The procedure results in 1,511 consistent boundary census tracts that partition the Chicago Metropolitan Area between 1950 and 2010. For the 780 of those already surveyed at the beginning of the 20th century, the data covers an entire century (on a 10-year interval between 1920 and 2010). The information available at this level of spatial granularity includes a wide range of households' socio-demographic characteristics and housing attributes. Below, I outline the main variables of interest and the procedure I followed to create the time series, grouping them by data source. Summary statistics for 1950 are reported in Table A1 in the Appendix A.

Censuses of population and housing The primary demographic of interest is the residents' race in 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 to consistently distinguish between two race categories only, namely "Black" and "non-Black".[27] Starting in 1980, race breakdown became more detailed. For all these later periods, I code as Black residents all the "Black, non-Hispanic" residents (following Logan et al., 2014). As a result, in the analyses that follow, the complementary quantity to the share of Black residents is the share of non-Black residents (which includes white, people of Hispanic origin, and others).

Since data on average household income are available at the census tract level from the US censuses of the population starting only in 1950, I complement granular demographic data with an estimate of the share of college graduates. The information consistently covers the period between 1940 and 2010. The statistic is computed as the share of individuals above 25 who completed four or more college years.

Land and road network data I complement the data from the US population and housing censuses with a few other sources.

First, to overcome the concern that the data does not include information on multi-unit buildings, I rely on the information contained in Olcott's Land Value Blue Book, an account unique to Chicago. This collection reports estimates of land value for every city block in the city of Chicago for most of the 20th century. The data, available with a spatial granularity of 300×300 foot-wide grid cells, were digitized and made available in Ahlfeldt and McMillen (2014; 2018).

Second, contemporaneous transport networks are from the US Census Bureau. From the network of all roads in Chicago, I extracted the expressways that traverse the area under study.[28] Starting

[27] One exception is the 1940 census, which only records race in terms of "white" as opposed to "non-white". I had to recode the race categories registered in 1940 to make them comparable with the rest of the time series. Given the small influx of other non-white races in that period (Hispanic immigration was very scarce before the 1960s), I made the assumption that all individuals coded as "non-white" in 1940 were Black residents. To validate the procedure, I compared the resulting tract-level shares of Black residents with the information from a 1934 census of population and housing that was carried out in Chicago only. In 1934, the race variable recorded "White", "Negro", and "Other", in line with other census periods. For comparability, I then computed the tract-level share of Black residents (as opposed to non-Black residents) using the same weighting scheme as that for the 1940 census. Reassuringly, I find that the correlation between those two measures (the one computed in 1934 and the other in 1940) is 98.83%.

[28] One of the reasons why I restrict the analysis to expressways only (and do not include highways and other major roads) is their technical attributes. Expressways must comply with standards, one of the most important being the controlled access nature of this type of road, which helps identify urban barriers.

from the present-day network, I then constructed snapshots of the expansion of the expressways with a 10-year interval corresponding to the census years. The opening dates of the expressways are initially from Baum-Snow (2007). For the precise assignment of the opening year for each road segment within the city, I relied on Illinois and Indiana State Maps issued in the census years.

Finally, the 1940 road network is available from the Urban Transition HGIS Project (Shertzer et al., 2016).[29]

2.2.1 Sample

The original sample consists of 1,511 consistent-boundary census tracts (normalized to 2010 boundaries) covering the area that was part of the metropolitan area of Chicago from the 1950 census. Of these, 791 are within the boundaries of the city of Chicago, and the remaining 720 constitute the suburban area. For the earliest periods, the information is only available for the subset of census tracts (757) already surveyed at the beginning of the 20th century.

Notorious public housing projects (like the Cabrini-Green or the Taylor Homes) were developed in Chicago by the Chicago Housing Authority as part of its urban renewal process around the mid-20th century. They were large housing developments consisting of multiple high-rise buildings whose residents over time were nearly all Black. To isolate the neighborhood effects of expressways, I hence remove from the sample the census tracts that hosted such projects (see Map A4 in Appendix A) or larger radii around them in robustness checks. I also present the results, including public housing neighborhoods, in the appendix. Results remain stable.

3 Overview of the empirical analysis

Expressways, mainly aimed at connecting distant locations, might have the unintended consequence of increasing local segregation. In this section, I outline the empirical strategy and present reduced-form evidence of their impact on segregation along two dimensions. The first considers the expressways to create permanent reductions in residential amenities in the neighborhoods they cross through. By making some places worse than others due to increases in pollution, noise, and other disamenities in nearby locations, expressways might affect the socio-demographic composition of the neighborhoods through a decrease in the valuation of locations reflected by differences in house prices. The second starts from the widely observed phenomenon that racial segregation in US cities tends to occur along man-made barriers such as railroads, highways, or large city roads. As mentioned above, I focus on expressways because (i) they are heavily trafficked and large multilane roads, difficult to cross, and (ii) they were built when the city was already racially mixed.

To identify the possible long-lasting effects of expressways on the composition of the neighborhoods, I exploit the time dimension of the empirical setting, allowing for the possibility of dynamic treatment effects. First, I test for the disamenity effect of expressways running a difference-in-differences specification with multiple periods. The time span covers the period between 1950 and

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

2010 (the first expressway was built in the city in 1955) for all units in my data, and it goes back to 1920 for the portion of the city that was already surveyed at the beginning of the 20th century. Second, I estimate the barrier effect of expressways running a long-difference empirical specification where I measure the effect of changes in exposure to Black residents on the change in the racial composition of the neighborhoods in Chicago. To the extent that expressways create within-city barriers that affect the degree of accessibility to different parts of the city, I test whether neighborhoods become racially more similar to the areas they are exposed to once these urban barriers are in place.

4 Disamenity effect of expressways

I employ multi-period difference-in-differences specifications to estimate the dynamic impact of proximity to expressways on the valuation of neighborhoods. I compare the average outcomes of census tracts near expressways to those of the comparison group. 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 the post-construction period; 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

[30] In the baseline specification, I consider as treated all census tracts that lie within 1 km from the nearest expressway. This corresponds to the largest distance at which both pollution and noise are estimated to reach the benchmark levels of areas with no highways. Concerning pollution, Karner et al. (2010) – integrating the results of 41 monitoring studies of the dispersion of near-road air pollutant concentrations – report that the concentration of ultrafine particles (UFPs) achieves the background level (of no highways) at a distance of 910 meters from the source. As for the noise produced by expressways, it is estimated to vanish at a distance on average smaller than the pollution derived from the same source. In a free field (i.e., assuming equal sound propagation in all directions), noise obeys the inverse square law: sound intensity decreases by nearly 6 decibels for each doubling distance from the source. Under these conditions, the sound produced by expressways – estimated at around 75 decibels by the Federal Highway Administration – reaches the ambient noise level recommended by the WHO of 40 decibels at a distance of 320 meters. In the real world, in the presence of reflections of reverberations, sound propagation does not follow precisely this law, but the estimates seem relatively close. From the transportation noise map developed by the US Department of Transportation – representing the approximate average noise by mode – in 2018, the noise produced by expressways in Chicago faded at a distance of around 250 meters. For an illustration, a section of the interactive map produced by the Bureau of Transportation Statistics and its source is reported in Figure A8 in the Appendix A.3.

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 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 following the two-way fixed effect estimator proposed by de Chaisemartin and D'Haultfoeuille (2020), which is valid even when the treatment effect is heterogeneous across groups or over time, as it may be in this setting. In two-way fixed effects regressions where the treatment effect is not constant, the estimated coefficient is equal to a weighted sum of several difference-in-differences that compare the evolution of the outcome between consecutive time periods across pairs of groups. However, since the control group may effectively be treated in both periods in some of these comparisons, some weights may be negative. This may be an issue when the average treatment effects are heterogeneous across groups or periods because the estimated coefficient may be of a different sign than the average treatment effects of the pairwise comparisons. To test the severity of this concern in my setting, I run the *twowayfeweights* command in de Chaisemartin and D'Haultfoeuille (2020) in 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 (in the specification with no controls, 78.0%), with weights summing up to 1.041, while 13.9% receive negative weights (and their sum is equal to -0.041).[31]

The baseline 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). This variable is likely to affect both the outcome variables – Black households and minority groups more generally settled first in the central parts of the city – and the treatment status due to the radial structure of expressways. Second, I include a "city center" fixed effect – which effectively splits the sample into central and suburban areas.[32] This additional control is particularly useful to isolate the disamenity effect of expressways.[33] Under the assumption that distance to the expressways within the city does not affect the likelihood of moving to the suburbs, the city fixed effect isolates the change in relative residential amenities induced by the disamenity effect of expressways – net of suburban

[31]The command also reports two summary measures of the robustness of the estimated coefficient. The first corresponds to the minimal value of the standard deviation of the treatment effect between the treated groups and time periods under which β and the average treatment effect on the treated could be of opposite signs. I find a value of 0.762 (after standardizing the outcome variable to make the magnitude clearer to interpret). Instead, the second summary measure corresponds to the minimal value of the standard deviation of the treatment effect across the treated groups and the time periods in which all the average treatment effects are of a different sign than β. The reported value is 3.889 (after standardizing the outcome variable). Reassuringly, both summary measures appear to be large, suggesting that β and the average treatment effects could be of opposite signs only if there is a lot of treatment effect heterogeneity across groups or time periods.

[32]Central areas are 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, the focus is on the latter in this paper.

movements.[34] Third, I control for baseline population density since it likely correlates with both treatment status assignment and the primary outcome of interest (Black and minority groups more generally tended to live in denser areas). Finally, I control for baseline neighborhood characteristics proxied by the grades assigned by the Home Owners Loan Corporation (HOLC) in the 1930s (Fishback et al., 2020).[35] Given the history of discrimination and unequal treatment during the settlement of the Black population and European immigrants in industrialized US cities, minorities tended to live in disadvantaged and economically distressed neighborhoods. The 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 in Appendix B, I report the results without controls and show that the effects remain quantitatively similar (Figures B1 and B19 respectively for share Black and population as outcome).

The empirical specification assumes that treatment and control group outcomes would have evolved similarly in the absence of expressways. The 1920s were characterized by large population movements, which posit concerns about the validity of the identification assumption. The city was heavily expanding its area. At the same time, however, the Black population was residing only in the city's center (and often in the area on the south side named Black Belt). As a result, finding a reliable comparison group in this earliest period is difficult, as Figure B.1.9 in Appendix B shows. In what follows, I omit the year 1920 from the analysis. However, I report the main results, including 1920, showing that, indeed, the pre-trend in outcome in this early period vanishes once I account for the areas that experienced contemporaneous changes in population due to factors unrelated to the expressways (see Section B.1.9 of Appendix B).

4.1 Main results

Following Brinkman and Lin (2022), I begin by reporting the results of proximity to expressways on changes in residential population, a measure that summarizes the changes in the quality of life of affected neighborhoods. The estimated coefficients from regression (1) on the residential population are reported graphically in Figure 2. Event times to the right of the red vertical bar denote post-treatment periods, with event time 1 coinciding with the decade in which the expressway opens to traffic. Event times to the left of the dotted red vertical bar instead correspond to pre-treatment periods. Finally, event times between the two vertical bars denote the period between the first plan of expressway construction was in place and the period in which the expressway was in operation.

The results show a persistent decline in the residential population living in affected areas compared to control units. In the construction phase (before expressways opened to traffic), there is an average drop in residential population of 331.52 (s.e. 118.77), corresponding to about 8% of the full sample mean. After expressways are in operation, the residential population keeps declining

[34] One threat would be if displaced households near the expressway were disproportionately forced to move to the suburbs because of the lack of alternative housing opportunities downtown. However, this scenario does not seem to be supported by historical evidence.

[35] See Appendix A.2 for a brief description of redlining and the boundaries drawn in Chicago.

[36] Recent studies have shown their long-term consequences in terms of home ownership, house values, and rents (Aaronson et al., 2021; Krimmel, 2020).

by around 500 people each decade, reaching a drop of around -2,000 people by decade four into treatment. The average treatment effect is estimated at -1,359.84 (s.e. 216.25). Reassuringly, β coefficients of the pre-treatment periods are consistent with the assumption of parallel trends in outcomes between the treated and control groups.

The estimated coefficients from regression (1) on the share of Black residents are reported graphically in Figure 3. Being close to an expressway is associated with a sharp increase in the share of Black residents, all else equal. On average, areas close to the expressways experience an increase of 15.43 p.p. (s.e. 0.02) in the share of Black residents in the first decade into treatment and an average of around 20 p.p. increase in the following decades, relative to the pre-expressways period. The average treatment effect, as reported in de Chaisemartin and D'Haultfoeuille (2020), is equal to 15.72 p.p. (s.e. 0.03). The β coefficients in the periods before expressway construction are consistent with the assumption of parallel trends in the outcome variable between treated and control neighborhoods before intervention. During the construction phase, eventually affected locations experienced both a decline in residential population and, at the same time, a slight change in the demographic composition of the neighborhoods, exacerbated in the post-treatment periods.

4.2 Robustness checks

I show that the results are robust and quantitatively similar to (i) removing controls; (ii) the use of a balanced panel (restricting the analysis to observations for which data cover the whole period 1930-2010); (iii) weighting observations by baseline population; (iv) changing treatment and control groups bandwidths; (v) removing portions of the city; (vi) changing clustering; (vii) alternative empirical design; (viii) the use of Callaway and Sant'Anna (2020) semi-parametric difference-in-differences estimator. In addition, below, I report the results of a set of IV regressions aimed at specifically targeting the potential non-random selection of locations into the treatment group. The estimated effects are quantitatively similar to the event-study results.

Robustness exercises are described in detail in Appendix B and are summarized here. First, I report the results for both changes in the share of Black residents and residential population without controls and show that the results remain quantitatively the same. Second, I restrict the analysis to a balanced panel of 760 observations each period. Since the time span covers the entire period between 1930 and 2010, the data exists back to 1930 for these census tracts. They cover the portion of the City of Chicago enumerated at the time and correspond to the most historical sites. The results go in the same direction. Third, to ensure that my results are not driven by low-populated and non-representative census tracts, I weigh observations by population density at baseline. The results remain strong.

Fourth, I show that the results do not significantly vary with the choice of the bandwidth that assigns census tracts to either the treatment or the control group. In my baseline specification, I conservatively account for the possibility of spatial spillovers between treated and control units by leaving a buffer of 2 km between the treated observations (whose centroid is within 1 km from the closest expressway) and those of the control group (with centroid farther than 3 km away from the nearest expressway). The choice gave me almost equally sized groups (388 and 454 observations at baseline, respectively), but at the cost of losing around 40% of the sample units (i.e., those whose centroid is located between 1 and 3 km from the expressway). Nevertheless, Appendix B shows that the results are robust to different definitions of treated and control units. When I compare spatially closer groups (especially when I allow the control group to be at a shorter distance from the expressway), the estimated coefficients are attenuated but still highly significant. In comparison, these results indicate that my empirical design captures well the effect of expressways on neighborhoods' racial composition and changes in demographics.

Fifth, I provide additional evidence that the main results are not driven by certain areas that underwent notable changes during this period. I restrict the analysis to the area within the boundaries of the City of Chicago only and show that the results remain virtually unchanged. Results remain strong also after removing the area that historically hosts the vast majority of the Black population (i.e., the so-called Black Belt). The treatment effects are not driven by these locations. For completeness, I also report the results, including the areas where the big public housing projects were developed. To account for potential spillover effects in neighboring areas around these public housing projects, I run robustness checks where I remove census tracts within a certain radius (500 meters, 1 km) from a public housing project. In all cases, results do not change.

Sixth, I report the results for different, conservative clustering approaches to account for spatial correlation in the errors. For the sample within the boundaries of the city of Chicago, I show that the results remain mostly strong after partitioning the city into 25 equally sized cells (of 6x6 km) and clustering the standard errors at this small grid cell level. As an additional exercise, I also cluster standard errors at the broad region level (even though this leads to just three clusters: north, west, and south side of Chicago) and show that the estimates remain strongly statistically different from zero. For the full sample, including the metropolitan area, I cluster standard errors after partitioning the city into 60 equally sized cells of 8x8 km each. The standard errors become larger, but the main results stay strong.

Seventh, I further exploit the (negative) relation between the share of Black residents and the distance to the expressway by running a distance-based regression categorizing the continuous variable that measures the distance to the closest expressway into five roughly equally-sized distance grid cells (Appendix B.3). I find that for both the City of Chicago and the suburban areas subsamples, the share of Black residents is decreasing in the distance to the expressway. In the city, the share of Black residents increases by an average of between 33.5 and 9.6 p.p. (from the closest to the farthest bin) relative to suburban areas farther than 4 km from the closest expressway. In the suburbs, the magnitudes are smaller, but the negative relation between the share of Black residents and the distance from the expressway still emerges (Figure B31).

Finally, I show that the estimated causal effects of expressway proximity on outcomes remain robust to the use of the Callaway and Sant'Anna (2020) difference-in-differences estimator (Appendix B.4). Like the estimator developed by de Chaisemartin and D'Haultfoeuille (2020), the estimator produces unbiased estimates when there are multiple time periods and variation in treatment timing. In two-by-two designs, it estimates group-specific average treatment effects for all groups across all periods, imposing a weaker parallel trend assumption.

4.2.1 IV results

The identification assumption from estimating regression (1) above is that without expressways, census tracts would have evolved similarly in the control and treatment groups, conditional on controls. Under this assumption, the β coefficients capture any deviations from a parallel evolution in the outcomes between the treatment and control groups due to the expressways' rollout.

The richness of temporal data in my empirical setting allows testing for the presence of pre-trends in the evolution of the outcome variable between treated and untreated units before treatment – thus providing evidence in support of the parallel trends assumption.

Nevertheless, here, I specifically address the possibly non-random selection of locations into the treatment group by running IV regressions and show that the results remain comparable across specifications. In Appendix B.5, I report the IV results using static instruments widely used in the literature for the assignment of transportation improvements within cities that plausibly satisfy the exclusion restriction (Redding and Turner, 2015).

Various instrumental variables for expressways' routes can be used in this setting. On the one hand, the development of a straight-line instrument. Instruments of this type exploit the fact that the policy set at the national level intended to connect the country and not to facilitate metropolitan area development (Baum-Snow, 2007). The instrument is constructed as straight lines connecting Chicago to the cities targeted by the 1947 Interstate Highway System plan. It isolates variation in the location of expressways due to the fact that expressways are long-distance road infrastructures built with the primary purpose of connecting cities targeted by the national plan. As a result, the locations receiving the expressway are those that happened to lie in the directions of the targeted cities connected to Chicago. On the other hand, another suitable set of instruments uses historical routes. I use proximity to the 1898 railroad network as an instrument for the current location of expressways. In this case, identification relies on the concern that historical routes are unlikely to be correlated with current changes to neighborhood characteristics. At the same time, the instrument's relevance is achieved by considering that expressways tend to follow the lines of pre-existing railroads because of cheaper rights of way. Finally, unique to this context is the use of proximity to routes shown in the 1909 Burnham Plan as an instrument for proximity to an actual expressway. The plan was developed before the Great Migration and is hence uncorrelated with more recent changes in neighborhood demographics.

The IV results are reported in Appendix B.5. In the preferred specification that uses all available instruments together (column 6), every extra km away from the closest expressway is associated with a reduction in the share of Black residents of -0.04 p.p., all else equal. The results are quantitatively similar to the event study results.[37] The IV estimates are slightly larger in magnitude than the corresponding OLS estimates in the static 2x2 design (reported for comparison in the same table), implying that the observed changes in neighborhood composition in areas close to the expressways

[37] The average distance from the closest expressway in the control group of the event study (census tracts with centroid further than 3 km from the closest expressway) is 5.3 km, whereas the average distance in the treatment group (tracts within 1 km from the closest expressway) is 0.5 km. As a result, the average difference in the share of Black residents between treated and control group locations from the IV estimates is equal to $(5.3 - 0.5) * 0.04 = 0.192$, i.e., 19.2 p.p. higher on average (the baseline event study specification reports an average treatment effect of 15.7 p.p.).

are somewhat understated. Larger IV estimates suggest that expressways were generally allocated to growing neighborhoods, hence producing more severe effects, and not to declining neighborhoods (a result also found in Brinkman and Lin, 2022). These results alleviate the negative selection concern of expressway placement. They do not seem to have been targeted primarily towards locations expected to decline.

4.3 Effects by wave of expressway construction

A concern may, in principle, regard the non-random timing of expressways' construction – that is, whether the decision of which segments to build first dictates local factors. However, two considerations suggest that this potential issue likely does not pose a serious concern here: (i) data is available at a temporal frequency of 10 years from the censuses (hence, selection concerns only apply over larger time horizons); (ii) 97% of the eventually treated units in the sample were connected to the expressway network within two consecutive census waves only (i.e., with only one decade running between these two treatment groups). It is also worth mentioning that all expressways close to the center were connected in the first two decades (see Figure 1). Only a few suburban ring routes are of the more recent period (built between 1971 and 2010).

Since virtually all treated units enter into treatment either in 1960 or 1970 (jointly corresponding to 97% of the treated units), I also run leads and lags regressions for each group separately. This specification allows us to estimate the average treatment effect of proximity to the expressways in each census year by treatment group. By analyzing the average treatment effects for each group separately, I allow the treatment effects to vary depending on the period of construction of the roads.

The results are reported in Appendix B.6. To increase precision, observations are weighted by population density at baseline. Figure B36 panels (a) and (b) plot the estimated average treatment effects on the share of Black residents for units treated in 1960 relative to never treated (control group) and units treated in 1970 relative to never treated units, respectively. As one may observe, the impact of proximity to expressways on outcomes differs between units treated in 1960 and those treated in 1970, a degree of heterogeneity masked in the event study results.

In census tracts treated in 1960, on average, the share of Black residents increased by around seven p.p., relative to 1940 levels, already in the decade before expressways opened to traffic, suggesting changes in the demographic composition of the impacted neighborhoods took place to some extent during the construction phase. The share of Black residents kept increasing in those neighborhoods: in 1960, the share of Black residents in treated units was more than 20 p.p. higher than in 1940, and it reached a stable 40 p.p. increase in the following years. By looking at Appendix Figure B37 panel (a), the population in census tracts treated in 1960 systematically dropped relative to pre-expressway periods but with no anticipation effect. The previous results suggest that non-Black residents tended to leave the neighborhoods designated to receive the expressways. On average, their place was fully occupied by incoming Black residents.

Figures from 1970 depict a different story. The results show that the share of Black residents decreased consistently following expressway construction, mildly already during the construction phase – by four p.p. on average already in 1960. The drop in the share of Black residents is accompanied by a decline in the residential population that fell by more than 700 (corresponding to 19% of the full sample mean) already in 1960, the decade before expressways were in operation. These results are consistent with the findings presented in Brinkman and Lin (2022), which shows that since the mid-1960s, expressways tended to be increasingly located in Black neighborhoods, and in Carter (2023) study of Detroit.

The evidence suggests that in 1970, expressways were more likely to pass through densely populated areas (causing some degree of displacement), and they disproportionately targeted Black neighborhoods. Expressways built in 1960 instead did not seem to have had an analogous effect: the total population dropped, but only after expressways were in operation, not before. The results are consistent with the fact that expressways created local disamenities, making nearby places less attractive to live in. The consistent drop is also indicative of the increasing deterioration of these neighborhoods. Results show that expressways have a persistent and reinforcing effect on the valuation of nearby neighborhoods – and, in turn, on the residential population.

4.4 Additional evidence

The Appendix B.7 reports a number of additional results that are summarized here.

First, I document the 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 the control group locations. The number of housing units kept declining in the decades following expressway construction, reaching a stable reduction of around -600 units (corresponding to 44.6% of the full sample mean). While part of this drop is likely to be mechanically driven by the fact that expressways occupy space in the city, the fact that the numbers kept decreasing suggests lower investments in those locations relative to comparable areas further away from expressways.

To further corroborate that the decline in residential population can be ascribed to diminishing quality of life in affected neighborhoods and, in turn, to a reduction in the valuation of nearby locations, I present evidence of the effects of proximity to the expressway on house value and land value.[38] In addition, to better understand compositional neighborhoods' dynamics, I look at the effect of expressways on college share. This set of additional results is in line with what is found in Brinkman and Lin (2022).

Figure B42 plots the estimated β coefficients of the regression using average house value (real terms) as the outcome of interest. The results show that in the first decade after expressways were open to traffic, (self-reported) house values remained stable to the pre-expressways period. However, one decade later, house value goes down by an average of -$24,072.40 (s.e. 4,871.94), corresponding to 16.25% of the full sample mean. The graph also seems to show a mean reversion in the latest decades, so the average treatment effect is estimated to equal -$14,359.72 (s.e. 4,627.94). When looking at the raw means between eventually treated and never treated units (Figure B43), separately for the suburbs and the central areas, the reversion in the trend observed in the event study specification

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

seems to be driven by the 2000 housing bubble and the consequent subprime mortgage crisis. House values dramatically dropped between 2000 and 2010 census records, and more so among control group units (both in the center and the suburban area).

Figure B44 plots the estimated β coefficients for land value. Because Olcott's land value data only covers the most central part of the Chicago Metropolitan Area, the analysis is restricted to the geographic extent of the City of Chicago for which information is available. The results are quite noisy. In general, it seems that locations that receive the expressway were on an increasing trend in land value, completely offset after expressways were in operation. On average (albeit suggestively), land value drops by around 0.2 log points in the first decades into treatment before becoming indistinguishable from zero from decade four onward. Also, in this case, the estimated coefficients seem to exhibit a mean reversion, starting already by decade two after treatment. By looking at raw means between eventually treated and never treated units (Figure B45), the mean reversion in the latest periods seems to be driven by the housing boom (and potentially to gentrifying central neighborhoods).

I finally explore the effect of expressway construction on neighborhoods' demographics using the share of college graduates as the outcome of interest. I consider college share as a proxy for income, a self-reported variable included in the census records only starting in 1950.[39] The results are reported in Figure B46. The average treatment effect of expressways on the share of college graduates corresponds to a reduction of -0.03 p.p. (s.e. 0.01), equivalent to 17.6% of the full sample mean. Similar to the results on house value, the effect is strongly negative, starting only in the second decade into treatment.

4.5 Discussion of the disamenity effect of expressways

The first empirical design of the paper isolates the dynamic impact of proximity to expressways on racial segregation and neighborhoods' valuation. Running multi-period difference-in-differences specifications, using de Chaisemartin and D'Haultfoeuille (2020) two-way fixed effects estimator, I show that, on average, expressways are associated with an increase of around 15 p.p. in the share of Black residents living in nearby neighborhoods in the first decade of treatment and an average of 20 p.p. increase in the following decades. The effect of expressways on within-city racial sorting is persistent: more prolonged exposure to expressways causes a permanent increase in the share of Black residents living in the affected areas. Consistent with the idea that expressways create a negative shock to residential amenities, I also find that the residential population permanently drops in nearby affected places in the post-expressways period. On average, affected areas lose approximately 30% of the full sample population mean in the post-treatment period. I also find that neighborhoods closer to expressways tend to experience lower house value, land value, and college share (as a proxy for income).

I conclude the section by briefly addressing several remaining confounding factors. On the one hand, part of the drop in residential population (and in the number of housing units) that follows

[39] The two measures are highly correlated, with a sample correlation of 0.77. Besides being available already since 1940, college share is also less likely to be affected by measurement error. Appendix Figure A10 plots binned scatterplots of their relationship.

expressway construction is likely due to the physical space needed to construct these roads. In Appendix B.8, I compare the change in outcome in locations treated early as opposed to treated at a later stage, with the idea that these places should be roughly comparable to one another in the process undergoing construction. The persistent and increasing reduction in the residential population of affected neighborhoods cannot be explained by the need to make space alone. On the other hand, the decrease in population (and housing units), especially in central areas, may be due to increased demand for commercial space by firms. This concern is addressed in Brinkman and Lin (2022). Using travel surveys conducted in Chicago (1956-2000) and in Detroit (1953-1994), they overall find "little evidence that central freeways caused local negative effects [on population growth] by attracting jobs."

5 Barrier effect of expressways

In this section, I examine the presence of a barrier effect of expressways. I define as barrier effect the increase in the cost of crossing an expressway. These higher costs affect the degree of accessibility of different parts of the city, characterized by different racial distributions. To the extent that expressways create within-city barriers, I test whether neighborhoods become racially more similar to the areas they are 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 the (racial) divergence between areas that lie on opposite sides of the road while increasing the similarity between neighborhoods on the same side. In an ideal experiment, within each pair of census tracts cut by an expressway, the one that experiences the largest increase in exposure to Black residents should hence become increasingly more Black over time, relative to the census tract located on the opposite side of the road. The identification assumption required to causally estimate the barrier effect of expressways is that in the absence of expressways, census tracts located on one side would have evolved similarly to the respective census tract on the opposite side of the road within each pair of census tracts.

I leverage the intuition behind this example 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 the neighborhoods in Chicago. Places that experience the largest increase in exposure to Black residents are expected to become more Black over time.

To measure the change in exposure to Black residents, I compute a novel metric of accessibility, which is a location-specific weighted average of the share of Black residents living in each neighborhood – where the weights are a decreasing function of the bilateral travel time between each origin location and all the other neighborhoods in the city. The weights depend on the development of the underlying road network (in particular, with the construction of expressways in the city), and higher weights are placed in locations that are more easily accessible (at shorter distances). As a result, this summary measure captures, for each origin neighborhood, the change in the degree of exposure to Black residents over time induced both by the sorting of people and by changes in transportation infrastructure that affect how accessible the other neighborhoods in the city are.

The estimating equation in first differences is the following:

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

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); $\Delta S_i = \sum_{j \neq i} e^{-\rho \tau_{ij\,post}} share\,Black_{j\,post} - \sum_{j \neq i} e^{-\rho \tau_{ij\,pre}} share\,Black_{j\,pre}$ measures the change in exposure to Black residents induced by both sorting and by changes in the transportation infrastructure; $Dist.\,expressway$ measures the (km) distance between the centroid of each census tract and the closest expressway;[40] city side fixed effects for being in the north, west, or south of the city are always included. Baseline standard controls are added sequentially, as stated below each table, to partially control for changes in observables that might be correlated with neighborhood dynamics. Standard errors are clustered at the census tract level unless indicated differently.[41]

A concern with estimating regression (2) above is that the variable that measures the change in exposure to Black residents (ΔS) is likely correlated with unobserved shocks to neighborhoods' residential amenities that are 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.[42] I hence instrument for the change in exposure to Black residents holding the racial composition fixed to the baseline period. The instrument isolates variation in exposure to Black residents that is only due to changes in the 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 $\rho = 0.019$ as the estimated elasticity of consumption travel cost with travel times from Miyauchi et al. (2022) – the most pertinent estimate in this context. To isolate the barrier effect, I also set the cost of crossing the expressway network to infinity. As a result, I only capture changes in exposure within neighborhoods located on the same side of the expressway, helping identify the barrier effect. In the Appendix, I also report two series of additional results where I increase the value of the parameter ρ and set it in such a way that the weights used to compute the change in exposure to Black residents become virtually zero at a distance of 10 and 20 km ($\rho = 0.167$ and $\rho = 0.083$, respectively). The resulting exposure measures can hence be considered iso-areas, i.e., network-based versions of buffers. The local exposure measure is the weighted average of the racial composition of neighborhoods within a certain distance (10 or 20 km, depending on the measure) from the origin location when traveling on the road network.

[40] Based on the previous reduced-form results, this variable holds fixed 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 closest expressway and change in exposure to Black areas is -0.28.

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

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

Figure 4 panel (a) and (b), respectively, show the change in exposure to Black residents (ΔS) and the instrumental variable (ΔSMA). Census tracts are grouped into deciles based on the value of the respective variable, with darker colors indicating larger increases in value. As we may observe, on the one hand, there is a large independent variation with distance from the expressway network. On the other hand, both variables show a high degree of spatial correlation, which reflects an unequal distribution of races on different sides of the city – with the IV displaying the highest values in the south of the city and the lowest values in the north.

To address the concern that the IV may be capturing features that are spatially clustered within the city, I perform the following checks. First, I always include region-fixed effects, which imply that the identifying variation always comes within the city's north, west, and south sides. Second, I add a control variable that captures the change in exposure to rich neighborhoods in the city. It is computed as the weighted average of the share of college graduates that live in each location (to proxy for neighborhoods' income levels), similar to the measure of exposure to Black residents.[43] The inclusion of this variable aims to control that changes in neighborhoods' accessibility might affect not only the level of exposure to Black residents in the city but also a location's accessibility to different sets of residential amenities (e.g., parks or restaurants). Finally, as mentioned above, I replicate the results using more localized values of exposure (namely, setting the weights so that locations on the road network further than 10 or 20 km from each origin location effectively receive close to zero weights). These local levels of exposure are indeed less spatially correlated, as can be seen from the maps plotted at the beginning of Sections C.5 (using a 20 km cutoff) and C.6 (10 km cutoff) in Appendix C.

5.1 Results

Table 1 reports the estimated coefficients of interest from regression (2) where the outcome variable is the change in the share of Black residents. Region-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 change in the (standardized) share of Black households living in the origin neighborhood. The estimated coefficient is large and significant at the 1% level: a one sd increase in exposure to Black residents is associated with an average 0.496 sd increase in the share of Black households living in the neighborhood. In column (2), I add a regressor of distance to the closest expressway (in km). The estimated coefficient of exposure to Black residents remains stable.

Columns (3) to (5) sequentially add more and more controls to partially control for changes in observables that might correlate to changes in neighborhoods' composition. In column (3), I control for basic census tract level controls: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to the water. In the next column, I extend the set of controls to capture historical conditions.[44] In column (5) I also add a control for the change in exposure to rich areas in

[43]The weights are the same that I used to compute the metric of exposure to Black residents.

[44]The complete set of historical controls includes distance to railroads in 1898, HOLC grade, historical outcomes in level,

the city (ΔY).[45] The point estimate remains largely stable after the inclusion of additional controls. The estimated coefficient of distance to the expressway shows a strong and negative relation between the share of Black residents living in the neighborhood and distance to the road: the share of Black residents drops by around 0.2 sd for every extra kilometer distance from the expressway, on average, holding all else fixed.

In columns (8) to (11), I instrument for the change in exposure to Black residents holding the distribution of races within the city fixed to the pre-period. The estimated coefficient of ΔS captures what is predicted to happen if exposure to other parts of the city changes over time and all other neighborhoods in the city do not change their racial composition. The type of variation that the instrument isolates can be considered the immediate effect of placing an uncrossable barrier in the city before residents update their location decisions. The estimated coefficient remains large and statistically significant at the 1% level ($\beta = 0.158$). The point estimate dropped because the OLS was largely inflated by sorting effects. In column (11), I additionally instrument for the change in exposure to rich neighborhoods in the city with an instrumental variable (ΔYMA) that is constructed similarly to ΔSMA.[46] Both the point estimates of the change in exposure to Black residents and the point estimate of the distance to the expressway remain stable and highly statistically different from zero. These results also suggest a high degree of independent variation between the computed measure of the accessibility of the neighborhoods and the distance from the road, as the maps show. The estimated coefficient of the change in exposure to rich areas of the city (ΔY) is not statistically different from zero in the estimated regressions.

Next, Table 2 reports the estimated coefficients from regression (2), where the outcome variable is the change in land value (as a proxy for the change in the valuation of neighborhoods) between 1950 and 1990. On average, an increase in exposure to Black residents reduces the land value by around 0.3 sd (s.e. 0.051) in the regression with the full sets of controls of column (5). After accounting for the sorting effects, the results remain largely stable in the IV specifications, though smaller in magnitudes (around -0.25 in column 11). The results also show that the estimated coefficient of distance to the expressway is, on average, positive, though only statistically different from zero in the IV specifications. Point estimates above zero are in line with the disamenity effect of the roads.

To summarize, the main takeaways from this estimation exercise are the following. First, a neighborhood's higher exposure to Black residents in the city on average increases the likelihood that the neighborhood becomes more Black over time, and it decreases its valuation in the long run (as proxied by changes in land value). Second, changes in the degree of exposure to rich areas in the city do not seem to affect the racial composition of the neighborhood – controlling for distance to the expressway and changes in exposure to Black residents. Third, both the disamenity and the barrier effect of expressways seem to impact the racial distribution of races in the city strongly. Land value

and the change in population density between 1920 and 1940. Since the extent of the city was smaller at the beginning of the sample period, the inclusion of historical controls results in the sample size falling from 764 to 727 observations.

[45]Similarly 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.

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

appears to respond more strongly to changes in neighborhood composition induced by the barrier than to the disamenity of being in its proximity.

5.1.1 Long-difference results over time

Here, I report the results of the long-difference regressions run between 1950 and 1980 and between 1950 and 2000. One limitation in conducting these exercises is that I do not have complete snapshots over time of the road network in use, but I only observe the road network as of 2019 for the post-period and the road network as of 1940 for the pre-period. As a result, the weights used to compute the change in exposure to Black areas in the city are the same as those used in the baseline specification, but the changes in sorting and outcomes reflect the changing dynamics over time. Despite the limitation, this additional set of results helps understand neighborhood dynamics and possibly the degree of persistence of the results.

Results are reported in Sections C.3 and C.4 in the Appendix C. On average, the estimated barrier effects of expressways remain quantitatively similar. Despite the magnitudes of the estimated coefficients not being directly comparable to one another, since they are estimated from different regressions, the relative importance of the regressors on neighborhoods' demographics appears to hold across periods. The exposure to Black areas and the distance from expressways are relevant determinants of changes in the neighborhood's racial composition and their valuation. Over time, there is a decline in the relative importance of proximity to expressways relative to the exposure to Black measure on both changes in Black share and land value.

5.2 Robustness checks

I report a number of robustness checks. First, I allow for arbitrary spatial correlation of the errors across census tracts that are within the same grid cell or within a certain distance from each other. Second, I restrict the sample to include only census tracts that at the beginning of the century had fewer than 20% share Black residents (95% of the data) to address the concern that a few historically highly Black neighborhoods might drive the results. Third, I rerun the same analysis, keeping only census tracts further than 5 km from the central business district (this exercise removes 12% of the data). The results are robust to all these alternatives. Fourth, in Appendix C, I report the results for more localized exposure measures and show that the main takeaways still hold. Finally, I provide additional evidence using house value and college share as 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 described below. Columns (6) and (7) report the results of the specification with the full set of controls, allowing for some degree of spatial correlation of errors across observations. Columns (6) display the standard errors, assuming that the census tracts within the same grid cell are spatially correlated (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 between tracts within 3 km of each other (results remain similar at different cutoff values, e.g., 5, 10 km cutoffs). The point estimates of interest remain highly statistically different from zero.

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

Columns (10) report the estimated coefficients after removing 12% of the census tracts in the original sample within 5 km of the central business district. The exercise aims to partially control the gentrification process in the downtown areas – and, more generally, to show that the results are not driven by central areas alone, which might have undergone recent redevelopments. The results become slightly stronger in the regression with the share of Black residents as the outcome, consistent with the idea that gentrification might indeed affect the racial composition of neighborhoods in the city center. Similarly, the results on land value become stronger in absolute terms, showing that gentrification might partly offset the negative neighborhood effects.

The Appendix Sections C.5 and C.6 report the 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 the change in the regressor of interest (ΔS) and the IV. In all cases, the maps show a higher degree of spatial variation than those plotting the change in the variables used in the primary analysis. This is because the weights to compute 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 higher degree of spatial variation alleviates the concern that both the IV and the endogenous regressor might capture some unobserved characteristics shared between units clustered in the same geographic area, which might affect neighborhood dynamics. At the same time, however, these variables are more likely to suffer from bias resulting from local unobservable characteristics. When looking at the OLS columns, we see an even higher correlation between the measure of exposure to Black and the change in the share of Black residents living in the neighborhood. In the OLS specifications, a one sd increase in exposure to Black residents is associated with a high 0.8 sd increase in outcome, on average, across specifications. Comparing these results to the even larger point estimates when looking at a 10 km cutoff, it seems that the racial composition of nearby neighborhoods highly affects the racial mix of the area itself. At the same time, it is reassuring to observe that when sorting is held fixed to the pre-expressway period, the point estimates largely drop and become closer to the values observed in the baseline specification.[47] The estimated effects of the instrumented change in exposure to Black residents induced by the construction of expressways using a 20 or 10-km cutoff on land value are qualitatively in line with the main results. The point estimates from the IV regression in the last column become however strongly attenuated after instrumenting for the change in exposure to rich areas in the city.

Finally, in Appendix C.7, I estimate the barrier effect on two additional outcomes (house value

[47]The estimated coefficients after instrumenting for the change in exposure to Black neighborhoods drop to around 0.2-0.3 sd.

and college share), considered proxies for changes in the relative valuation of the neighborhoods. In both tables, the results show that house value and college share respond strongly to changes in the exposure to rich areas in the city but are unaffected by changes in exposure to Black areas once the change in exposure to rich neighborhoods is controlled for.

5.3 Discussion of the barrier effect of expressways

The second empirical design evaluates the barrier effect of expressways. I define a barrier effect as the increase in the cost of crossing an expressway, which affects the degree of accessibility of different parts of the city, characterized by different racial distributions. To the extent that expressways create within-city barriers, I test whether neighborhoods become racially more similar to the areas they are exposed to once these urban barriers are in place.

I find that higher exposure to Black areas in the city increases the likelihood that a neighborhood becomes more Black over time. The effect is sizable: depending on the specification, a one sd increase in exposure to Black residents is associated with a 0.16-0.20 sd increase (in the IV specifications) in the share of Black residents living in the neighborhood, on average. The results remain stable to the inclusion of a rich set of controls, including distance to the closest expressway and a measure that captures changes in exposure to rich areas in the city. I then estimate the barrier effect of expressways on changes in land value between 1950 and 1990, used as a proxy of changes in neighborhoods' valuation. An increase in exposure to Black residents reduces the land value by 0.24-0.32 sd in the long run. These results also show that taken together, both the disamenity and the barrier effects of expressways affect the racial distribution of races in the city. Land value instead seems to respond more strongly to changes in the neighborhood composition induced by the barrier than to the disamenity of being in its proximity.

6 A quantitative spatial urban model with racial preferences

The theoretical framework follows the canonical Alonso (1964), Muth (1969), and Mills (1967) monocentric city model but with an internal city structure à la Ahlfeldt et al. (2015). I consider a city embedded within a wider economy. The city consists of discrete locations indexed by $j = 1, ..., J$. The time subscript is omitted everywhere, but the following expressions hold in each period. Land K_j can only be allocated to residential use, supplied by a competitive floorspace sector. The city is populated by an endogenous number of residents N^o of one of four types $o \in \{WH, WL, BH, BL\}$ – i.e., two-by-two race (B Black, W white) by educational attainment (H high-educated, L low-educated) categories. 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 or not before observing idiosyncratic utility shocks for each location within the city. If an individual chooses to move to the city, she observes the realization of idiosyncratic utility and chooses the residence location that maximizes her utility. The locations differ in terms of residential amenities, residential land availability, and access to the transport infrastructure, which determines the travel times between locations.

6.1 Preferences

The city is populated by an endogenous measure of residents in each period N^o of either one of four types $o \in \{WH, WL, BH, BL\}$. Individuals' utility consists of residential amenities, a consumption index, and an individual-specific idiosyncratic shock that varies with residence location. This shock captures the idea that individuals may have personal reasons to live in a specific neighborhood.

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

$$U(\omega)_j^o = B_j^o C(\omega)_j^o z(\omega)_j \tag{3}$$

Residential amenities B_j^o capture common features that make a location a more or less desirable place to live.[48] The consumption index $C(\omega)_j^o$ depends on the consumption good $c(\omega)_j^o$ which is chosen as numeraire and residential land $L(\omega)_j^o$.

The consumption index $C(\omega)_j^o$ is assumed to take the Cobb-Douglas form:[49]

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

Individual heterogeneity is modeled as in the 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.[50]

Once the idiosyncratic utility for each residence location is revealed, households choose where to live to maximize their utility, taking residential amenities and prices as given and the location decisions of the other households. Households, hence, sort into the city depending on the characteristics of the locations and their idiosyncratic preference shocks.

I assume that all households supply one unit of labor in the Central Business District (C) 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

[48] By assuming that households' taste for residential amenities varies by education and race, I allow that types may value certain amenities differently.

[49] I the baseline model I assume that all types spend the same share of income on residential floorspace, as captured by the common term α. This assumption could, however, be relaxed, allowing for type-specific expenditure shares.

[50] In principle, I could allow the distributions of the idiosyncratic preferences to be also type specific, in terms of both the average idiosyncratic preferences for the amenities in a given location (the scale parameter T_j) and the variance of the preferences across locations (captured by the shape parameter ϵ). This would result in an additional source of heterogeneity that the model could capture. In particular, depending, for instance, on the difference in the dispersion of the idiosyncratic preferences across types, households may react differently to the same shock to the costs of commuting. The household type with less dispersed idiosyncratic preferences will indeed be less affected by a change in commuting costs on average because the location choices of this group are more sticky. In practice, I assume that the idiosyncratic preference shocks are drawn by the same Fréchet distribution for all types (as common in the literature). Indeed, estimating type-specific shape parameters would require data on type-specific commuting flows, which are often unavailable (including in this setting).

absentee entrepreneurs.[51] Commuting to work is costly and depends on the mode of transportation, which is assumed to vary 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 $\frac{w^o}{d_{jC}^{H,L}}$. $d_{jC}^{H,L} = e^{\kappa \tau_{jC}^{H,L}}$ is the iceberg commuting cost, which increases with the travel time (τ_{jC}) between the location of residence (j) and employment (C).[52] Finally, the parameter κ controls the size of the commuting costs.

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

$$u(\omega)_j^o = \frac{B_j^o w^o R_j^{\alpha-1} z(\omega)_j}{d_{jC}^{H,L}} \tag{6}$$

Given that $z(\omega)_j$ is Fréchet distributed, also the indirect utility follows a Fréchet distribution. As a result, the probability that an individual ω of type o lives in 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 idiosyncratic shocks to preferences, these residential probabilities imply that individuals of a given type choose different residential locations when faced with the same prices or location characteristics. In particular, individuals are more likely to live in location j, the more attractive its residential amenities are (B_j), the higher its average idiosyncratic utility as determined by T_j, the lower the floorspace prices R_j, and the higher the effective wage (or equivalently, the lower the commuting cost $d_{jC}^{H,L}$). It should be noted that the denominator is type-specific but not location-specific: it indeed measures the expected utility of living in the city.

As an illustration, if we take the ratio between the probability that type o lives in j against the probability of type m living in j, we find:

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

That is, a worker of type o is more likely to live in j relative to a worker of type m; the higher her valuation of residential amenities, the higher her effective wage, and the lower the utility she gets

[51] I also assume that firms in the CBD do not occupy any physical space (i.e., land can be only allocated for residential use). These assumptions are necessary since workplace location decisions and land allocation for commercial as opposed to residential use are not observed.

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

from living outside the city. When both types have the same education level, both of the last two terms become constant across locations. This implies that they equally affect the relative probabilities of types o and m of living in each location j. However, since the two types value amenities differently, the relative probability of them living in j depends on the extent of their relative evaluation for amenities in j, captured by the first term on the right-hand side of the expression.

Given that in this setting, the employment location is assumed to be fixed to the CBD, there is no uncertainty concerning the wage that a household receives when choosing to live in location j: the expected worker income conditional on living in j is indeed simply equal to $\mathbb{E}(w^o|j) = w^o$. As a result, effective wage (i.e., net of commuting costs) is higher in residence locations with low commuting costs to the downtown area.

Finally, population mobility for each type implies that the expected utility from moving to the city is equal to the reservation level of 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.

Another implication of the distribution of utility being Fréchet is that residence locations with attractive features attract more residents on the extensive margin until the expected utility in each location is equalized. This means high amenities in a location increase the utility of a resident with a given idiosyncratic realization of utility z, thus increasing the expected utility from living in that location. At the same time, high amenities also attract individuals with lower realizations of the idiosyncratic utility z, reducing the expected utility from living in j. With a Fréchet distribution of utility, these two forces cancel each other.

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. I follow a standard approach in the literature and assume that 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 $L_j = M_j^{\mu} K_j^{1-\mu}$ (Combes et al., 2014; Epple et al., 2010; Ahlfeldt et al., 2015). Since the price of capital is the same across locations, the relationship between quantities of floorspace and land can be summarized as $L_j = S(L_j) = \phi_j K_j^{1-\mu}$, where $\phi_j = M_j^{\mu}$ is the density of development (Ahlfeldt et al., 2015).

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

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

where $\bar{W}_j = (1/N_j) \sum_o (w^o / d_{jC}^{H,L}) N_j^o$.

Land market clearing is hence 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

An equilibrium of the model is characterized by the assignment of type-specific residents to neighborhoods and of a vector of floor space prices, such that the land market clears in each location and no individual has the incentive to deviate by moving to a different location. Given the model's parameters $\{\alpha, \epsilon, \kappa, \lambda^o_{B,W}, \rho^o, g^o, \eta, \mu\}$, the vectors of exogenous location characteristics $\{T, B, n, \tau^{H,L}\}$, 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 vectors $\{R_j, \pi^o_j\}$ and by type-specific population scalars N^o.

The following system of nine equations determines the nine elements of the equilibrium vector: population mobility conditions for each type ($\times 4$), the residential choice probability for each type ($\times 4$), and the land market clearing condition. Ahlfeldt et al. (2015) provide proof for the existence and uniqueness of an equilibrium (uniqueness can be established only in the case of exogenous location characteristics). Given the model's parameters, recovered unobserved fundamentals, and starting conditions, I use an iterative procedure to find the equilibrium values of residence and floorspace prices (see Appendix D.3 for details).

7 Estimation

The estimation proceeds in three steps. First, I calibrate the necessary objects (e.g., commuting elasticity, wages).[53] Then, I invert the model in one year to recover overall amenities that perfectly rationalize the observed distribution of population in the city as being an equilibrium of the model. Finally, I use the shock to the urban structure induced by the construction of expressways in the city to estimate the parameters of interest (i.e., racial preferences and disamenity parameters) that best fit the change in the distribution of population within the city (subject to orthogonality conditions).

Before outlining the steps in more detail, I describe the data used for the estimation.

[53]In the urban models where commuting flows are observed in the data, the commuting elasticity can be estimated from a gravity equation of commuting flows, derived from the household's probability of living and working in different neighborhoods in the city. Exploiting the recursive structure of the model, location-specific wages, usually difficult to observe systematically, are recovered by solving the labor market clearing conditions in one period and obtaining inverted wages (generally up to a transformation).

7.1 Data

Three sets of data are required for the quantitative analysis of the model: residence by type, the price of floor space, and the traveling times between locations. I collect this information for Chicago for the periods before and after expressways were built (around the 1940 and 1990 census periods).

For neighborhood demographics, the two primary sources of data are the 1934 Special Census of Chicago and the 1990 Census of Population and Housing.[54] Differently from the censuses administered around those years, the 1934 census of Chicago reports census-tract-level information on race by educational attainment. Hence, employing this data source offers a significant advantage by providing reliable granular information on educational attainment by race before expressways were built. I then classify individuals according to their race (Black versus the residual category of non-Black) and education level (above versus below the city-wide median level in each period).[55] Normalizing the data consistently to 2010 census-tract boundaries, the information is available for the 791 census tracts that cover the city of Chicago.

I complement this information with the 1940 and 1990 land value data from Olcott's Land Value Blue Book (available thanks to the works of Ahlfeldt and McMillen 2014; 2018). I keep only census tracts with non-missing land information, which leads to a final sample of 767 observations.[56]

Finally, I compute commuting times between each pair of locations in the sample. I rely on the 1940 road transportation network, available from the Urban Transition HGIS Project (Shertzer et al., 2016)[57] and on the contemporaneous road transportation network from the US Census Bureau. Travel times are measured in minutes based on the transportation network available in each period. I assume average travel speeds for each mode of transport. I allow travel times to differ between low and high-educated individuals by assigning them different modes of transport.[58]

7.2 Step 1: Calibrate commuting elasticity and wages

From the commuting choice probability (the equivalent of the residential choice probability (7) introduced here, if both residence and workplace location choices were observed), it would be possible to recover the commuting elasticity in a gravity equation framework.[59] In this setting, however, "workplace location" is not observed and is hence assumed to be the same for each individual (corresponding to the central business district). As a result, the vector of distances from residence location to workplace location (d_{jC}) varies at the origin level only – it is multicollinear to origin fixed effects. In turn, the commuting elasticity cannot be consistently estimated in a gravity-type framework. As

[54] The 1934 census was conducted by the Chicago Census Commission (and not the US Census Bureau) to know (as reported by the then Major 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).

[55] In 1934, the median educational attainment level corresponds to completing grades 5-8. In 1990, it corresponds to completing high school.

[56] The 1990 sample consists of 766 observations, because of the redevelopment in the 1960s of the Midway Airport, located in one of the central census tracts.

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

[58] I consider highly educated individuals to move only by car in both periods. Low-educated individuals move exclusively by bus in 1940. In 1990, they are assumed to move by bus with 0.75 probability and by car with 0.25 probability. Further details are reported in Appendix D.1.1.

[59] The estimation follows from regressing commute flows on commute times and origin and destination fixed effects.

a result, I calibrate the commuting elasticity from the relevant literature. I set the Fréchet parameter to $\epsilon = 6$, corresponding to the central value found in the literature (Miyauchi et al., 2022), 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 (like in Ahlfeldt et al., 2015), (unobserved) workplace-specific wages are recovered by exploiting the recursive structure of the model after estimating the commuting elasticity. Using the resulting model's parameters and data, wages can be obtained from the commuting market clearing condition.[60] Lacking information that would allow me to recover wages, I calibrate them using the information at the national level each period, adjusted for the distribution of race by educational attainment observed in the city.[61]

7.3 Step 2: Recover overall amenities

From the expression of the residential choice probabilities (7), after multiplying both sides by the city's total number of residents of type o (N^o), and considering that $\pi_j^o N^o = N_j^o$, I get:

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

Since T_j enters the model isomorphically (and it cannot be separately identified from the overall residential amenities in the data), I define the following composite variable $\tilde{B}_j^o = T_j^{\frac{1}{\epsilon}} B_j^o$. 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 known values of the model's parameters $\{\alpha, \epsilon, \kappa\}$ and the observed data $\{R, N_j^o, \tau^{H,L}\}$. That is, there is a unique mapping between the model parameters and the observed data to the overall residential location characteristics (up to a normalization). Dividing N_j^o by its geometric mean on both sides and noticing that all constant terms cancel out, I get:[62]

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

[60]The commuting market clearing condition ensures that the total number of workers in a location equals the number of commuting residents that choose to work in that location and commute from every residence location.

[61]The calibrated wages in the pre-period ($2010) are as follows: $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, I find ($2010): $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 on the full procedure and data sources, see Appendix D.1.2.

[62]Denote the geometric mean of a variable X by $\bar{X}$, then: $\bar{X} = (\Pi_{s=1}^{S} X_s)^{\frac{1}{s}}$. It should be noted that the geometric mean of a product equals the product of the geometric means of its terms. Following Ahlfeldt et al. (2015), I choose the unit in which to measure adjusted residential amenities such that the geometric mean of adjusted residential amenities is equal to 1, i.e. $\bar{\tilde{B}}_j^o = (\Pi \tilde{B}_s^o)^{1/S} = 1$ for each type o.

Inverting the system, I hence find an expression of overall residential amenities only as a function of data, model's parameters, and calibrated values:

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

The maps plotting the distribution of recovered overall amenities by type (the left-hand side of equation 15) after inverting the model in each period are reported in Appendix D.2. Darker colors correspond to higher amenity levels.

Total recovered amenities consist of both an exogenous part (that depends on the physical attributes of the place) and an endogenous part (that depends on sorting and residential choices), as described in more detail below. As a result, they appear to be higher in proximity to the shore and lower in the vicinity of industrial corridors. At the same time, there is a high degree of heterogeneity both over time and between races, showing a polarization of the white population towards the northern neighborhoods by 1990 and the Black population favoring locations in the south.[63]

7.4 Step 3: Structural estimation

Before outlining the procedure to structurally estimate the parameters of interest, I allow total residential amenities to depend on residential fundamentals, the disamenity of expressways, and the demographic composition of the neighborhoods. First, residential fundamentals ($\tilde{b}_j^o$) capture features of the physical geography that make a location a more or less attractive place to live (e.g., the presence of green areas or proximity to the shore). Second, residential amenities are affected by proximity to the expressways. Following Brinkman and Lin (2022), I assume that the disamenity of expressways is a function of distance to the road. It is modeled as follows:

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

where $dist_j$ is the distance to the closest expressway; the parameter g^o governs the size of the disamenity, and η its spatial attenuation.[64]

Third, I capture residential externalities imposing structure on how the amenities in a given location are affected by the demographic characteristics of the other locations. Specifically, I model racial preferences as follows:

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

Residential externalities are hence modeled as a power function of distance-weighted exposures to

[63] For instance, in 1940, amenities were high for white high-educated residents along most of the southern shore, but by 1990 only the area that constitutes the campus of the University of Chicago is deemed as high-amenity location for this group.

[64] Note that g^o is type specific, but η is fixed, since it governs the rate at which expressway disamenities (like pollution and noise) decay in space – which depends on environmental factors.

Black and white residents living in every other neighborhood in the city, weighted by a function of the traveling times between locations. ρ^o captures the rate of spatial decay at which racial preferences matter, whereas $\lambda^o_{B,W}$ are the elasticities of amenities with respect to the concentration of nearby Black and white residents.

Finally, I include a term that captures local spillovers as a function of the share of adults with above-median education.[65] The term is intended to capture the value of the endogenous amenities that correlate with higher income (proxied by higher educational attainment), like safety, quality of schools, and the general level of public good provision. It is modeled as follows:

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

As a result, overall adjusted amenities consist of:

$$\tilde{B}^o_j = \tilde{b}^o_j H_j E^o_j \Omega^o_j \tag{19}$$

Together with equation (15), I get:

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

where the term on the left-hand side corresponds to location fundamentals (structural residuals of the model). As it is clear from the above expression, they are a function of data and model parameters only. I can then solve for these structural residuals for the entire city before and after the shock induced by expressways. I denote the change over time by Δ. Following Ahlfeldt et al. (2015), I further assume that these structural residuals consist of both a time-invariant fixed component ($\tilde{b}^{oF}_j$) and a time-varying stochastic shock ($\tilde{b}^{oV}_j$). With a first difference estimator, the time-invariant fixed effects are differenced out so that after taking logs of both sides (and making now time explicit with the subscript t), I get:

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

These structural residuals correspond to double-difference adjusted residential fundamentals: the first difference is before-after (over time), whereas the second difference is across locations within the city, and it is reflected in the normalization relative to the geometric mean, computed by dividing each term by the geometric mean of the variable in each period before taking logs. This second difference eliminates fixed effects that are common across locations within each period (like the reservation level of utility). Normalizing relative to the geometric mean is also advantageous in that this second difference ensures that the results are invariant to the choice of the units in which residential

[65] Fogli and Guerrieri (2019) propose the share of college graduates. In this setting, I use the share of adults with above median education since it is an endogenous variable of the model.

fundamentals are measured (since the choice is common to all units within one time period). By construction, it hence follows that the mean changes in (log) residential fundamentals are equal to zero.

The parameters of interest are, on the one hand, the ones governing the disamenity of expressways $\{g^o\}$ and, on the other hand, the ones governing racial preferences $\{\lambda^o_{B,W}, \rho^o\}$.

7.4.1 Moment conditions

To estimate the parameters of interest, I use analogous sources of variation as the ones employed in the reduced form analyses. The first set of moment conditions imposes that the changes in adjusted residential fundamentals in (21) are uncorrelated with the exogenous change in exposure to Black areas in the city induced by the construction of urban barriers. Similar to the reduced form results, I capture the exogenous change in the exposure to Black areas as follows. I compute distance grid cells from the centroid of the area with a historically high concentration of African Americans (the so-called Black Belt), interacted with whether or not the location is separated from the Black Belt by the presence of an expressway. The second set of moment conditions, used to isolate the disamenity parameters, imposes orthogonality conditions between changes in adjusted residential fundamentals and distance to the road. I further interact them with distance grid cells from the CBD to capture the idea that locations closer to the CBD tend to be more severely affected by proximity to expressways since the access benefits are lower. The two sets of moment conditions are as follows:

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

where $\mathbb{I}bb_k$ for $k \in \{1, ..., K_{\mathbb{I}bb}\}$ are indicator variables for distance grid cell k from the centroid of the Black Belt; $\mathbb{I}Barrier$ is an indicator for whether or not there is an expressway separating the location from the Black Belt; $\mathbb{I}cbd_{k'}$ for $k' \in \{1, ..., K'_{\mathbb{I}cbd}\}$ are indicator variables for distance grid cell k' from the CBD; $\mathbb{I}exp_{k''}$ are indicator variables for distance to the expressway network. I use 20 indicator variables based on percentiles of distance to the Black Belt; four indicator variables for distance to the CBD, and three for distance to the expressways.[66]

Following the construction of expressways in the city, residential patterns may change. These changes can happen for two reasons. On the one hand, the forces captured in the model. For instance, since expressways increase the effective distance between locations situated on opposite sides of the road, following the reduced-form results, we may expect neighborhood demographics to change in response. On the other hand, residential fundamentals may change over time for reasons unrelated to the construction of expressways in the city. The moment conditions impose restrictions on how residential fundamentals can change – i.e., changes should be mean zero in each distance bin interaction.

[66]The choice responds to the trade-off between increasing precision and the risk of picking up noise in the data.

7.4.2 Identification

I use the Generalized Method of Moments (GMM) with the moment conditions above to estimate the parameters of interest. Additional details on the procedure are reported in Appendix D.4. Those moment conditions can be used to identify the model's unknown parameters and, simultaneously, to recover the unobserved residential fundamentals (structural residuals). Equation (20) shows closed-form solutions for the structural residuals: they are only functions of the model's parameters and observed data. In principle, the moment conditions need not uniquely identify the model's parameters – there could be multiple local minima that correspond to different combinations of the unknown parameters and structural residuals that are consistent with the observed data. The objective function, however, appears to be well-behaved in the parameter space.[67]

Even though the construction of expressways in Chicago is a single shock, the framework allows separately identifying type-specific racial preferences and disamenity parameters. Overall adjusted amenities can indeed be recovered from the observed data using the equilibrium conditions of the model separately for each type (equation 15). It then remains to separately identify, for each type, the racial preference parameters and the disamenity parameter. The racial preference parameters could be estimated from a regression of changes in total amenities on changes in residential externalities (racial preferences), instrumenting for changes in residential externalities with the road-based change in exposure to Black areas in the city interacted with distance grid cells from the Black Belt. The disamenity parameter could be estimated from a regression of changes in total amenities on changes in the quality of life of the neighborhoods, instrumenting for the change in the quality of life of neighborhoods with distance from the closest expressway interacted with indicator variables for distance grid cells from the CBD (to separate the relative importance of access benefits as opposed to the disamenity). The GMM estimator operates similarly to these IV regressions but allows one to jointly estimate all the parameters of interest in the same system.

Because of the mechanics of the model, any change in residential amenities that is not explained by changes in the composition of neighborhoods (through local spillovers and/or residential externalities) and disamenity effects will be explained by changes in adjusted residential fundamentals. For instance, let's assume that in reality, racial preference elasticities are high for each type (i.e., white people prefer to live close to other white people, Black people choose to live close to other Black people), but I pick wrong (lower) values of these parameters. Then, all else equal, the model will predict high residential fundamentals for Black (white) residents in places with a high concentration of Black (respectively, white) population. Since the demographic composition of neighborhoods changes over time, the model will infer that these changes are due to changes in residential fundamentals (of each type) rather than the underlying racial preferences. Comparing the estimates between the pre-period and the post-period will look as if residential fundamentals have moved as well, together with the relevant population, likely resulting in some of the above moment conditions being different from

[67] Instead of plotting the results of a grid search over the parameter space – that would be difficult to interpret given the dimensionality of the objective function – I randomly choose the starting values of the iteration procedure and check whether it converges to the same parameter space. It does so in the vast majority of cases (100% for white, 90% for Black). See Appendix D.4.2 for details.

zero.

In Appendix D.4, I explore the sensitivity of the estimated parameters to the orthogonality conditions following Andrews et al. (2017). The parameters are generally sensitive to all moments in a similar way. The sensitivity measure of the decay parameter ρ is relatively similar in magnitude across moments. The parameter appears quite sensitive to the moments associated with being on the outskirts of the city (those related to longer distances from the Black Belt and the CBD), which could be due to the fact that the estimation does not take into account all the areas surrounding these locations (since they are outside of the city boundaries). The sensitivity measure of the parameter estimating the rate of spatial decay of the disamenity g is mostly sensitive to the set of moments related to distance to the expressways. The racial elasticity parameters $\lambda_{B,W}$ in general are similarly sensitive to all the moments.

7.4.3 GMM estimation results

Table 3 reports the efficient GMM estimation results. I find large and statistically significant racial preferences and disamenity parameters. To better understand how to interpret the estimated results and their magnitudes, I discuss them in order below.

First, the racial preference parameters show large heterogeneity by type, particularly when comparing Black and white individuals. The estimates are consistent with high degrees of homophily, with both Black and white residents exhibiting higher preferences for living close to same-race neighbors. Residential externalities appear to be an important agglomeration force, particularly in relation to the concentration of same-race residents in the vicinity. For white individuals, the estimated elasticity of amenities with respect to the concentration of nearby residents is notably higher for same-race neighbors compared to different-race neighbors: 3.3 times larger for white low-educated individuals and six times as large for white high-educated individuals. Conversely, estimates for Black residents align with substantial agglomeration forces linked to the density of same-race residents nearby while suggesting congestion forces concerning the density of white residents in the surrounding locations.

Second, residential externalities are highly localized and appear more localized for Black households than for white households. The rate of spatial decay of racial preferences is equal to 0.674 (s.e. 0.181) for low-educated Black individuals and 0.747 (s.e. 0.167) for high-educated Black individuals. For low-educated white residents, it equals 0.229 (s.e. 0.047) and 0.291 (s.e. 0.048) for high-educated white residents. The average value of the rate of spatial decay of racial preferences, weighted by the population shares, is $\rho_{whgt} = 0.342$.[68] To give a sense of the magnitudes, other things equal, residential externalities for Black residents fall to zero after around ten minutes of travel time, whereas for white residents after approximately 20 minutes of travel time. Figure 5 reports the proportional reductions in residential externalities with travel time (Table D3 in Appendix D show the same results

[68] To the best of my knowledge, this is the first estimate of this sort, making it difficult to benchmark its value. Nevertheless, it is reassuring to observe that it falls within the range of the most pertinent estimates found in the literature. On the one hand, the residential externalities parameter is equal to 0.76 in Ahlfeldt et al. (2015). On the other hand, the elasticity of consumption travel cost with travel times is estimated at 0.019 in Miyauchi et al. (2022).

but in comparison with the model-implied reduction in utility stemming from higher commuting times).

Third, the size of the disamenity, on average, appears larger for white residents than for Black residents, consistent with the reduced-form results. Black residents attach on average 22.0% inferior amenities to neighborhoods in proximity to expressways, whereas white residents 23.9% inferior amenities to the same neighborhoods (attenuating by 95% at 3.8 km from the expressway), comparable to the values recently found in the literature.[69]

7.4.4 Over-identification checks

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

First, I start with the number of housing units. In the structural estimation, I recover a measure of the adjusted density of development (the ratio of residential floor space to land area) – a structural residual that ensures that the demand for floor space equals the supply of floorspace in each location.[70] To the extent that the density of development should be higher in dense residential locations, I investigate how it correlates with the reported number of housing units from the census. I find a positive relation (sample correlation of 0.698 in 1940 and 0.318 in 1990) between the (model-derived) density of development measure and the number of housing units reported from the census of the relevant year (both variables expressed in logs). Regression results are reported in the top panel of Table D4 in Appendix D.4. On average, a 1% increase in the number of housing units corresponds to a 0.765% increase in the density of development measure in 1940 and a 0.518% increase in 1990.

Second, I use information about zoning regulations today and check how the density of development measure correlates with the share of land for residential use in each location. The density of development (the model-derived ratio of residential floor space to land area) can be larger than 1 (which is possible with multistory buildings), but in the data, I can only compute the share of land allowed for residential use (as opposed for instance to commercial and industrial use, or for parks and open spaces). I find a strong and positive log-linear relationship (sample correlation 0.462 in 1990) between (log) ϕ and the share of land for residential use (zoning data).[71] Regression results are reported in the bottom panel of Table D4. Overall, the strength of the results presented in the table provides support for the model's predictions. I find that a 1% increase in the share of land for residential use is associated, on average, with a 0.018% increase in the density of development.

[69] Brinkman and Lin (2022) finds freeway neighborhoods having 18.4% lower amenities.

[70] Figure D9 in Appendix D.4 reports the maps of the deciles of the distribution of this structural residual in 1940 and in 1990. It is reassuring to observe that the two distributions are similar over time.

[71] This second over-identification check is computed exclusively for 1990 because I have access to zoning information covering only the present period.

7.5 Counterfactual exercises

I then use the model to run a set of counterfactual exercises. They consist of assuming alternative values of location characteristics or model parameters and solving for the model's counterfactual equilibrium. First, I begin by using counterfactuals to provide further evidence of the model's fit. I analyze the extent to which the effects of the construction of expressways on neighborhood demographics can be explained by the endogenous forces of the model rather than by changes in location fundamentals over time. Second, I run a counterfactual where I set racial preferences to zero. Third, I examine the relative importance of the disamenity as opposed to the barrier effects of expressways by shutting them down one at a time.

In the first counterfactual, I test the model's fit. I simulate the shock induced by the construction of expressways using the estimated parameters, but holding location fundamentals $\{\tilde{b}_j^o, \phi_j\}$ (i.e., residential fundamentals and density of development) fixed to the pre-period. As standard, I use the values of the endogenous variables from the observed equilibrium (in 1990) as the initial guess for the counterfactual equilibrium. I also set the reservation level of utility in the wider economy in the post-period so that the total population (for each type) living in the city is equal to its value in 1990. The correlation between the distribution of the share of Black in 1990 (data) and its counterfactual value is 0.815. The model thus can explain well the observed changes in neighborhoods' demographics (the binned scatter plot of the two variables is reported in Figure D10 in Appendix D).[72]

The counterfactual treatment effects on racial sorting for the remaining counterfactual exercises are reported in Figure 6. It plots the distribution of population in Chicago by neighborhood racial composition. The two counterfactual distributions are reported against the observed equilibrium in 1990 (yellow dots). In 1990, Chicago was largely segregated: 50% of the total population in the city lived in neighborhoods that were at most 10% Black, and 30% of the population lived in neighborhoods that were 90% or more Black.

In a counterfactual exercise, I study the implications of removing the 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 amenities with respect to the concentration of one's own race.[73] 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. I find that the counterfactual population of Chicago lives in more integrated neighborhoods. The share of individuals living in neighborhoods with 90% or more Black shares drops to around 5%, and the share of residents living in a neighborhood with at most a 10% Black share drops from 50% to less than 300%. The population appears more evenly distributed across all neighborhood configurations.

I then conduct an additional counterfactual exercise to analyze the implications of mitigating the neighborhood effects of expressways. I investigate the counterfactual treatment effects of simultaneously removing (i) the disamenity ($g^o = 0$) and (ii) the barrier effect of expressways. To set the

[72] By looking at plot, the model predicts well the distribution of races in Chicago following the construction of expressways. It slightly underestimates the share of Black living in highly Black locations, implying that, for these locations, the change in residential fundamentals must be high (see Figure D10 in Appendix D).

[73] For Black types (both high and low educated), I set $\lambda_W^* = \lambda_B$; for white high and low educated types, I set $\lambda_B^* = \lambda_W$ (where the asterisk denotes the counterfactual value).

barrier effect of expressways to zero, I follow Brinkman and Lin (2022). I define pairwise travel time as $\tau_{ji} = \tau^*_{ji} + c_{ji}$ where τ^*_{ji} is the travel time in the absence of the expressway and c_{ji} is the extra cost of crossing after the urban barrier is built. From their estimates, I calibrate $c_{ji} = 2$ minutes for trips less than 5 km that cross the expressway. Before running the counterfactual, I hence recalculate the matrix of pairwise travel times, setting travel times to 2 minutes faster for trips shorter than 5 km crossing an expressway. I find that the distribution of races in the counterfactual equilibrium is characterized by a drop of 10 percentage points in the share of residents of Chicago living in a neighborhood with 90% or more Black individuals. At the same time, almost 20% of Chicago's population would end up residing in perfectly integrated neighborhoods (those characterized by around 30% Black share) – nearly a seven-fold increase relative to the observed equilibrium.

In addition, removing the disamenity alone leads, on average, to a doubling in the population living within 1 km of the expressway (relative to the observed equilibrium) – offsetting the effects evaluated in the reduced-form analysis – and an average increase of 50% in the population living within 2 km of the expressway, with larger effects closer to the city center.

Finally, I calculate how segregated Chicago would be if we removed the adverse neighborhood effects of expressways (canceling both the disamenity and the barrier effect). The index of dissimilarity from the counterfactual experiment is equal to 0.702.[74] In comparison, it is calculated at 0.844 in the observed equilibrium, meaning that in 1990, 84% of Black residents would have had to change location with white residents to achieve full spatial integration in the city. Mitigating the neighborhood effects of expressways is associated with a reduction of 16.8% in racial segregation in Chicago.

8 Conclusion

This paper deepens our understanding of the role of urban structures and urban forms in shaping the allocation of people within cities. Although 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 this link, providing a setting and an empirical strategy to plausibly make causal estimates of the relationship.

I provide evidence of the importance of the dual nature of expressways in evaluating their impact on racial sorting. First, similar to a policy that creates within-city shocks to residential amenities and hence makes neighborhoods more or less desirable places to live, the impact of expressways operates through a price or disamenity channel. Since Black households are, on average, poorer than white households, they are more likely to live closer to the expressways because of cheap housing. Second, expressways are physical barriers that affect the degree of exposure to the neighborhoods in the city and, hence, to different demographic compositions. I show 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. This finding suggests that this feature of the expressways provides

[74] First proposed by Duncan and Duncan (1955), the index of dissimilarity is a widely used measure of spatial segregation of different racial groups (for an application, see, for instance, Cutler et al., 1999). It is measured as follows: $D = (1/2) \sum_i | \frac{Black_i}{Black_{total}} - \frac{non-Black_i}{non-Black_{total}} |$.

a second channel of racial sorting, which depends on individual preferences towards more or less integrated places to live in.

Motivated by these findings, I develop a quantitative spatial urban model with racial preferences for residential locations. The setup follows the canonical Alonso (1964), Muth (1969), and Mills (1967) monocentric city model, but it features an internal city structure à la Ahlfeldt et al. (2015). Using the same type of variation of my reduced-form analyses, the model allows me to estimate racial preferences parameters, and then to undertake counterfactual exercises. Mitigating the neighborhood effects of expressways in Chicago would lead to a 16.8% reduction in racial segregation.

The findings shed light on the possible unintended long-lasting neighborhood effects of transportation infrastructure that are pervasive in the landscape of many cities. Future research could tackle the extent to which long-run effects can be ascribed to institutional changes (like modifications to school, police, and administrative boundaries) in response to the construction of urban barriers. In addition, the recent surge in widespread GPS data availability could allow us to explore how urban forms affect the accessibility to different sets of consumption goods and experiences within the city. Given the recent surge in the issue of social justice in the transportation sector, advocated by the Biden administration as one of the main challenges of our time, this research lies in an important space for current public policy.

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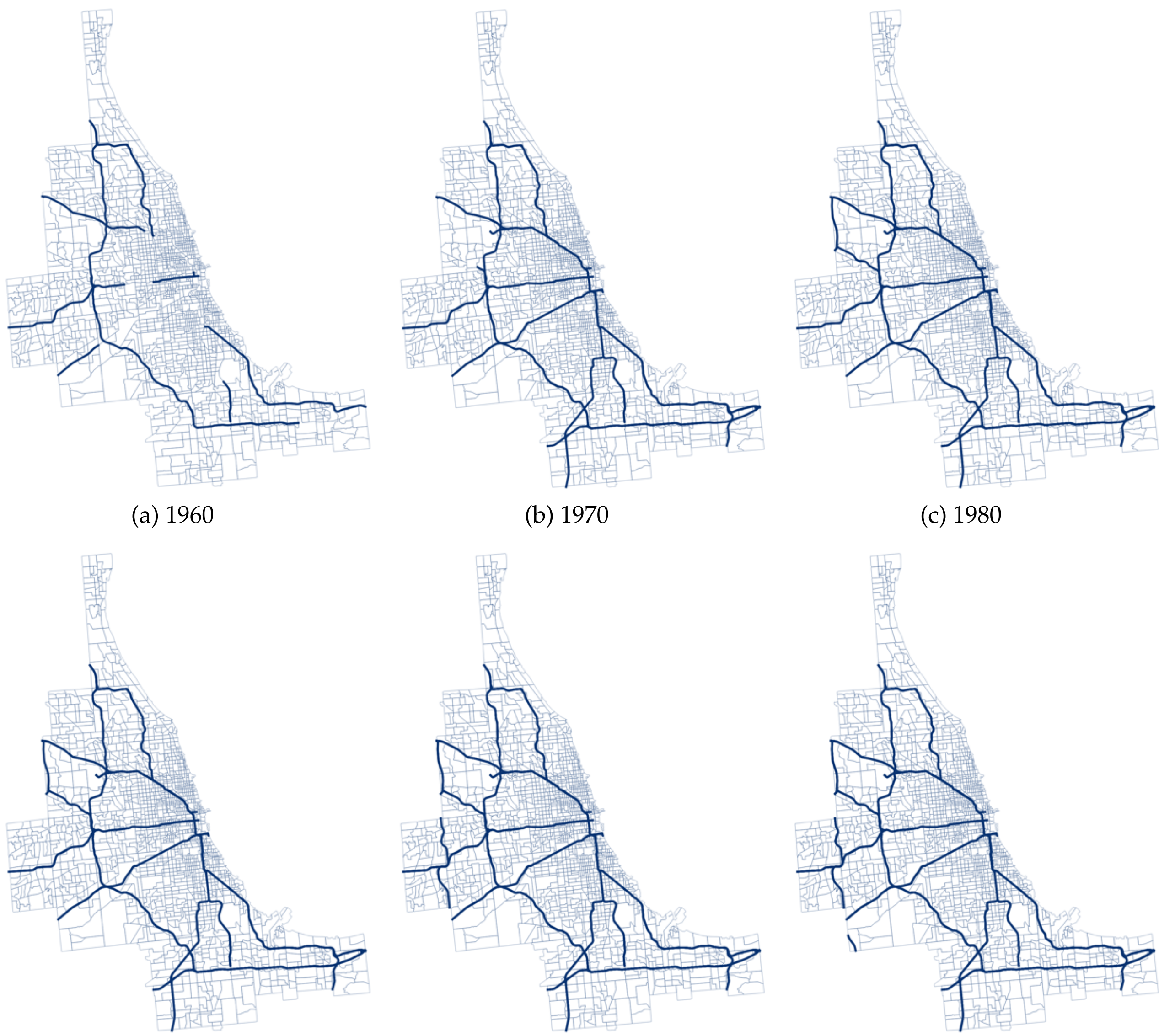
Figures

Figure 1: Timeline of expressway construction, 1950-2010

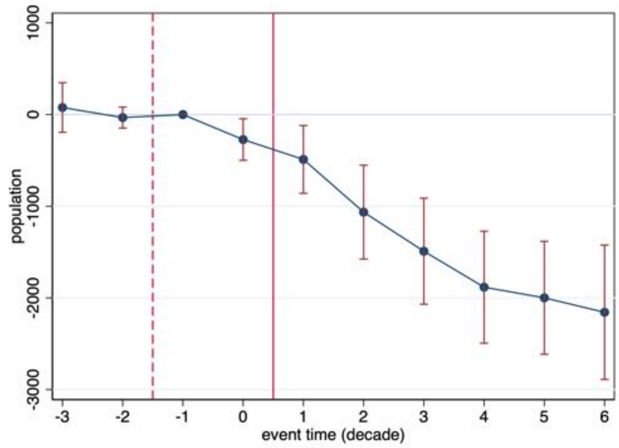


(a) 1960 (b) 1970 (c) 1980

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

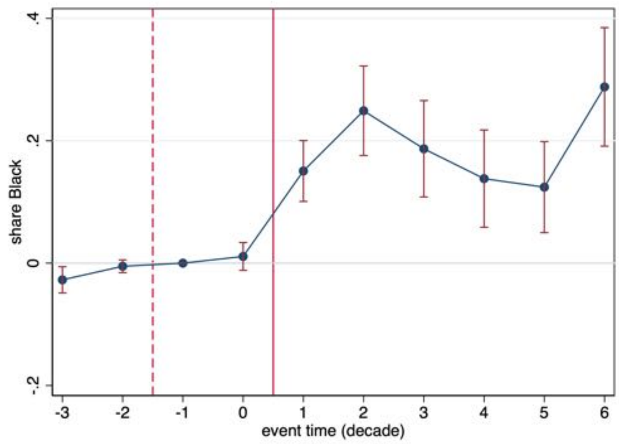
The maps show the rollout of the expressway network within the boundaries of the Chicago Metropolitan Area. The geographic extent of the city is determined by data availability in 1950. Polygons are the 1,511 consistent-boundary census tracts that constitute the units of analysis.

Figure 2: Effect of proximity to expressways on residential population



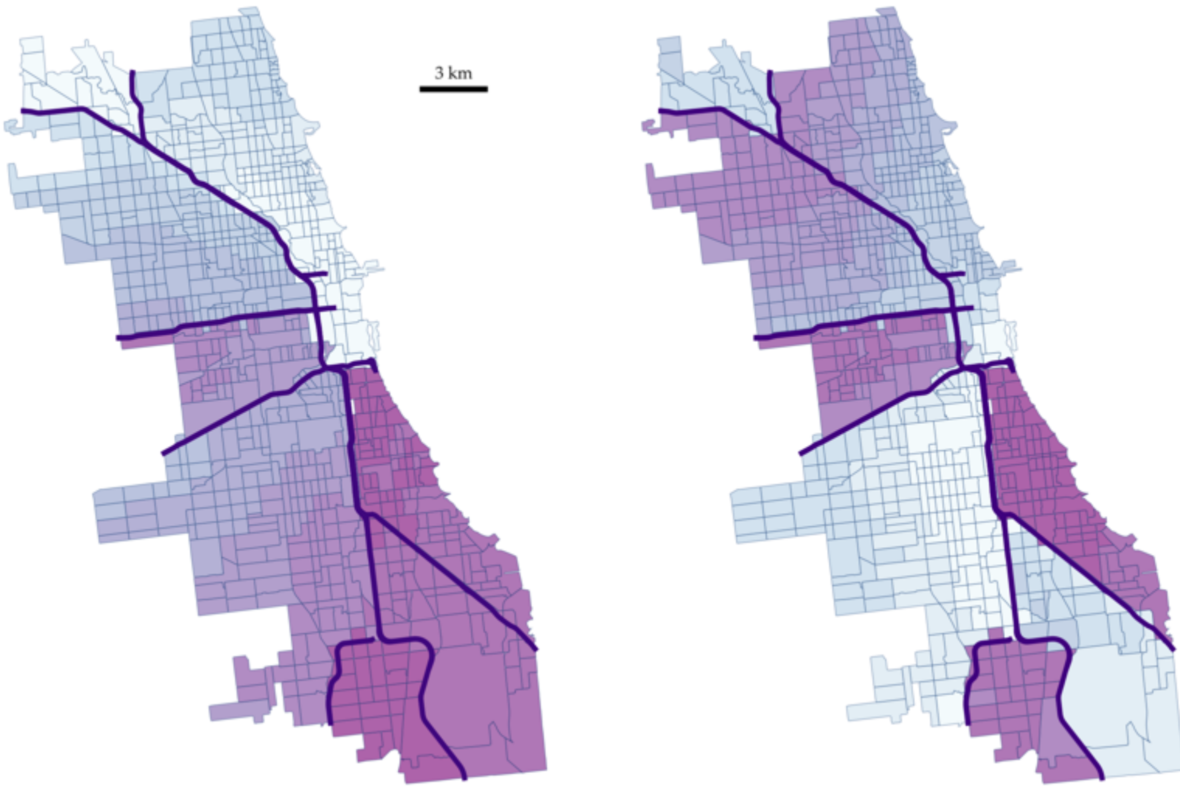
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is residential population. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds to 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

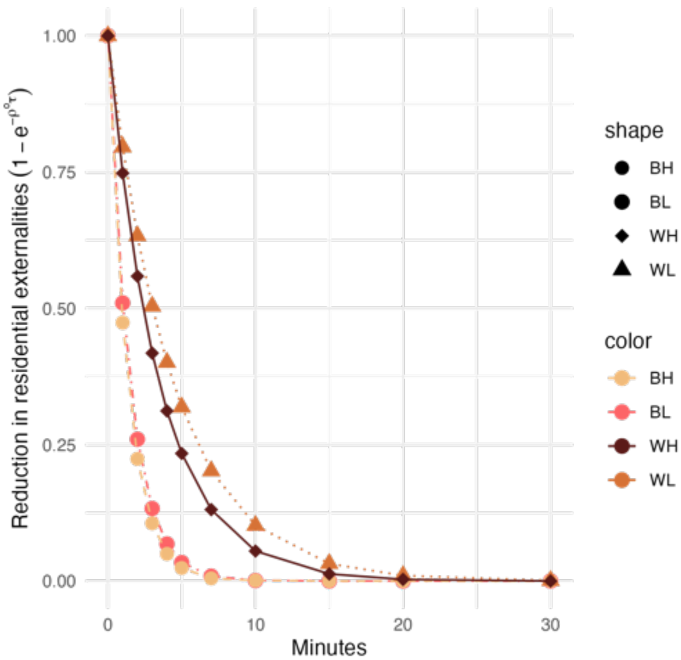


(a) Change in exposure to Black residents (ΔS)

(b) Instrument (ΔSMA)

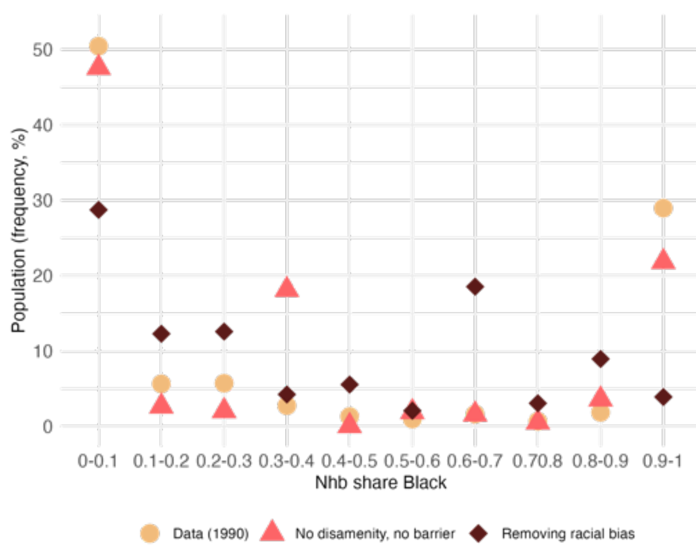
Note: Panel (a) plots the overall change in exposure to Black residents ΔS_i (panel a) and for each neighborhood in the city. The overall change includes both the change in exposure due to the spatial resorting of people between 1950 and 1990 and the change due to the development of the road network. Panel (b) plots the baseline instrument for the change in exposure to Black residents. The instrument isolates the variation that is due only to changes in traveling times through expressway construction. To isolate the barrier effect, I set the costs of crossing the expressway network to infinity. Census tracts are grouped into deciles based on the change in exposure to Black residents, with darker colors indicating larger increases in exposure. The purple lines show the expressways route as of 1990.

Figure 5: Spatial decay of racial preference ρ^o



Note: The figure plots the estimated reductions in residential externalities with travel time (in minutes), $1 - e^{-\rho^o \tau}$ separately for each type. Additional details are reported in Table D3 in Appendix D.

Figure 6: Counterfactual racial distributions



Note: The figure plots the distribution of population in Chicago, by neighborhood racial composition. The counterfactual distributions are reported against the observed equilibrium in 1990 (yellow dots). In 1990, Chicago was largely segregated: 50% of the total population in the city lived in a neighborhood that was at most 10% Black, and 30% of the population lived in a neighborhood that was 90% or more Black. In the two counterfactual scenarios reported here, segregation goes down. Fewer people live in largely segregated neighborhoods, and more people live in mixed neighborhoods.

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

The table reports the estimation results from regression (2) on the change in the share of Black residents. The regressors of interest are: ΔS (standardized) measures the change in exposure to Black areas in the city; *Dist expressway* measures the km distance from the closest expressway; ΔY measures the change in exposure to rich areas in the city. Region FE for being in the north, west, or south side of the city are always included. Tract controls are: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to water. Historical controls include: distance to railroads in 1898; HOLC grade, historical outcomes in levels, and the change in population density between 1920 and 1940. Column (6) shows standard errors assuming that census tract within the same grid cell are spatially correlated (for this exercise, I partitioned the city into 25 squares). Column (7) computes Conley (1999) standard errors to allow arbitrary spatial correlation of errors between tracts within 3 km from each other. Column (8) shows the IV results after instrumenting for the change in exposure to Black residents holding the distribution of races within the city fixed to the pre-period. Column (9) reports the IV results after removing the 5% of the sample that in 1920 already had a large concentration of Black residents (i.e., removes all area with more than 20% share in 1920). Column (10) reports the estimated IV coefficients after removing the 12% of the census tracts in the sample that are within 5 km of the CBD. Column (11) additionally instruments for the change in exposure to rich neighborhoods in the city, with an instrumental variable (ΔYMA) that is constructed similarly to ΔSMA. Supplementary detail is available in the main text. Standard errors clustered at census tract level in parentheses (unless specified differently). *** 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 regressors of interest are: ΔS (standardized) measures the change in exposure to Black areas in the city; *Dist expressway* measures the km distance from the closest expressway; ΔY measures the change in exposure to rich areas in the city. Region FE for being in the north, west, or south side of the city are always included. Tract controls are: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to water. Historical controls include: distance to railroads in 1898; HOLC grade, historical outcomes in levels, and the change in population density between 1920 and 1940. Column (6) shows standard errors assuming that census tract within the same grid cell are spatially correlated (for this exercise, I partitioned the city into 25 squares). Column (7) computes Conley (1999) standard errors to allow arbitrary spatial correlation of errors between tracts within 3 km from each other. Column (8) shows the IV results after instrumenting for the change in exposure to Black residents holding the distribution of races within the city fixed to the pre-period. Column (9) reports the IV results after removing the 5% of the sample that in 1920 already had a large concentration of Black residents (i.e., removes all area with more than 20% share in 1920). Column (10) reports the estimated IV coefficients after removing the 12% of the census tracts in the sample that are within 5 km of the CBD. Column (11) additionally instruments for the change in exposure to rich neighborhoods in the city, with an instrumental variable (ΔYMA) that is constructed similarly to ΔSMA. Supplementary detail is available in the main text. Standard errors clustered at census tract level in parentheses (unless specified differently). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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)

The table reports the GMM estimates. Cluster robust standard errors in parentheses.

Appendix to: "The (Express)Way to Segregation: Evidence from Chicago"

Contents

A Data and sources

A.1 Setting

A.1.1 Highways vs. expressways

Among the various types of highways, I only consider expressways (interstates) due to their distinct physical attributes. Expressways are controlled-access roadways only, which implies that exits and entrances are limited. All traffic merges on or off ramps that connect them to highways, secondary, or tertiary roads. Therefore, any route crosses an expressway only through overpasses or underpasses. Other highways instead do have intersections, even with minor roads. While they can be limited-access roads in some portions of their routes, in most parts they are free-access roads, with private drives exiting and entering it. Figure A1 below shows two portions of the US Highway 41 going through Chicago, with both controlled and uncontrolled rights of way. Most US highways passing through the city have uncontrolled rights of access, including pedestrian crossings (see Figure A2). To avoid the potential endogeneity concern of which portions of US highways are controlled-access roads, which are likely correlated with local unobserved factors, I do not include generic highways in my analyses, despite in some segments their technical features make them pseudo-barriers as well (like the South Lake Shore Drive).

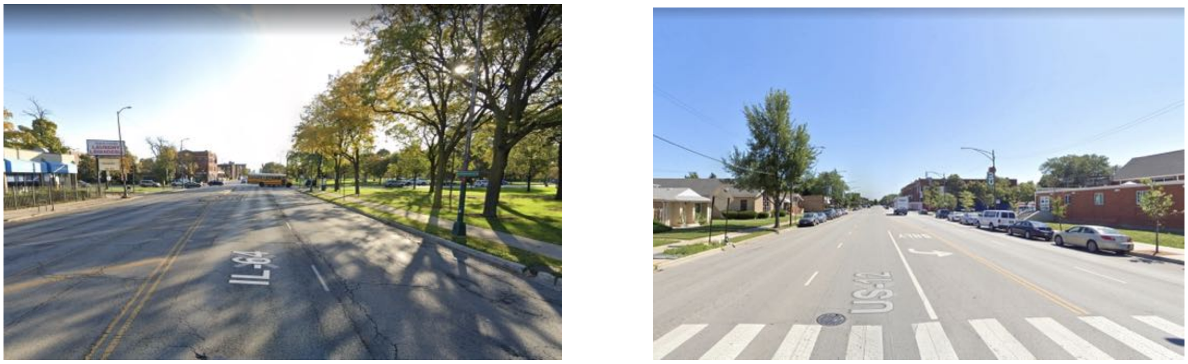
Figure A1: US Highway 41 in Chicago

(a) S. Lake Shore Drive

(b) Chicago North Side

Note: Google Maps street views of two portions of the US Highway 41 within the Chicago Metropolitan Area. Retrieved on August 26, 2021.

Figure A2: Other US Highways in Chicago



(a) Illinois Route 64 (b) US Route 12

Note: Google Maps street views of two portions of the Illinois Route 64 (state highway) in panel (a) and the US Route 12 (east-west US highway) in panel (b), within the Chicago Metropolitan Area. Retrieved on August 26, 2021.

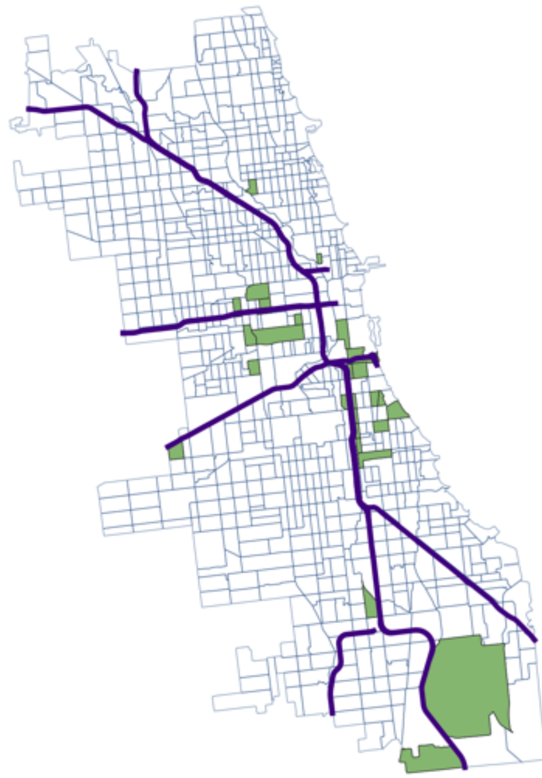
Figure A3: The construction of the Eisenhower Expressway, 1949

Note: Source: The Chicago Tribune.

A.1.2 Public housing

Notorious public housing projects (like the Cabrini-Green or the Taylor Homes) were developed in Chicago by the Chicago Housing Authority as part of its urban renewal process around the mid-20th century. They were large housing developments, consisting of multiple high-rise buildings whose residents over time were nearly all Black. To isolate the neighborhood effects of expressways, I hence remove from the baseline sample the census tracts that hosted such projects (colored in green in Figure A4 below), or larger radii around them in robustness checks. For completeness, I also present the results including public housing neighborhoods. Results remain stable.

Figure A4: Census tracts with public housing projects



Note: The map plots together the 27 census tracts where public housing projects were located and the expressway network. Source of raw data: The Encyclopedia of Chicago.

A.1.3 Community settlement in Chicago

When expressways were laid out, Chicago was populated by a multitude of minority groups that gained importance in terms of size since the late 19th century. In 1890, Chicago was a city of 1 million inhabitants, three-quarters of them either foreign-born or children of the foreign-born (with Irish, Germans, and British being the largest immigrant groups). At that time, only 1% of the population was Black, slowly rising in the next few decades. During the first wave of the Great Migration, between 1910 and 1920, more than 50,000 African Americans moved to Chicago from the rural South attracted by job opportunities – increasing the city-wide share to 4.1%. In the years of the Great Depression, the city experienced a decrease of 20% in the foreign-born population, balanced by a 20% increase in the Black population. World War II further reduced foreign immigration while the share of the Black population kept increasing: in 1944, there were 337,000 Black residents, almost 1 in 10 people.

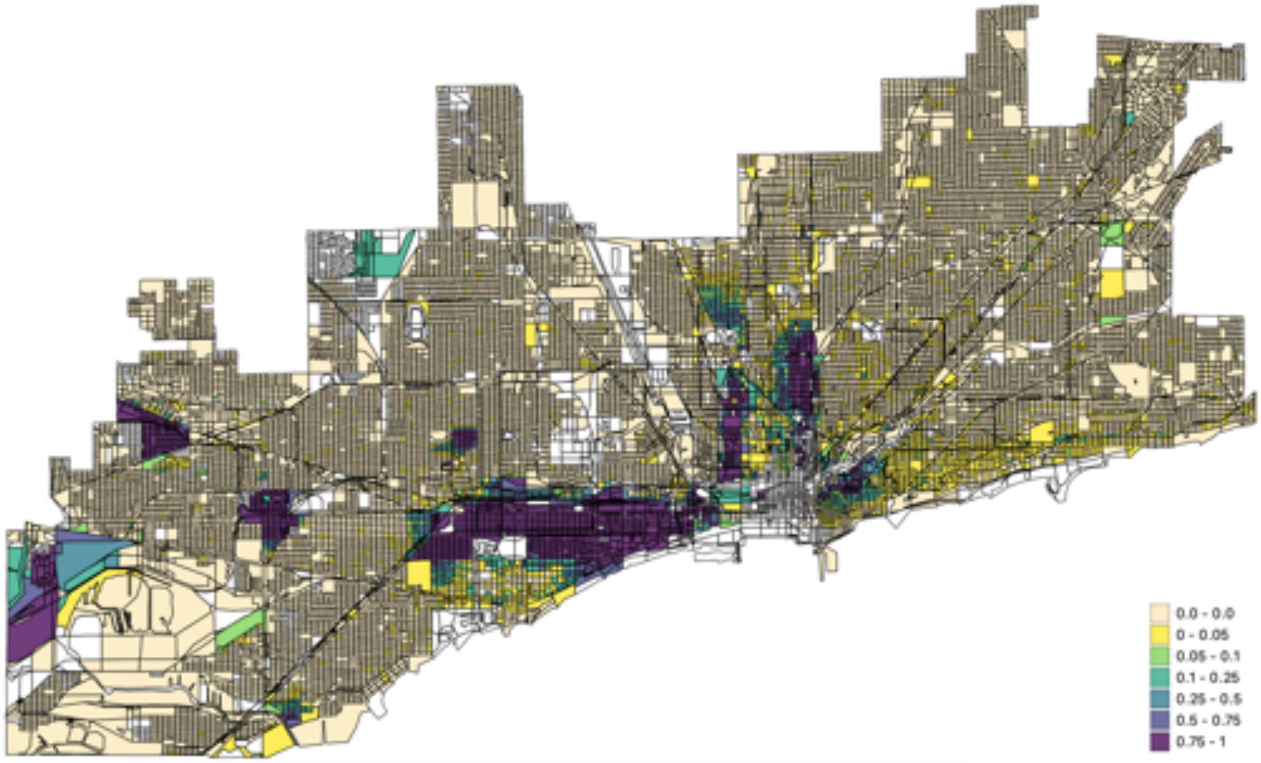
At first, the various groups of immigrants tended to settle in clusters based on common language and national origin. As they assimilated, however, some households moved to more desirable places to live. While the communities of the foreign-born grew smaller, Black neighborhoods assumed increasing importance and the so-called "Black Metropolis" emerged in the south side of the city. In the late 1940s, over 90% of the total Black population living in Chicago was residing there (corresponding to the largest purple area in Figure A5).[75] Hispanic immigration instead grew steadily only in the second half of the 20th century. Before, many workers were only hired temporarily, in occupations and jobs where there was a labor shortage. In 1960, only about 1.5% of the total population in the city of Chicago was Hispanic – mostly Mexicans and Puerto Ricans. In 1970, however, they constituted 7.3% of the total population. The share doubled in the next decade and reached almost 20% in 1990.[76] In population censuses – my primary source of demographic data – Hispanic origin as a racial breakdown appears only after 1970. In the analyses reported in the main text, I only distinguish between Black and non-Black individuals, nevertheless a sufficient categorization when studying the segregation of one minority group from others. Given the data limitation, people of Hispanic origin are, together with other racial minorities, consistently grouped with white.

Below, I report (i) the block-level share of Black residents in 1950 (data and digitization of the 1950 block-boundary map was collected and realized by the author); and (ii) the community settlement map of Chicago in the same year, produced by the Department of Development and Planning of the City of Chicago.

[75] With the vast majority of Black population living in the narrow tongue of land on the South Side, Chicago was a segregated city already before expressways were built, as it can be seen from the figure. Nevertheless, the area was too small to accommodate the growing number of African Americans that migrated to the city. Since then, the Black population has indeed increased threefold and the spatial arrangement of people within the city has dramatically changed.

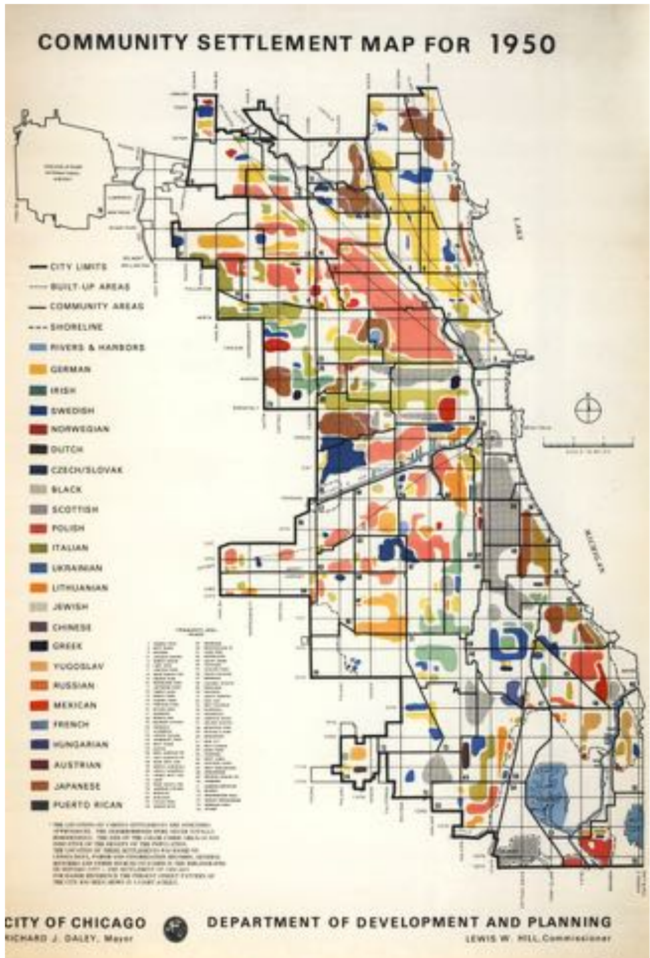
[76] Today, Chicago is one of the most diverse US cities, since its majority races are split in almost equal shares within the city: https://fivethirtyeight.com/features/the-most-diverse-cities-are-often-the-most-segregated/

Figure A5: Block-level share of Black residents in 1950



Note: The figure plots the blocks within the City of Chicago, rotated by 90 degrees clockwise. A census block covers an area of approximately 0.1 sq. km. The heat map shows a snapshot of the block-level share of Black residents in 1950. The original data are from the 1950 US census of housing, block level statistics, normalized to the 1990 block boundaries. The extent of the city corresponds to data availability in 1950. The 1950 boundary blocks were drawn manually from the original books. Blocks in white are those with no data available (i.e., blocks of no residential use or with fewer than three households).

Figure A6: Chicago Community Settlement Map for 1950



Note: The map portrays the settlement of ethnic groups in Chicago as of 1950, as reported by the Department of Development and Planning of the City of Chicago.
Source: https://www.arcgis.com/apps/Cascade/index.html?appid=eb82cf9c0e4f4abeab8f2fa8dd0e7134

A.2 Redlining

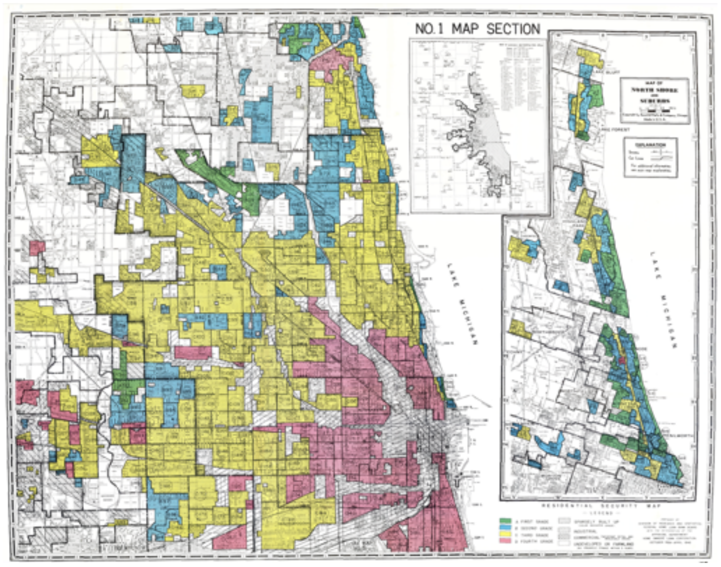
In response to the Great Depression, the federal government created the Home Owners Loan Corporation (HOLC). It was meant to purchase existing mortgages that were subject to imminent foreclosure and then to issue new amortized loans (Rothstein, 2017).[77] To assess the risk of default, the HOLC collected information about the condition of the house and of the surrounding houses in the neighborhood, to see how likely the property would maintain its value. To do so, the HOLC drew maps of every metropolitan area in the country, documenting neighborhood-specific riskiness of mortgage lending. Neighborhoods were classified based on detailed characteristics that were meant to inform of their riskiness: age of housing, occupancy status, quality of the homes, and prices. However, details on the racial and ethnic composition of the neighborhoods were also collected. The

[77] The HOLC itself purchased and refinanced over 1 million troubled non-farm mortgages and by 1936 it held roughly one tenth of all non-farm US mortgages (Fishback et al., 2020).

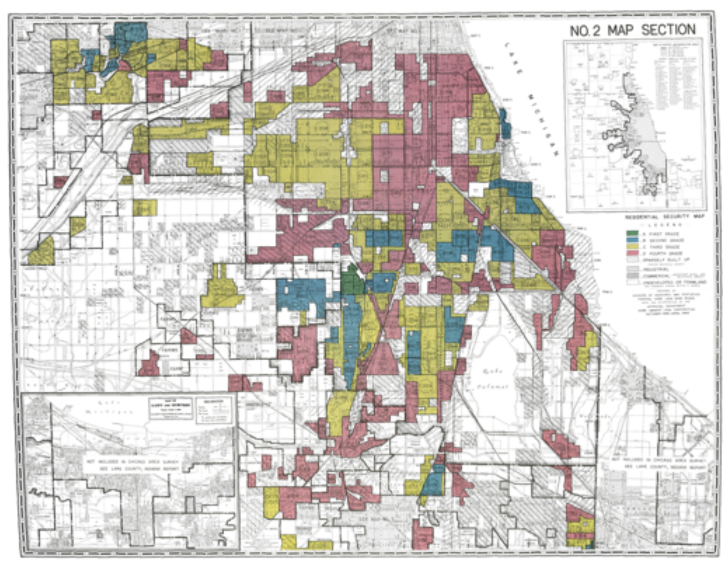
HOLC gave grades A, B, C, and D to neighborhoods with map colors of green, blue, yellow, and red, respectively – with A being the highest grade and D the lowest grade (hence the term "redlining").[78] Despite they were only guidelines and not legal requirements, areas receiving a lower grade have been found to experience worse housing market outcomes with respect to home ownership, house values, and rents – suggesting the presence of persistent disinvestment as a consequence of restricted credit access (Aaronson et al., 2021; Krimmel, 2020).

[78] Figure A7 reports the 1939 redlining map of Chicago, digitized and made available by the University of Richmond, Mapping Inequality Project.

Figure A7: Redlining map of Chicago



(a) North side



(b) South side

Note: These color-coded maps show the grades assigned to residential neighborhoods that reflected their "mortgage security" by the Home Owners' Loan Corporation between 1939 and 1940. Neighborhoods receiving the highest grade of "A" – colored in green – were viewed as minimal risks for banks and mortgage lenders, while those receiving the lowest grade of "D" – colored in red – were considered "hazardous". The maps and the data are from the University of Richmond, Mapping Inequality application: https://dsl.richmond.edu/panorama/redlining

A.3 Transportation noise map

The figure shows a partition of the interactive transportation noise map developed by the Bureau of Transportation Statistics. Used for illustration purposes, it tracks trends in transportation-related noise separately by mode and aggregated, for 2016 and 2018. The figure below shows the average noise isolating the noise that is due to road transportation only, in 2018 for a section of the city of

Chicago.

Figure A8: Road-related noise map, Chicago (2018)

Note: The results reported in the map represent the approximate average noise due to road-transportation sources over a 24 hours period from the receptors and it is expressed in decibels. Source: https://data.bts.gov/stories/s/National-Transportation-Noise-Map/ri89-bhxh

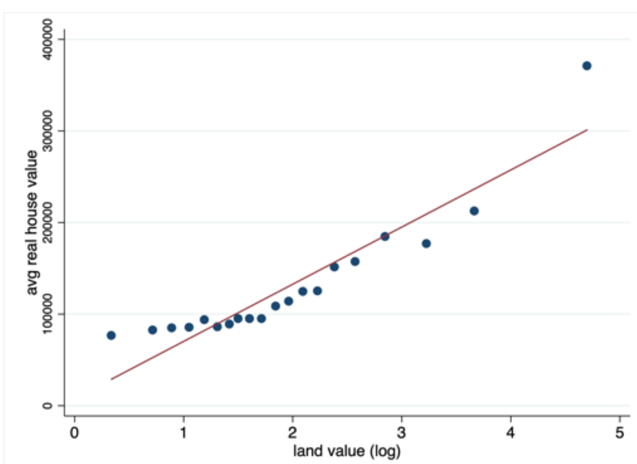
A.4 Additional descriptives

Table A1: 1950 Summary Statistics

	Treatment ($\leq 1km$) N = 388		Control ($> 3km$) N = 454		All N = 1,511		Raw baseline difference	
Variable	Mean	*SD*	Mean	*SD*	Mean	*SD*	Difference	*t*-stat
Land area (sqkm)	2.17	*2.80*	2.20	*3.33*	2.01	*2.81*	0.03	0.16
Pop. density (,000)	6.26	*7.21*	4.63	*5.95*	5.88	*6.82*	-1.64***	-3.56
Share black	0.13	*0.29*	0.02	*0.07*	0.06	*0.20*	-0.11***	-7.13
Dist. 1898 rails (km)	0.86	*1.08*	0.99	*0.99*	0.93	*1.01*	0.12	1.72
Dist. shore (km)	10.48	*9.30*	12.04	*11.01*	11.14	*9.82*	1.56*	2.23
Dist. CBD (km)	18.23	*11.73*	24.54	*14.28*	20.24	*12.63*	6.31***	7.04
N. housing units (,000)	1.09	*0.89*	0.88	*0.75*	1.00	*0.82*	-0.21***	-3.62
Avg. house value (,000)[a]	87.29	*20.74*	102.32	*18.08*	94.71	*20.24*	15.03***	11.06
Land value (log)[a]	1.10	*0.75*	1.47	*0.70*	1.26	*0.72*	0.37***	5.13
College share	0.05	*0.05*	0.10	*0.08*	0.08	*0.07*	0.04***	9.51

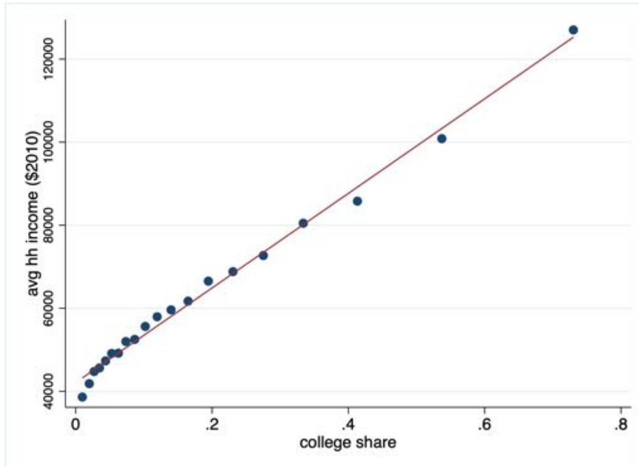
The table reports summary statistics for 1950, separately for census tracts eventually within 1 km from the closest expressway and census tracts further than 3 km away. The two groups correspond to the treatment and control groups in the baseline regression specification, respectively. For reference, the table also reports summary statistics for the full sample in 1950. The last two columns show the raw baseline differences in means between control and eventually treated units. [a]\$2010 dollars. *** p<0.01, ** p<0.05, * p<0.1.

Figure A9: Correlation between house value and land values



Note: The figure shows the relationship between average real value of houses (\$2010) and the logarithm of land real values (\$2010) from a binned scatter-plot. Land value data have been grouped into 20 equal sized bins. Within each bin, the mean of the x-axis and y-axis variables have been computed and plotted. No controls are added. The data are based on the full sample.

Figure A10: Correlation between hh income and college share



Note: The figure shows the relationship between median income ($2010) and share of college graduates from a binned scatter-plot. College share data have been grouped into 20 equal sized bins. Within each bin, the mean of the x-axis and y-axis variables have been computed and plotted. No controls are added. The data are based on the full sample.

B Additional event-study results

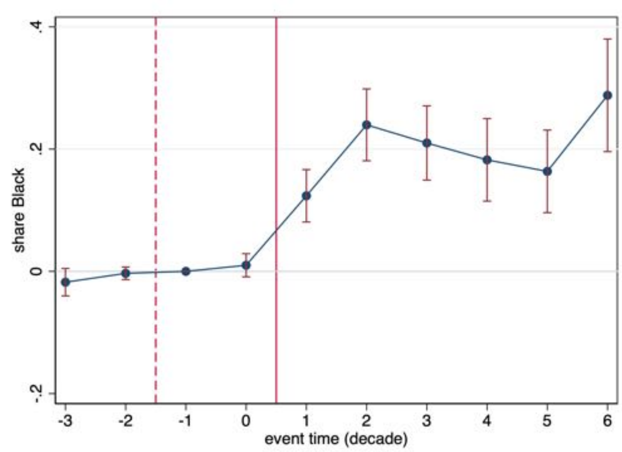
In this section, I present robustness checks separately for each dependent variable and additional results. First, I show that the results of the effect of proximity to the expressway on residential population and on the share of Black residents are invariant to a host of robustness checks. Finally, I provide additional evidence from this empirical design.

B.1 Dep. variable: Share of Black residents

B.1.1 Robustness: No controls

Below, I report the estimated coefficients from the de Chaisemartin and D'Haultfoeuille (2020) estimator and show that the results remain invariant to the exclusion of the baseline controls that were added in the main regression in the text.

Figure B1: No controls
Dep. variable: share of Black residents

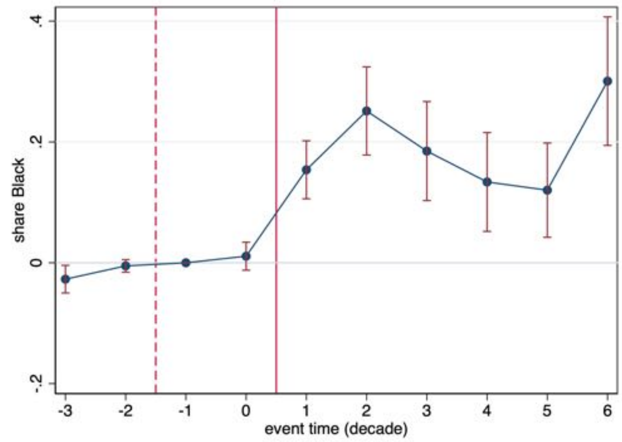


Note: The figure plots the β coefficients estimated from regression (1) using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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. No controls added. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

B.1.2 Robustness: Balanced panel

Now, I restrict the analysis to a balanced panel of 760 observations each period. Since the time span covers the whole century between 1920 and 2010, these tracts are those for which information exists back to the 1920. The unit of analysis corresponds to census tracts whose boundaries have been fixed to 2010, covering the geographic extent of the city in 1950. In 1920, its geographic extent was smaller, which leaves us with 760 consistent-boundary census tracts. The results of the event study are reported in Figure B2 below. Not reported here, I also run the same analysis with different sets of controls and for different definitions of what constitutes treatment and control groups. The results go in the same direction.

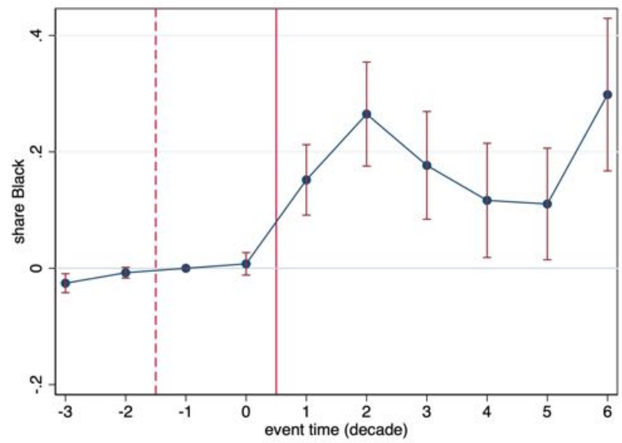
Figure B2: Balanced panel
Dep. variable: share of Black residents



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.

B.1.3 Robustness: Population density weights

Figure B3: Weights by population density at baseline
Dep. variable: share of Black residents

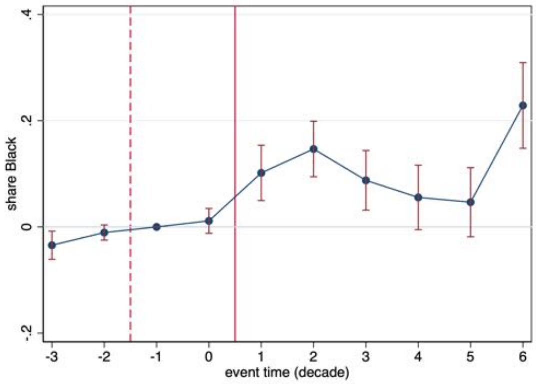


Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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. Observations are weighted by 1940 Pop.D. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

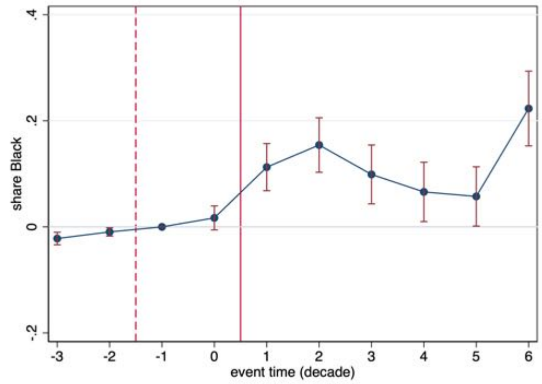
B.1.4 Robustness: Flexible bandwidths for treatment and control groups

Below, I replicate the same specification but for different definitions of treatment and control groups. The results go in the same directions.

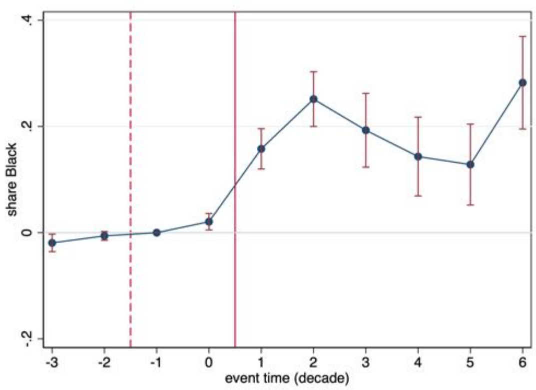
Figure B4: Change of bandwidths for treatment and control
Dep. variable: share of Black residents



(a) $\leq 1km$ vs. $> 2km$



(b) $\leq 2km$ vs. $> 2km$



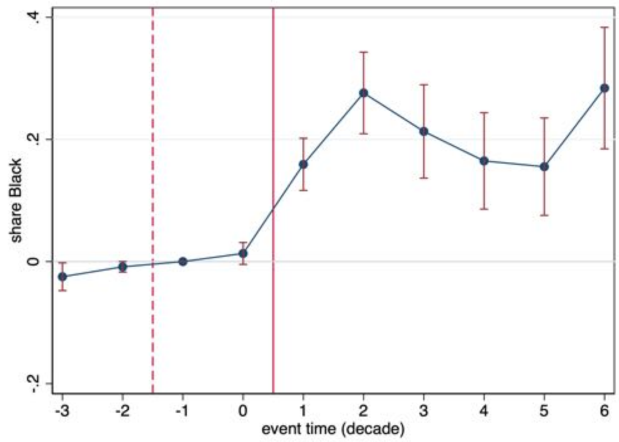
(c) $\leq 2km$ vs. $> 3km$

Note: The figure plots the event time coefficients (β coefficients) estimated from regression (1) with 3 different sets of data. The omitted category is event time dummy at $t = -1$. In panel (a), the treatment group consists of census tracts tracts with centroid within 1 km from the closest expressway; the control group consists of census tracts with centroid farther than 2 km away from the closest expressway. In panel (b), treated units are those whose centroid lies within 2 km from the closest expressway, whereas control units are those farther than 2 km away. In panel (c), I compare units whose centroid lies within 2 km from the closest expressway (treatment group) to those farther than 3 km away. 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.

B.1.5 Robustness: No Black Belt

Below, I show that the main results are not driven by the historically highly Black neighborhood (the so-called Black Belt).

Figure B5: No Black Belt
Dep. variable: share of Black residents



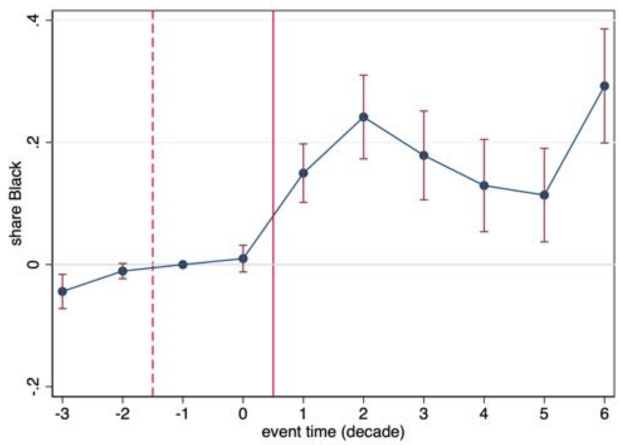
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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.

B.1.6 Robustness: Addressing public housing projects

Below, I show the results including the census tracts that had a public housing project administered by the Chicago Housing Authority. I omit them in the main results because these tended to be large housing developments, consisting of multiple high-rise buildings often almost exclusively inhabited by African Americans (for instance, the Robert Tailor Homes). Since they were often located close to expressways, and tended to host mostly Black households, the neighborhood effects of these type of urban projects can be thought as reinforcing the effects of expressways. In my main results, I hence isolate the effect of expressways by removing these locations from the analysis. For completeness, I provide the results including them and show they are virtually unchanged.

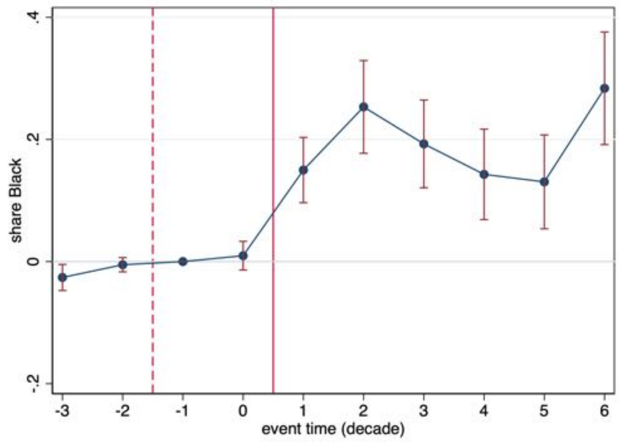
As additional check, I also provide the results after removing census tracts at a certain radius from public housing projects (500 meters and 1 km). Results remain stable.

Figure B6: Including public housing
Dep. variable: share of Black residents



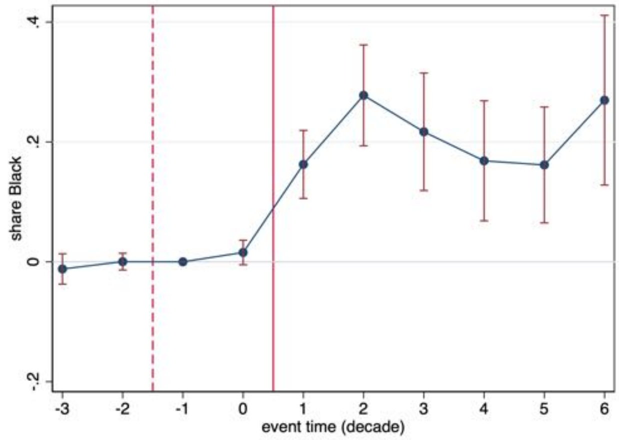
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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 B7: Removing areas within 0.5 km from public housing
Dep. variable: 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 B8: Removing areas within 1 km from public housing
Dep. variable: share of Black residents

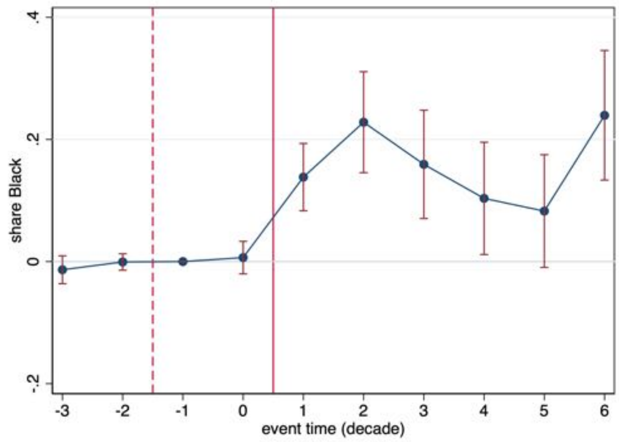


Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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.

B.1.7 Robustness: City of Chicago only

Here, I restrict the analysis to the area withing the boundaries of the City of Chicago (corresponding to 790 observations as of 2010). The results go in the same direction.

Figure B9: City of Chicago only
Dep. variable: share of Black residents

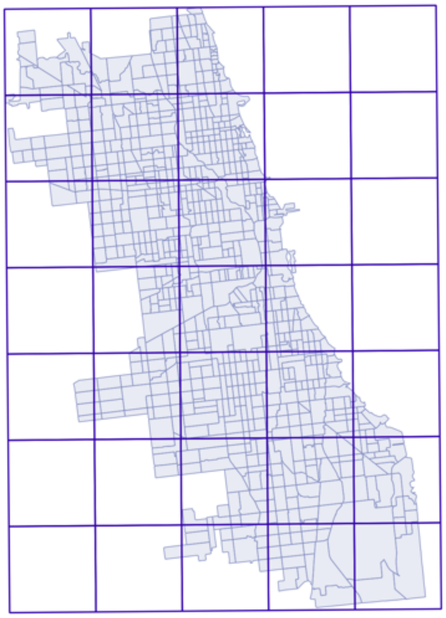


Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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 × Year FE, Quadratic Dist. to CBD × Year FE, HOLC Grade × Year FE, 1940 Pop.D. × Year FE, City × 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.

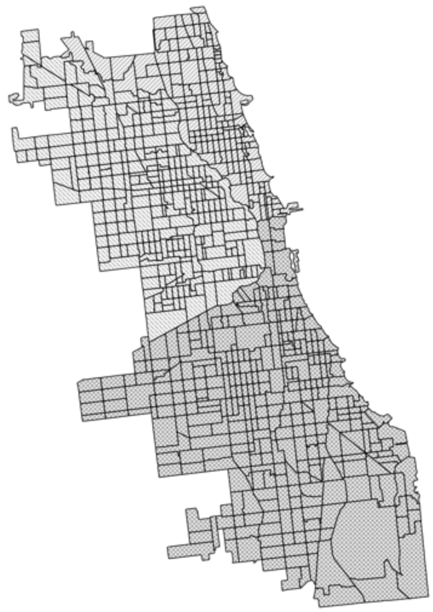
B.1.8 Robustness: Changing clustering

I report the results allowing for more conservative clustering approaches to account for spatial correlation in the errors. For the sample within the boundaries of the city of Chicago, I cluster standard errors after partitioning the city into 25 equally sized cells of 6x6 km each. As an additional exercise I also cluster standard errors at the broad region level (even though this leads to just three clusters: north, west, south side of Chicago). For the full sample including the metropolitan area, I cluster standard errors after partitioning the city into 60 equally sized cells of 8x8 km each. I first map the clusters in the Figure B10 below, then I show the results.

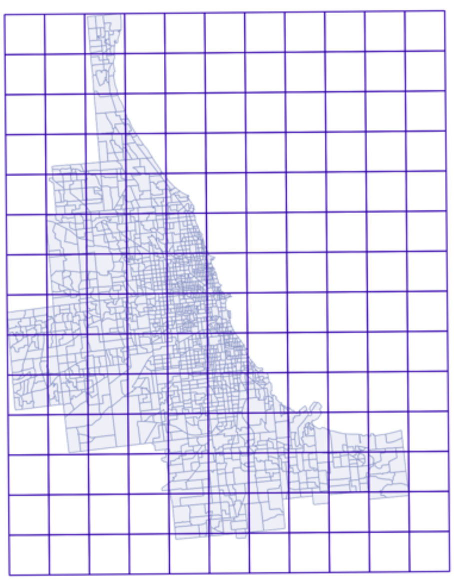
Figure B10: Clusters to account for spatial correlation



(a) City sample: 25 grids



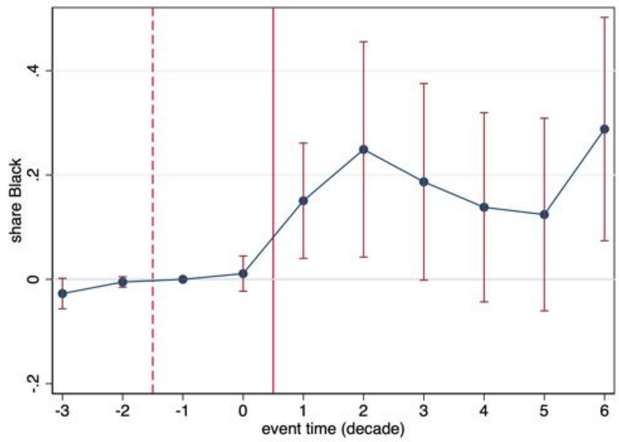
(b) City sample: the three sides of Chicago



(c) Full sample (metropolitan area): 60 grids

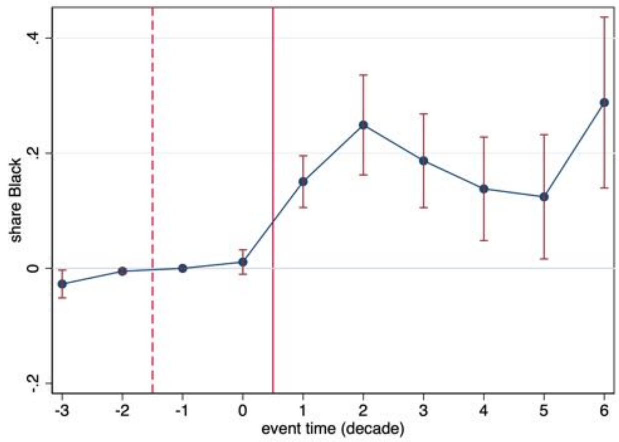
Note: The figures show different clustering approaches. Panel (a) plots the 25 equally sized cells of 6x6 km each; panel (b) the three sides of Chicago (north, west, and south); panel (c) the 60 equally sized cells of 8x8 km each covering the full metropolitan area.

Figure B11: Clusters 25 grids (city only)
Dep. variable: share of Black residents



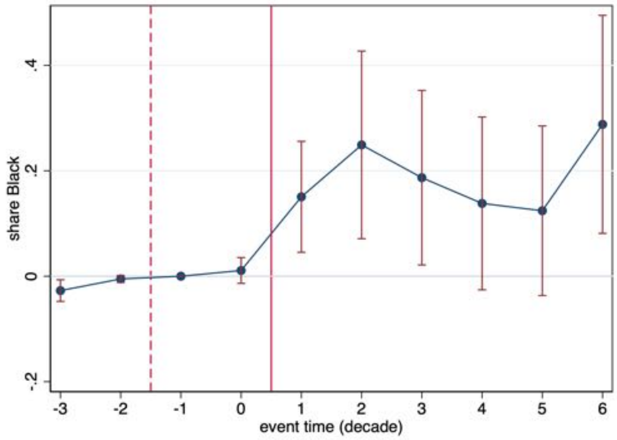
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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 after partitioning the city in 25 equally sized squares of 6x6 km each. Census Tract FE and Year FE are always included.

Figure B12: Clusters three sides (city only)
Dep. variable: 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 the three historical sides of Chicago (north, west, south). Census Tract FE and Year FE are always included.

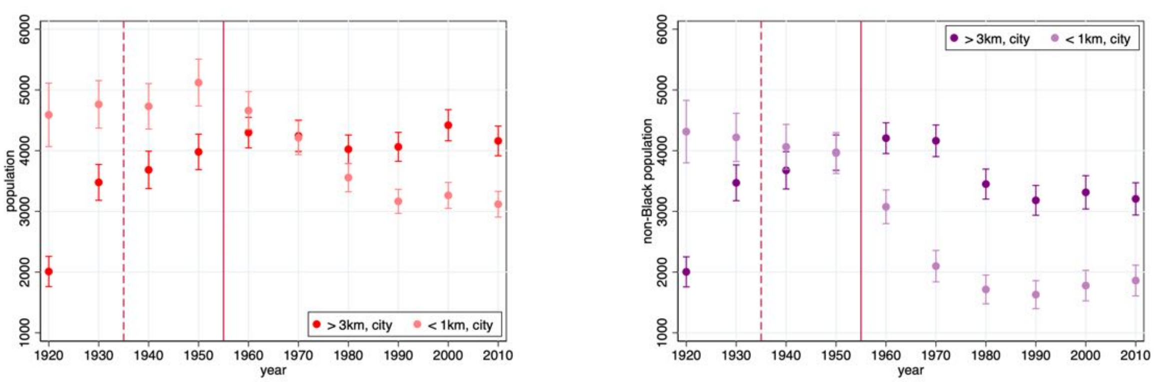
Figure B13: Clusters 60 grids
Dep. variable: share of Black residents



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 after partitioning the metropolitan area in 60 equally sized squares of 8x8 km each. Census Tract FE and Year FE are always included.

B.1.9 Including 1920

Figure B14: Total population, raw means (city only)

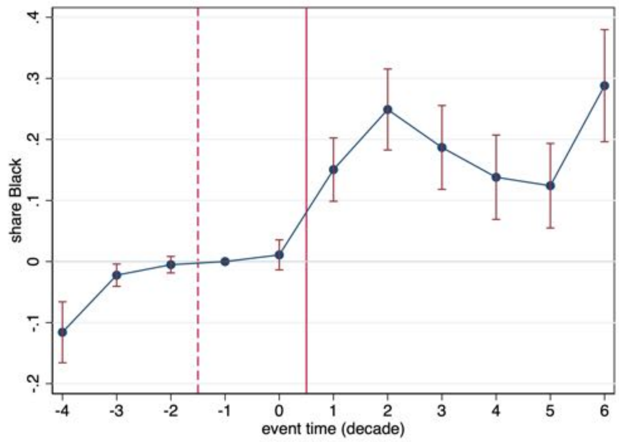


(a) Total population

(b) Total non-Black population

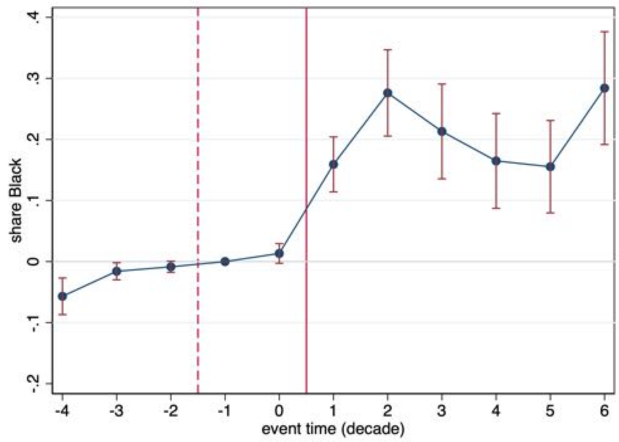
Note: The figures plot average residential populations in (eventually) treated vs. control areas over time from a binned regression. No controls added. The solid red vertical line separates pre-treatment from post-treatment periods.

Figure B15: Including 1920
Dep. variable: share of Black residents



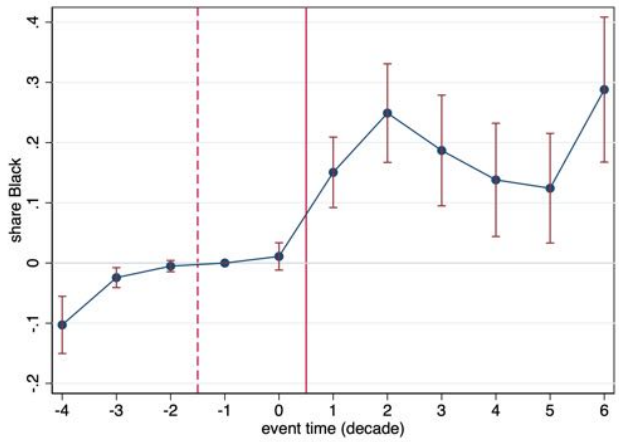
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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 B16: Including 1920, no Black Belt
Dep. variable: share of Black residents



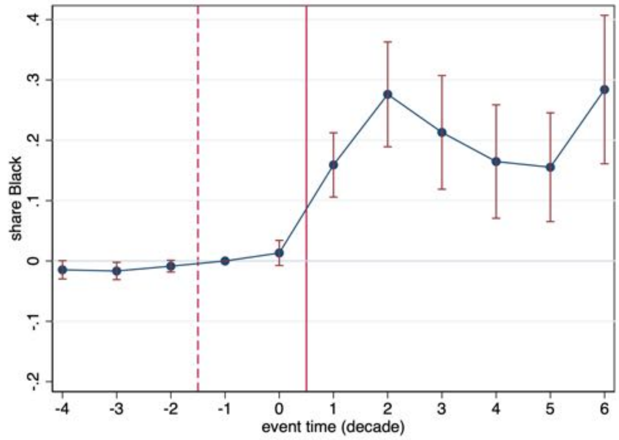
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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 sample removes the area corresponding to the so-called Black Belt. 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 B17: Including 1920, no outskirt of city
Dep. variable: 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 sample removes the areas in the outskirt of the city (further than 16 km from the CBD). 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 B18: Including 1920, no Black Belt & no outskirts of city
Dep. variable: share of Black residents

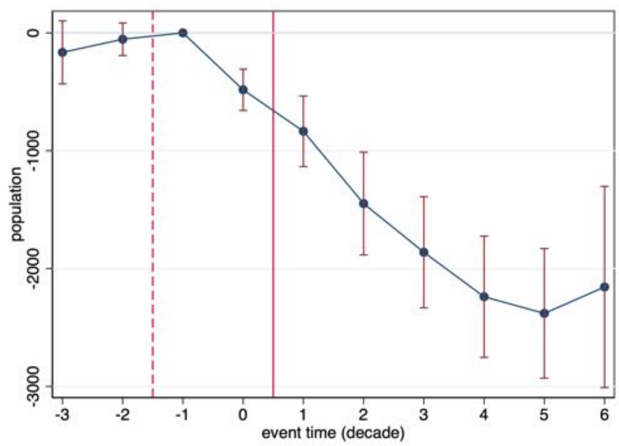


Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is the census tract average share of Black residents. The omitted category is event time dummy at $t = -1$. 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 sample removes the area corresponding to the so-called Black Belt and the outskirts of the city (locations further than 16 km from the CBD). 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.

B.2 Dep. variable: Residential population

B.2.1 Robustness: No controls

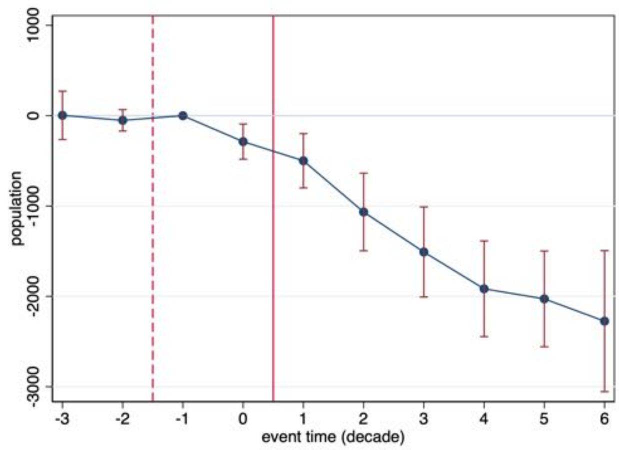
Figure B19: No controls
Dep. variable: residential population



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. No controls added. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

B.2.2 Robustness: Balanced panel

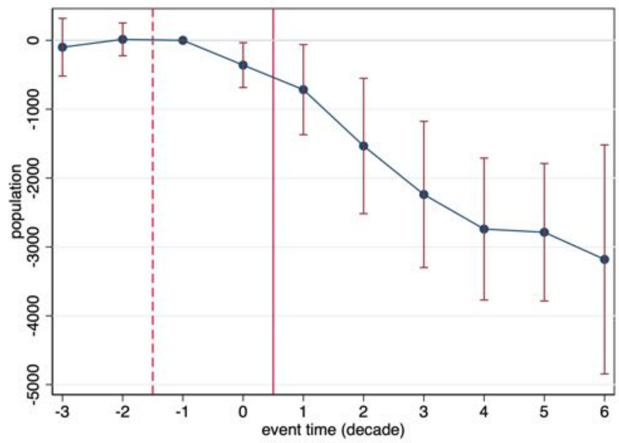
Figure B20: Balanced panel
Dep. variable: residential population



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.

B.2.3 Robustness: Population density weights

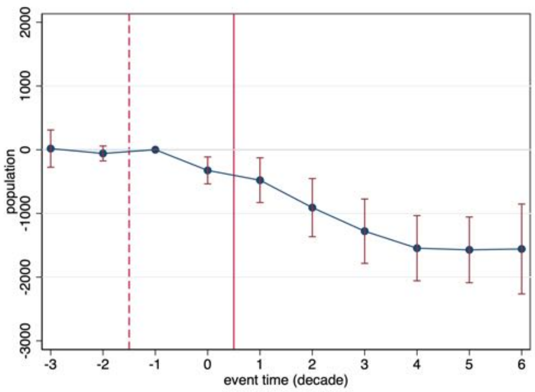
Figure B21: Weights by population density at baseline
Dep. variable: residential population



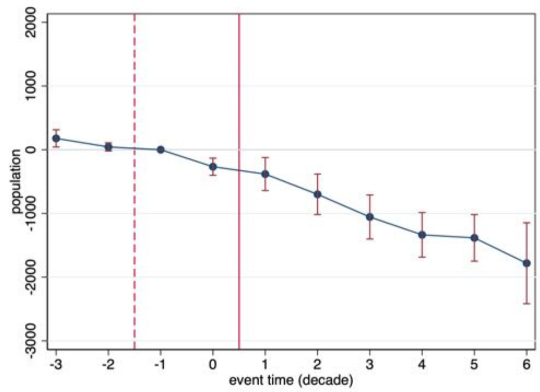
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is residential population. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds to 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. Observations are weighted by 1940 Pop.D. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

B.2.4 Robustness: Flexible bandwidths for treatment and control groups

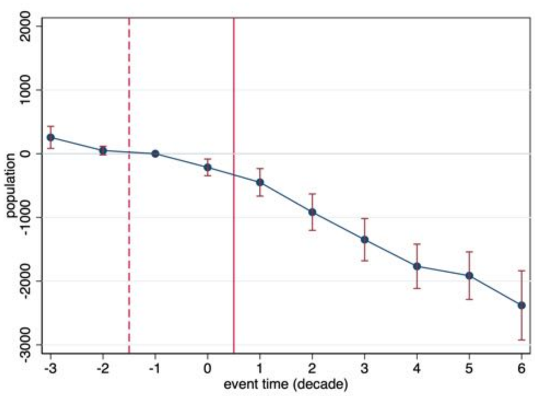
Figure B22: Change of bandwidths for treatment and control
Dep. variable: residential population



(a) $\leq 1km$ vs. $> 2km$



(b) $\leq 2km$ vs. $> 2km$



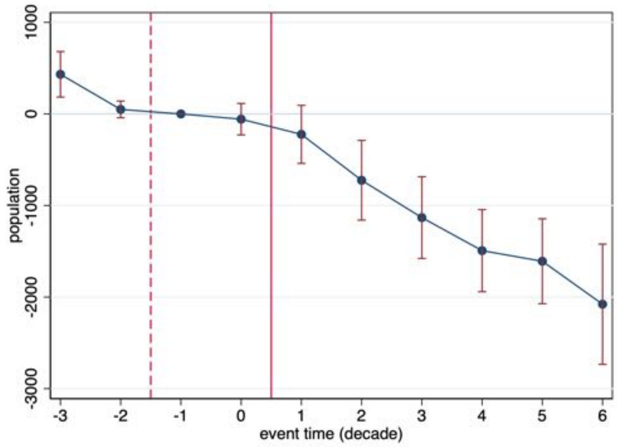
(c) $\leq 2km$ vs. $> 3km$

Note: The figure plots the event time coefficients (β coefficients) estimated from regression (1) with 3 different sets of data. The omitted category is event time dummy at $t = -1$. In panel (a), the treatment group consists of census tracts tracts with centroid within 1 km from the closest expressway; the control group consists of census tracts with centroid farther than 2 km away from the closest expressway. In panel (b), treated units are those whose centroid lies within 2 km from the closest expressway, whereas control units are those farther than 2 km away. In panel (c), I compare units whose centroid lies within 2 km from the closest expressway (treatment group) to those farther than 3 km away. 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.

B.2.5 Robustness: No Black Belt

Below, I show that the main results are not driven by the historically highly Black neighborhood (the so-called Black Belt).

Figure B23: No Black Belt
Dep. variable: residential population

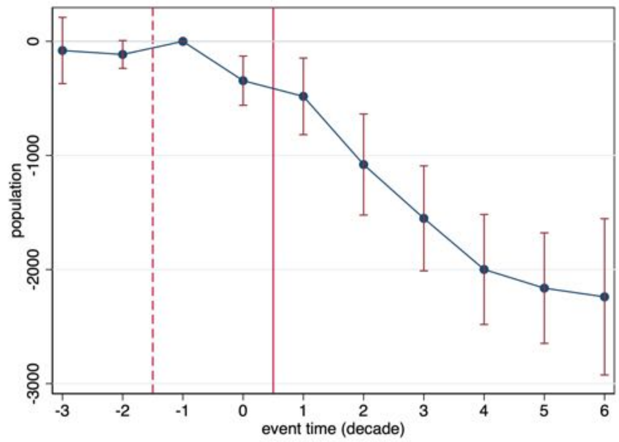


Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is residential population. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds to 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.

B.2.6 Robustness: Addressing public housing projects

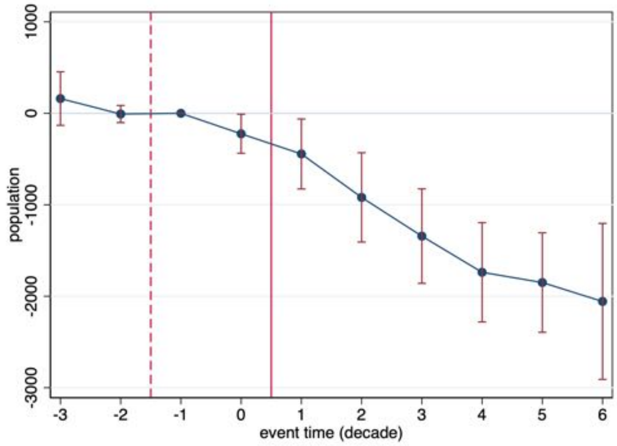
I provide two sets of robustness. The first is including neighborhoods where public housing projects were located. The second is removing neighborhoods at a certain radius from the closest public housing project (500 meters, 1 km). In both cases, results remain stable.

Figure B24: Including public housing
Dep. variable: residential population



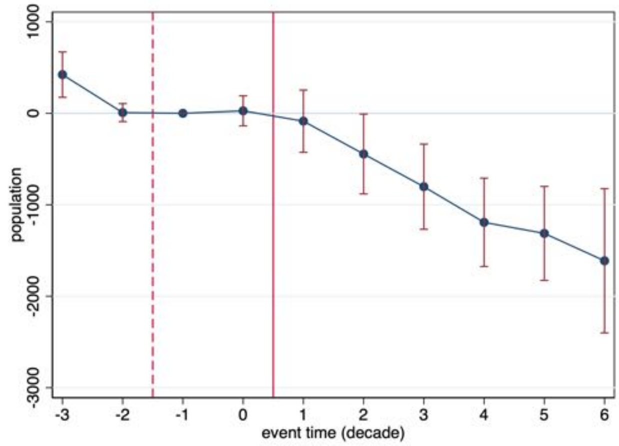
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is residential population. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds to 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 B25: Removing areas within 0.5 km from public housing
Dep. variable: 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 B26: Removing areas within 1 km from public housing
Dep. variable: residential population

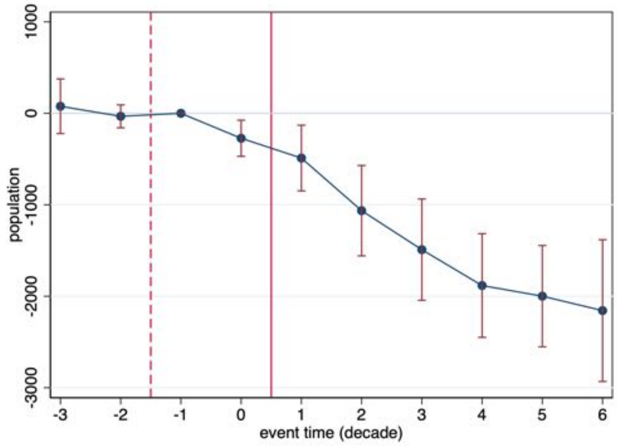


Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is residential population. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds to 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.

B.2.7 Robustness: City of Chicago only

Here, I restrict the analysis to the area withing the boundaries of the City of Chicago (corresponding to 790 observations as of 2010). The results go in the same direction.

Figure B27: City of Chicago only
Dep. variable: residential population

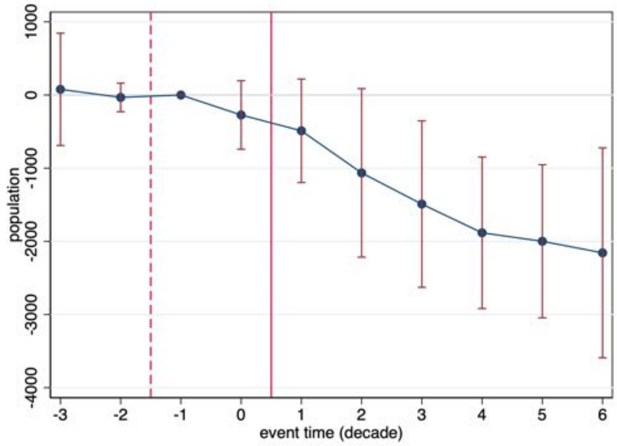


Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is residential population. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds to 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.

B.2.8 Robustness: Changing clustering

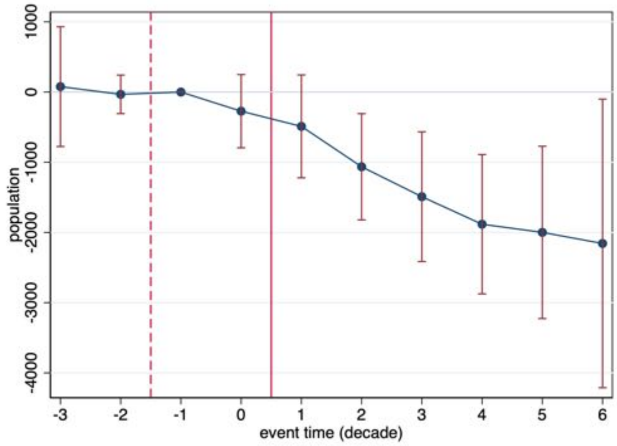
I report the results allowing for more conservative clustering approaches to account for spatial correlation in the errors. For a description of the clusters and their mappings in space, see Appendix Section B.1.8 above.

Figure B28: Clusters 25 grids (city only)
Dep. variable: residential population



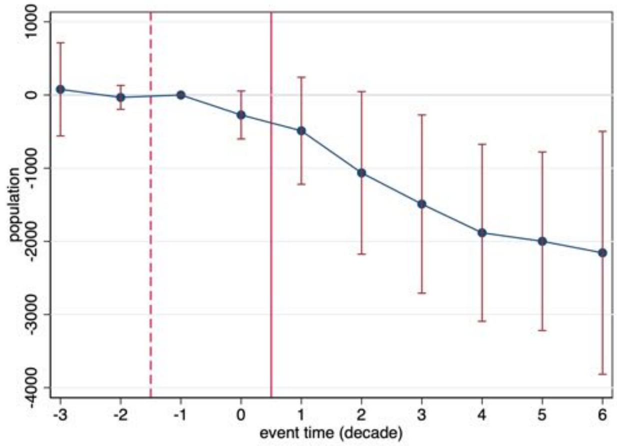
Note: The figure plots the β coefficients estimated from regression (1). using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is residential population. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds to 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 after partitioning the city in 25 equally sized squares of 6x6 km each. Census Tract FE and Year FE are always included.

Figure B29: Clusters three sides (city only)
Dep. variable: 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 after partitioning the city in 25 equally sized squares of 6x6 km each. Census Tract FE and Year FE are always included.

Figure B30: Clusters 60 grids
Dep. variable: 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 × Year FE, Quadratic Dist. to CBD × Year FE, HOLC Grade × Year FE, 1940 Pop.D. × Year FE, City × Year FE. The 95% confidence intervals are based on standard errors clustered after partitioning the metropolitan area in 60 equally sized squares of 8x8 km each. Census Tract FE and Year FE are always included.

B.3 Distance-based regressions

I replicate the main results also running regressions of distance to the closest expressway on the share of Black residents.[79] To increase precision, I categorize the distance to expressway variable into 5 groups of roughly similar size: between 0 and 0.5 km (13% of data); between 0.5 and 1.5 km (27% of data); between 1.5 and 2.5 km (22% of data); between 2.5 and 4 km (21% of data) and above 4 km (17% of data). I call this variable $KMDE$.[80]

The estimating equation is the following:

$$shareblack_{it} = \gamma_t + \alpha_i + \sum_k \delta_k KMDE_{ik} \times City_i + \sum_k \beta_k KMDE_{ik} \times Post_t \times City_i + controls_{it} + \epsilon_{it} \quad \text{(B1)}$$

where i is a census tract; t is a census-year; the dependent variable measures the share of Black residents in census tract i at time t; $KMDE_{ik}$ is an indicator variable for whether census tract i lies within

[79]Not reported here for brevity, I also replicate the analysis using house value as the dependent variable. The results are in line with what I find in the main analysis, namely that house value is an increasing function of distance to the expressway, particularly for areas within the boundaries of the city of Chicago. This heterogeneity is consistent with the idea that the costs associated with proximity to the expressways (their disamenity effect) in central areas are not counterbalanced with the connectivity benefits associated with them because central areas tend to be already well connected and close to economically relevant parts of the city.

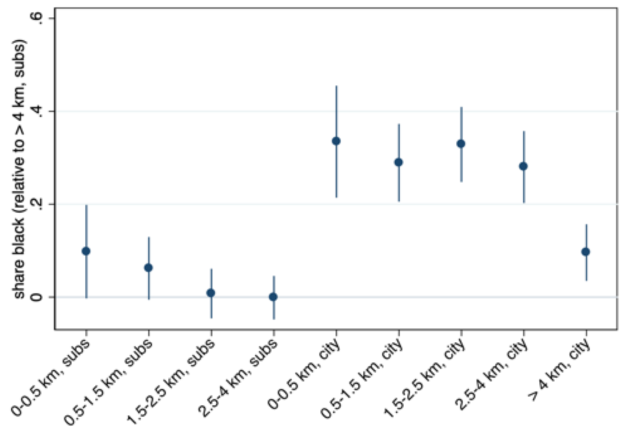
[80]The results are robust to alternative categorizations of the variable, but also to different clustering and controls.

a distance grid cell k from the closest expressway; $Post_t$ is a dummy equal to 1 if the year is post-1970 (considering that, indeed, virtually all treated units enter into treatment either in 1960 or in 1970); $City_i$ is a dummy equal to 1 if the census tract lies within the city of Chicago boundaries (as opposed to the suburban area); $controls_{it}$ are the same as in the baseline specification in the main text, namely (Distance to CBD, Distance to CBD squared, HOLC grade, City X 1950 Pop. Density) X Year FE; finally, α_i are census tract fixed effects and γ_t is a set of time fixed effects. The coefficients of interest are β_k, which capture the effect of being in a grid cell of a certain distance from the closest expressway, separately for the central and suburban areas. All plotted coefficients take the pre-expressway period as base year. The omitted category consists of areas in the suburbs that are further than 4 km from the closest expressway.

As we may observe from the figure below, the share of Black residents is a decreasing function of distance from the nearest expressway both within the boundaries of the City of Chicago and within suburban areas. On average, the share of Black residents increased more in the city in the post-expressway period, almost everywhere, compared to the suburbs.[81] All else equal, being between 0 and 0.5 km from the closest expressway in the city is associated with an increase of 33.5 p.p. in the share of Black residents with respect to being located further than 4 km from the closest expressway in the suburbs. Instead, being further than 4 km away from the closest expressway in the city as opposed to the suburbs is associated with an increase of 9.8 p.p., conditional on controls. When comparing suburban areas, the magnitudes are smaller but the negative relation between the share of Black residents and distance from the expressway still emerges. The same pattern is confirmed by combining all census waves and central and suburban areas and using a continuous measure of distance to the closest expressway (Figure B32 below).

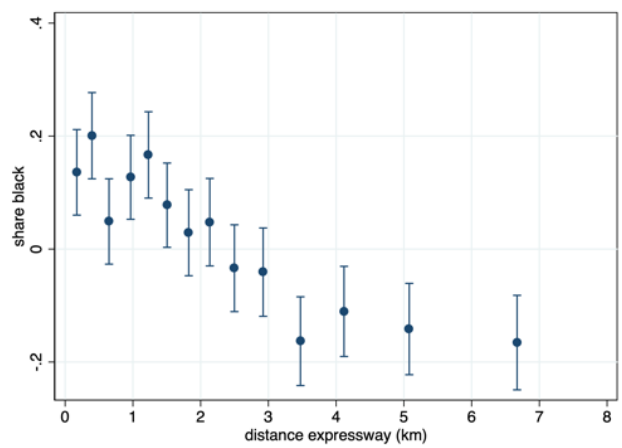
[81] These results are largely robust to changing clustering to allow for varying degrees of spatial dependence. For instance, clustering the standard errors at 6 grid cells at the metropolitan area level, the estimated coefficients for the City of Chicago remain strongly significant (except for the distance grid cell of $>$ 4 km within the city), but all the estimated coefficients in the suburban areas become not statistically different from zero (results not reported).

Figure B31: Bin-distance to expressways and share of Black residents



Note: The figure plots the β_k coefficients from the regression above. Plotted coefficients take the pre-expressway period as base year. The omitted category consists of areas in the suburbs that are further than 4 km from the closest expressway. The full set of controls includes: Dist. to CBD $\times$ Year FE, Quadratic Dist. to CBD $\times$ Year FE, HOLC Grade $\times$ 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 B32: Raw means: share of Black residents and distance to expressway

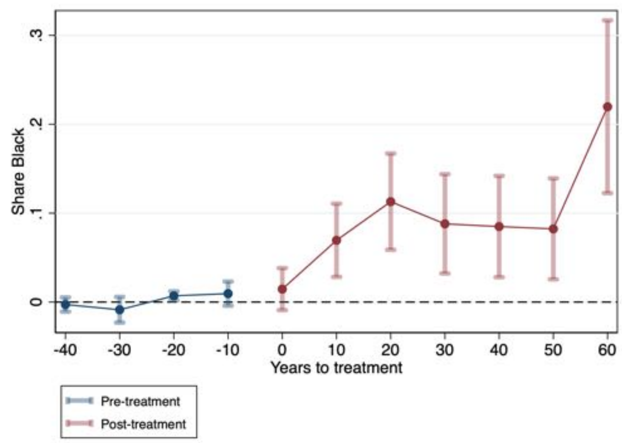


Note: The figure plots the average share of Black residents by distance to the closest expressway, from a binned regression. The full set of controls includes: Dist. to CBD $\times$ Year FE, Quadratic Dist. to CBD $\times$ Year FE, City $\times$ Year FE. Region FE and Year FE are also included.

B.4 Callaway and Sant'Anna (2020) DiD estimator

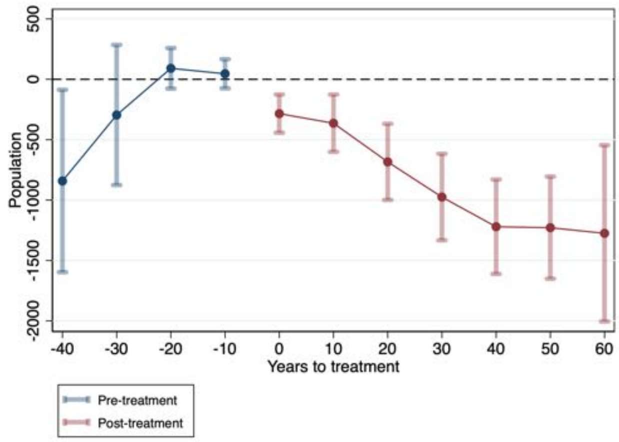
Below, I present the results of implementing the Difference-in-Differences estimator proposed by Callaway and Sant'Anna (2020). The results remain robust to the ones presented in the main text. Similar to the estimator developed by de Chaisemartin and D'Haultfoeuille (2020), the estimator produces unbiased estimates when there are multiple time periods and variation in treatment timing. The main difference is that Callaway and Sant'Anna (2020) impose a weaker parallel trend assumption. It corresponds to the minimal assumption ensuring that all treatment effects can be unbiasedly estimated (de Chaisemartin and D'Haultfoeuille, 2023). To estimate pre-treatment trends across groups, the two estimators use slightly different approaches, resulting in the Callaway and Sant'Anna (2020) method being able to produce a larger number of pre-treatment ATTs. It should be noted that the latest pre-treatment effects (30 and 40 years before treatment) are computed only for the few census tracts that received treatment in the most recent periods (corresponding to the suburban ring routes). The estimated coefficients reported below are computed considering never-treated units only as controls – the default when running the command *csdid* in Stata (Callaway and Sant'Anna, 2020; Sant'Anna and Zhao, 2020). However, the results (not reported) remain similar when considering not-yet treated units as controls. The estimator estimates group-specific average treatment effects for all groups across all periods, in two-by-two designs.

Figure B33: Callaway and Sant'Anna (2020) DiD estimator: Share Black



Note: The figure plots the β coefficients estimated from regression (1). using the semi-parametric DiD estimator proposed by Callaway and Sant'Anna (2020). The dependent variable is residential population. 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. ATTs in red correspond to post-treatment periods. ATTs in blue correspond to pre-treatment periods. The full set of controls includes: Dist. to CBD, Quadratic Dist. to CBD, and Pop.Density. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

Figure B34: Callaway and Sant'Anna (2020) DiD estimator: Residential population



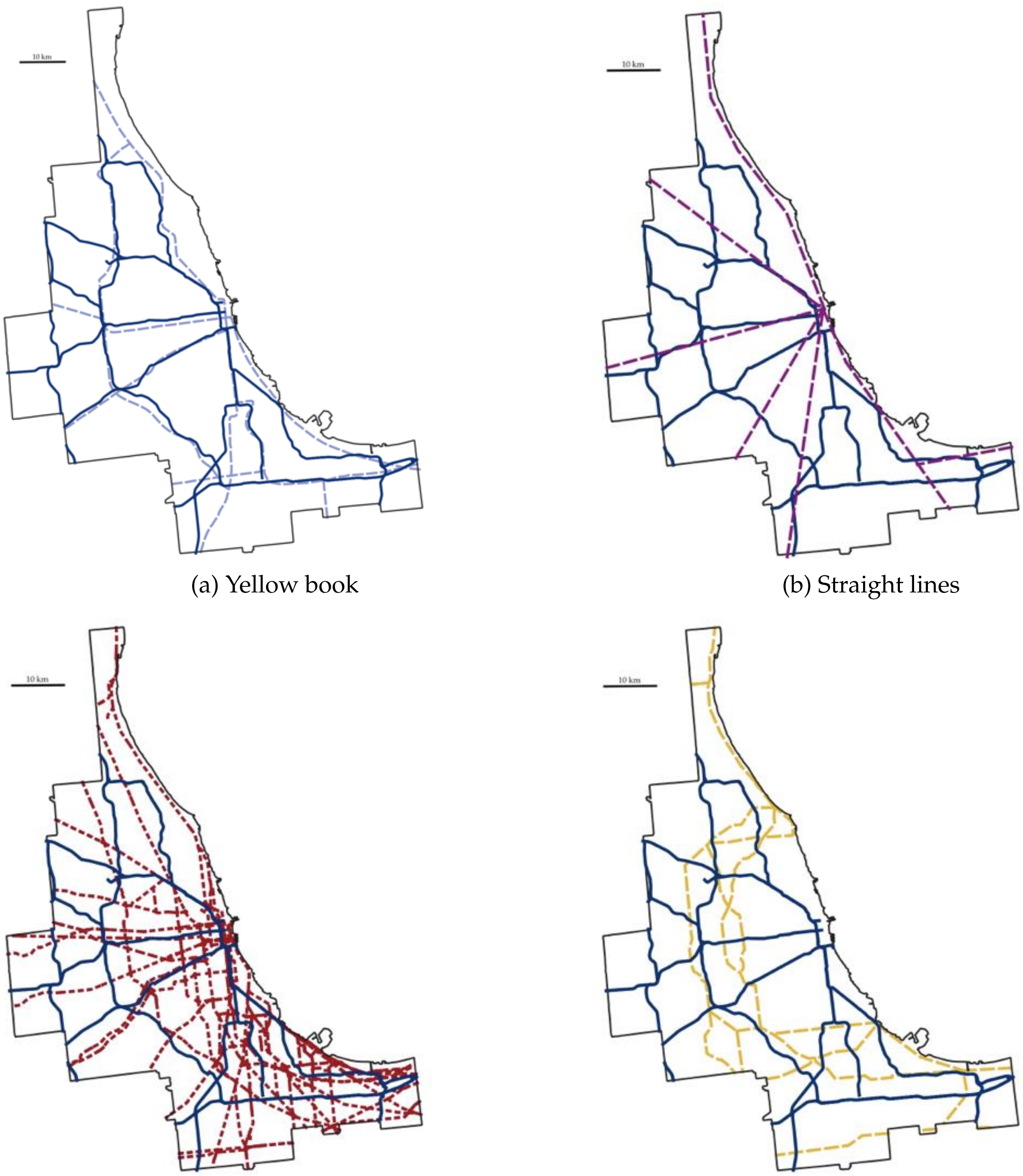
Note: The figure plots the β coefficients estimated from regression (1). using the semi-parametric DiD estimator proposed by Callaway and Sant'Anna (2020). The dependent variable is residential population. A census tract belongs to the treatment group if its centroid lies within 1 km from the closest expressway; it is part of the control group if its centroid is farther than 3 km from the closest expressway. ATTs in red correspond to post-treatment periods. ATTs in blue correspond to pre-treatment periods. The full set of controls includes: Dist. to CBD and Quadratic Dist. to CBD. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

B.5 IV regressions

I report the results from a set of difference-in-difference regressions where the location of the expressway network is instrumented with a host of static instrumental variables widely used in the literature. I first plot the maps of the respective IV against the expressway network in the Chicago Metropolitan Area as of 2010. The table results then follows.

B.5.1 IV maps

Figure B35: IVs vs. 2010 Expressway network



(a) Yellow book

(b) Straight lines

(c) 1898 railroads

(d) Burnham plan

Note: In all figures, the 2010 expressway network is reported in solid blue lines. In panel (a), the IV is the network as found from the Yellow Book. In panel (b), I computed straight lines connecting the Central Business District (CBD) of Chicago to the CBD of the targeted cities from the 1947 Interstate Highway Plan. In panel (c), I compare the 1898 railroad network to the 2010 expressway network in Chicago. In panel (d), I report the digitized highway plan as envisioned in the 1909 Burnham Plan.

B.5.2 IV results

The estimating regression is as follows:

$$shareblack_{it} = \alpha_i + \gamma_t + \beta Dist.expressway_i \times Post_{it} + \epsilon_{it} \tag{B2}$$

Results are shown in the table below. The first two columns report the OLS coefficients of the above regression for comparison with the IV results of the remaining columns. Column 1 shows the unconditional correlation between distance to the closest expressway and share of Black residents. Column 2 reports OLS results after the inclusion of the full set of controls. Columns 3-6 report the IV results using different sets of instruments (the regressions results using as instrument only the Burhnam Plan or the 1898 Railroad network are not reported because of weak instrument issues). Column (6) is the preferred specification (pooling together the available instruments is common in the literature). On average, every extra km away from the closest expressway reduces the share of Black residents by -0.04 p.p., all else equal. The magnitude is in line with the results from the baseline event-study design. The average distance from the closest expressway in the control group of the event study (census tracts with centroid further than 3 km from the closest expressway) is 5.3 km, whereas the average distance in the treatment group (tracts within 1 km from the closest expressway) is 0.5 km. As a result, the average difference in share of Black residents between treated and control group location from the IV estimates is equal to $(5.3 - 0.5) * 0.04 = 0.192$, i.e. 19.2 p.p. higher on average (the baseline event study specification reports an average treatment effect of 15.7 p.p.).

Table B1: IV regressions results

Dep. variable: Share black	(1) OLS	(2) OLS	(3) IV: Yellow book	(4) IV: Str. line	(5) IV: Str. line & Burnham	(6) IV: All
Dist exp (km)	-0.0105***	-0.0354***	-0.0637***	-0.0803***	-0.0304***	-0.0399***
	(0.0019)	(0.0051)	(0.0074)	(0.0189)	(0.0092)	(0.0071)
Adjusted R^2	0.6562	0.6872				
Observations	12,786	9,546	9,546	9,546	9,546	9,546
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tract controls	No	Yes	Yes	Yes	Yes	Yes
F-stat			970.6	27.43	29.97	430.7

Note: The table reports the estimated coefficients from regression B1 above. The first two columns report OLS results; the remaining for columns report IV results using as instrumental variable(s) the one(s) reported in the column titles. Tract controls include: Distance to CBD $\times$ Post, Quadratic Distance to CBD $\times$ Post, HOLC Code $\times$ Post, City $\times$ 1950 Pop.D $\times$ Post. Column (6) shows the IV results using all available instruments together, namely: Yellow Book, Straight line, Burnham Plan, and 1898 Railroads. The results of the IV regressions using only the Burhnam Plan instrument or the 1898 Railroads instrument are not reported because of weak instrument issues.

B.6 Leads and lags regressions

Since the vast majority of the units in my sample were treated between 1960 and 1970, I report the results from leads and lags regressions separately for each treatment group, using a simple two-way fixed effects estimator. This specification allows treatment effects to vary depending on the period of construction of the roads. For each treatment group separately, the estimating regression is the following:

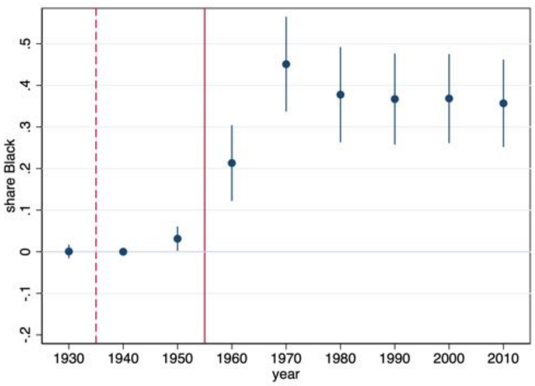
$$Y_{it} = \alpha_i + \gamma_t + \sum_{j=1930}^{2010} \beta_j D_i \times T_{t=j} + \epsilon_{it} \tag{B3}$$

where i is a census tract; t is a census year; Y_{it} measures the outcome of interest in the census tract i at time t; D_i is an indicator variable for being close to the expressway (it takes value equal to 1 if the census tract's centroid is within 1 km from the closest expressway and 0 if it is more than 3 km from the closest expressway);[82] $T_{t=j}$ is an indicator for census year j; 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). To increase precision, observations are weighted by population density at baseline. All standard errors are clustered at the census tract level.

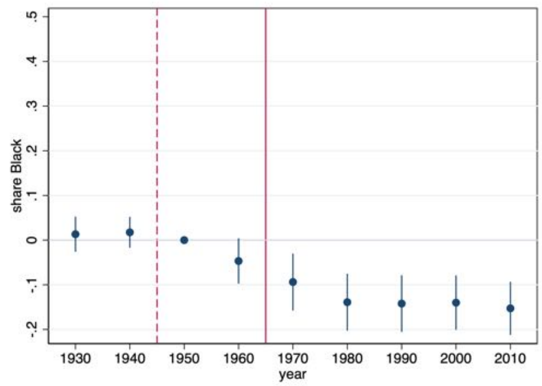
The coefficients of interest are β_j, which capture the effect of being into treatment in year j. Each β_j estimates the difference between the treatment and control group outcomes in year j. Negative values of j allow to check for the existence of pre-trends in the dependent variable. Unless otherwise stated, all beta coefficients are normalized relative to the year of planning of the expressway.

[82] In the 1960 regression, it hence takes value equal to 1 if the census tract is treated in 1960 and 0 if it is never treated. Similarly, in the 1970 regression, it takes a value equal to 1 if the census tract is treated in 1970 and 0 if it is never treated (as a result, units that are treated in a different period than the one under study (1960 or 1970) are excluded from the estimation).

Figure B36: Leads & lags regression
Dep. variable: Share of Black residents



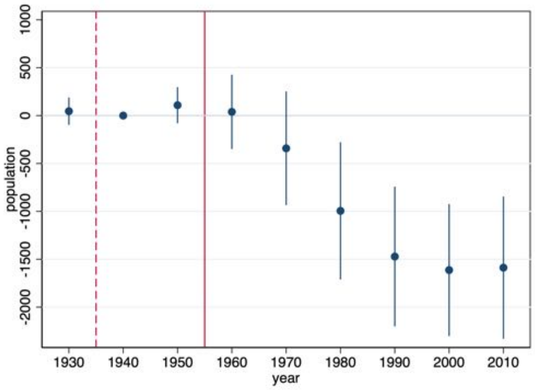
(a) Treated in 1960 vs. never treated



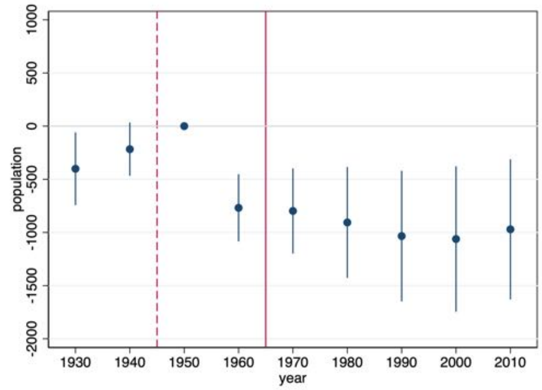
(b) Treated in 1970 vs. never treated

Note: The figure plots the beta coefficients estimated from regression (B3). The dependent variable is the share of Black residents. In panel (a), the treatment group consists of units treated in 1960. In panel (b), the treatment group is composed of units treated in 1970. Periods to the right of the red vertical bar correspond to post-treatment periods. Periods to the left of the dotted red vertical bar denote pre-treatment periods. The decades in between the vertical lines coincide with the periods in which the expressway was first planned and before it is found to be in operation. In panel (a), the omitted category is β_{1940}; in panel (b), the omitted category is β_{1950}. In both groups, treated units are those whose centroid lies within 1 km from the closest expressway. Comparison units are those whose centroid lies farther than 3 km away from the closest expressway. The full set of controls includes: Dist. to CBD $\times$ Year FE, Quadratic Dist. to CBD $\times$ Year FE, HOLC code $\times$ Year FE, 1940 Pop.D.$\times$ Year FE, City $\times$ Year FE. Observations are weighted by population density at baseline. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

Figure B37: Leads & lags regression
Dep. variable: Residential population



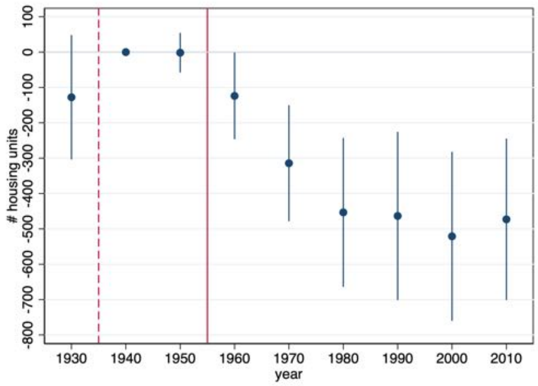
(a) Treated in 1960 vs. never treated



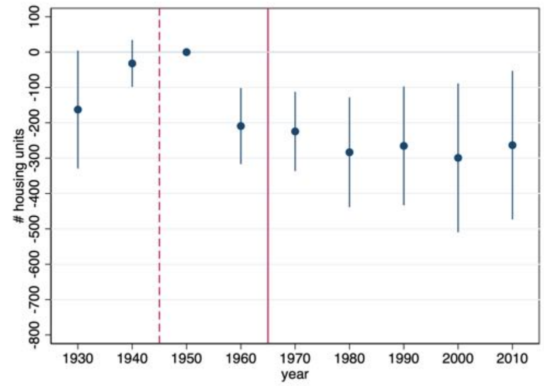
(b) Treated in 1970 vs. never treated

Note: The figure plots the beta coefficients estimated from regression (B3). The dependent variable is total residential population. In panel (a), the treatment group consists of units treated in 1960. In panel (b), the treatment group is composed of units treated in 1970. Periods to the right of the red vertical bar correspond to post-treatment periods. Periods to the left of the dotted red vertical bar denote pre-treatment periods. The decades in between the vertical lines coincide with the periods in which the expressway was first planned and before it is found to be in operation. In panel (a), the omitted category is β_{1940}; in panel (b), the omitted category is β_{1950}. In both groups, treated units are those whose centroid lies within 1 km from the closest expressway. Comparison units are those whose centroid lies farther than 3 km away from the closest expressway. The full set of controls includes: Dist. to CBD $\times$ Year FE, Quadratic Dist. to CBD $\times$ Year FE, HOLC code $\times$ Year FE, 1940 Pop.D.$\times$ Year FE, City $\times$ Year FE. Observations are weighted by population density at baseline. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

Figure B38: Leads & lags regression
Dep. variable: Number of housing units



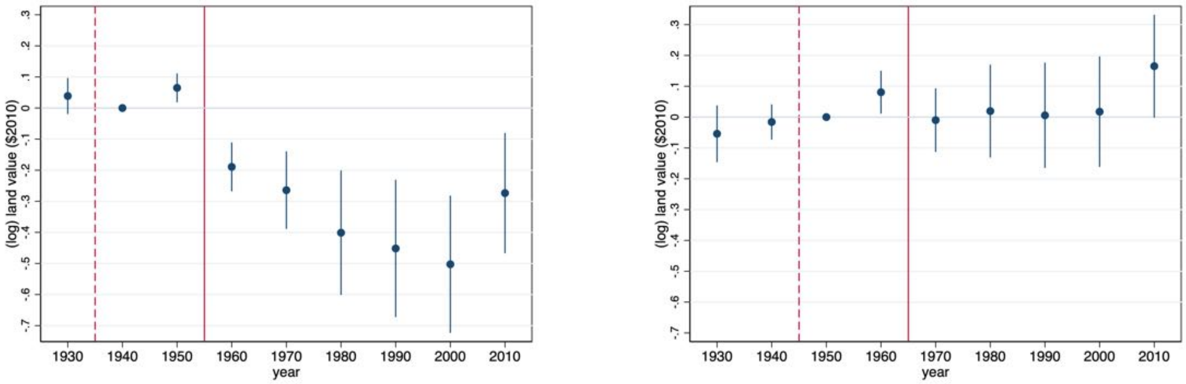
(a) Treated in 1960 vs. never treated



(b) Treated in 1970 vs. never treated

Note: The figure plots the beta coefficients estimated from regression (B3). The dependent variable is number of housing units. In panel (a), the treatment group consists of units treated in 1960. In panel (b), the treatment group is composed of units treated in 1970. Periods to the right of the red vertical bar correspond to post-treatment periods. Periods to the left of the dotted red vertical bar denote pre-treatment periods. The decades in between the vertical lines coincide with the periods in which the expressway was first planned and before it is found to be in operation. In panel (a), the omitted category is β_{1940}; in panel (b), the omitted category is β_{1950}. In both groups, treated units are those whose centroid lies within 1 km from the closest expressway. Comparison units are those whose centroid lies farther than 3 km away from the closest expressway. The full set of controls includes: Dist. to CBD $\times$ Year FE, Quadratic Dist. to CBD $\times$ Year FE, HOLC code $\times$ Year FE, 1940 Pop.D.$\times$ Year FE, City $\times$ Year FE. Observations are weighted by population density at baseline. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

Figure B39: Leads & lags regression
Dep. variable: Land value (log)

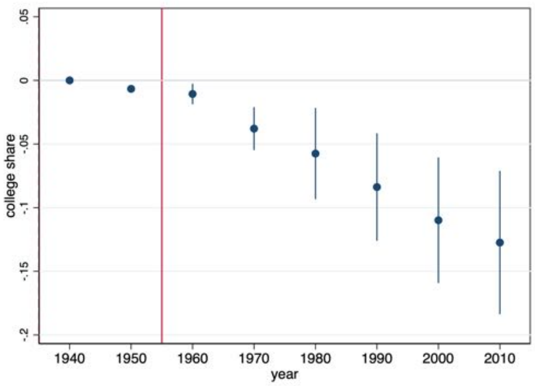


(a) Treated in 1960 vs. never treated

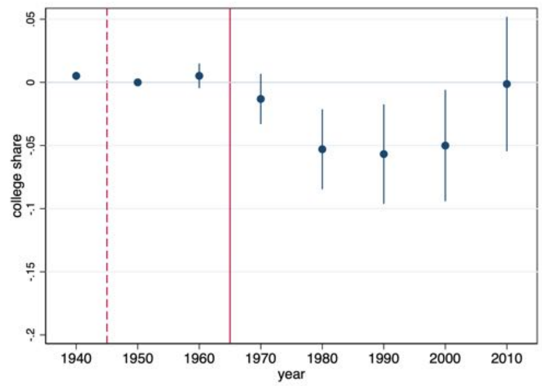
(b) Treated in 1970 vs. never treated

Note: The figure plots the beta coefficients estimated from regression (B3). The dependent variable is (log) land value ($2010). In panel (a), the treatment group consists of units treated in 1960. In panel (b), the treatment group is composed of units treated in 1970. Periods to the right of the red vertical bar correspond to post-treatment periods. Periods to the left of the dotted red vertical bar denote pre-treatment periods. The decades in between the vertical lines coincide with the periods in which the expressway was first planned and before it is found to be in operation. In panel (a), the omitted category is β_{1940}; in panel (b), the omitted category is β_{1950}. In both groups, treated units are those whose centroid lies within 1 km from the closest expressway. Comparison units are those whose centroid lies farther than 3 km away from the closest expressway. The full set of controls includes: Dist. to CBD $\times$ Year FE, Quadratic Dist. to CBD $\times$ Year FE, HOLC code $\times$ Year FE, 1940 Pop.D.$\times$ Year FE, City $\times$ Year FE. Observations are weighted by population density at baseline. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

Figure B40: Leads & lags regression
Dep. variable: College share



(a) Treated in 1960 vs. never treated

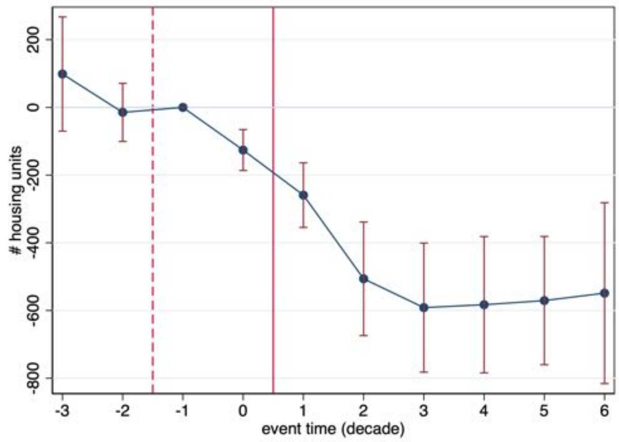


(b) Treated in 1970 vs. never treated

Note: The figure plots the beta coefficients estimated from regression (B3). The dependent variable is college share. In panel (a), the treatment group consists of units treated in 1960. In panel (b), the treatment group is composed of units treated in 1970. Periods to the right of the red vertical bar correspond to post-treatment periods. Periods to the left of the dotted red vertical bar denote pre-treatment periods. The decades in between the vertical lines coincide with the periods in which the expressway was first planned and before it is found to be in operation. In panel (a), the omitted category is β_{1940}; in panel (b), the omitted category is β_{1950}. In both groups, treated units are those whose centroid lies within 1 km from the closest expressway. Comparison units are those whose centroid lies farther than 3 km away from the closest expressway. The full set of controls includes: Dist. to CBD $\times$ Year FE, Quadratic Dist. to CBD $\times$ Year FE, HOLC code $\times$ Year FE, 1940 Pop.D.$\times$ Year FE, City $\times$ Year FE. Observations are weighted by population density at baseline. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE and Year FE are always included.

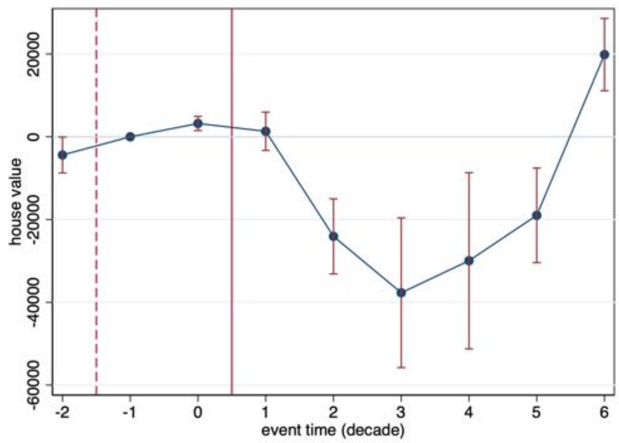
B.7 Additional evidence

Figure B41: Effect of proximity to expressways on number of housing units



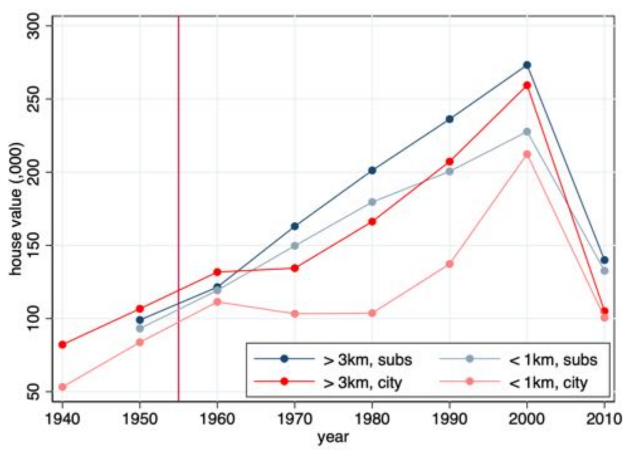
Note: The figure plots the β coefficients estimated from regression (1), using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is number of housing units. The omitted category is event time dummy at $t = -1$. Event time 1 corresponds 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 B42: Effect of proximity to expressways on house value (real, \$2010)



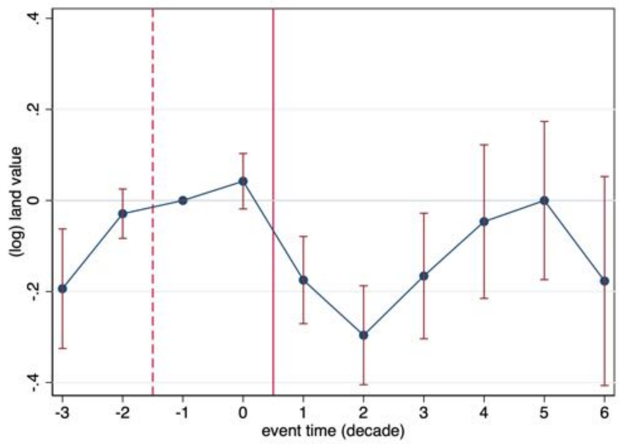
Note: The figure plots the β coefficients estimated from regression (1), using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is average house value (\$2010). The omitted category is event time dummy at $t = -1$. Event time 1 corresponds 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 B43: House value, raw means (city vs. suburban areas)



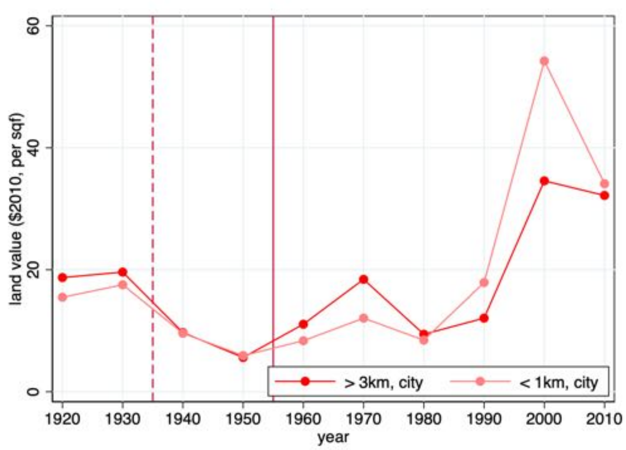
Note: The figure plots average house value (\$2010) in (eventually) treated vs. control areas over time. No controls added. The solid red vertical line separates pre-treatment from post-treatment periods.

Figure B44: Effect of proximity to expressways on land value (log, $2010)



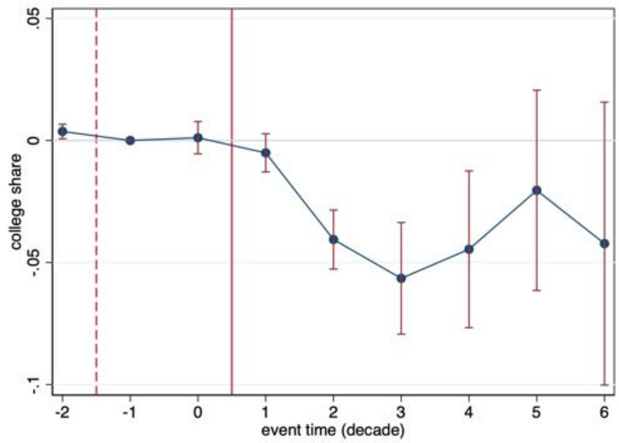
Note: The figure plots the β coefficients estimated from regression (1), using the two-way fixed effects estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). The dependent variable is (log) average land value ($2010). The omitted category is event time dummy at $t = -1$. Event time 1 corresponds 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 B45: Land value, raw means



Note: The figure plots average land value ($2010) in (eventually) treated vs. control areas over time. No controls added. The solid red vertical line separates pre-treatment from post-treatment periods.

Figure B46: Effect of proximity to expressways on college share



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 college share. 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.

B.8 Isolating the net demolition and displacement effects

Part of the drop in residential population (and in the number of housing units) that follows expressway construction is likely to be due to the physical space needed for the construction of these roads. Isolating the pure demolition and displacement effects caused by the physical space needed to build the expressway network is difficult in practice.

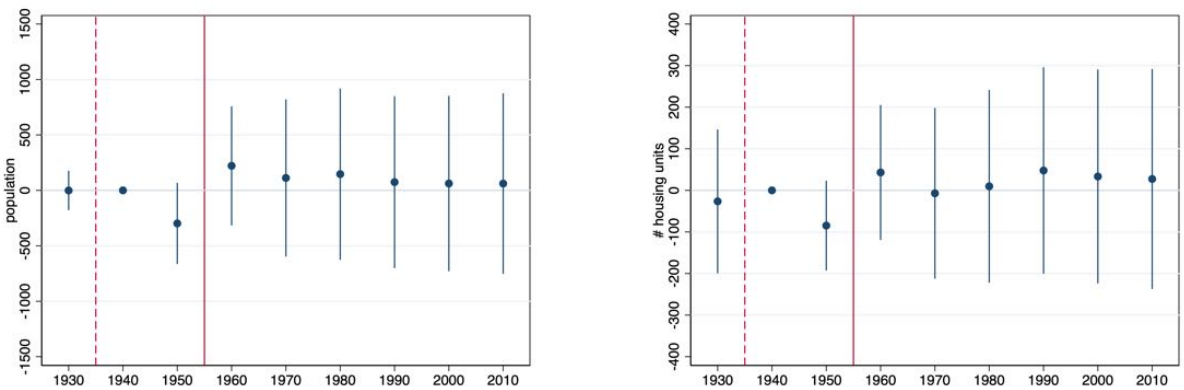
A way of trying to isolate these effects with the data available is to compare the change in outcome (residential population, housing units) in locations treated early as opposed to treated at a later stage, the argument being that these places should be roughly comparable to one another in the process undergoing construction. This empirical design comes at the cost of losing a vast number of observations, but it may help to understand how much of the observed change is due to the need to make space.

Below, I report the results of a difference-in-difference specification where I compare the diverging trajectory in outcomes between census tracts that received the expressway in the earliest period (baseline year 1940) and census tracts that were connected to the expressway network in the later period (baseline period 1950). Expressways in Chicago were built very rapidly (within less than 20 years), meaning that there is only one decade (namely, 1950), where we can observe construction taking place close to locations treated in the first wave, but arguably not yet in locations treated in the second wave.

Though suggestive, the results ascribe to the construction of expressways a displacement of 297.99

(s.e. 186.14) residents, and the demolition of 84.74 housing units (s.e. 54.92). The estimated coefficients in 1950 are a bit noisy, not surprising given the small sample size, and just fall out of the standard significance levels. Taken together, these results nevertheless compare well with the average number of inhabitants per housing unit in Chicago reported in the 1950 census of housing (mean 3.4, median 2.9). In support of the empirical design employed in this analysis, the point estimates to the right of the solid red vertical bar are reassuringly virtually zero. This is to be expected, since, beginning in 1960, also the locations that received the expressway in the second wave (the control group for the estimation of the treatment effect in 1950) started the construction phase.

Figure B47: Treated in 1960 vs. Treated in 1970



(a) Dep. variable: Residential population

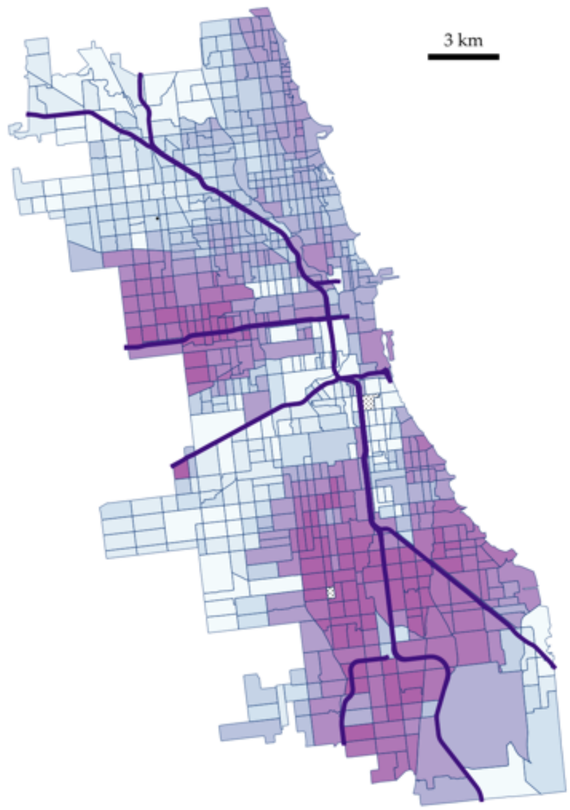
(b) Dep. variable: Number of housing units

Note: To the right of the solid red vertical line both treatment groups are treated. The omitted category is β_{1940}. In both treatment groups that are compared here, treated units are those whose centroid lies within 1 km from the closest expressway. Comparison units are those whose centroid lies farther than 3 km away from the closest expressway. The 95% confidence intervals are based on standard errors clustered at census tract level. Census Tract FE, Year FE, and City $\times$ Year FE are included.

C Additional long-difference results

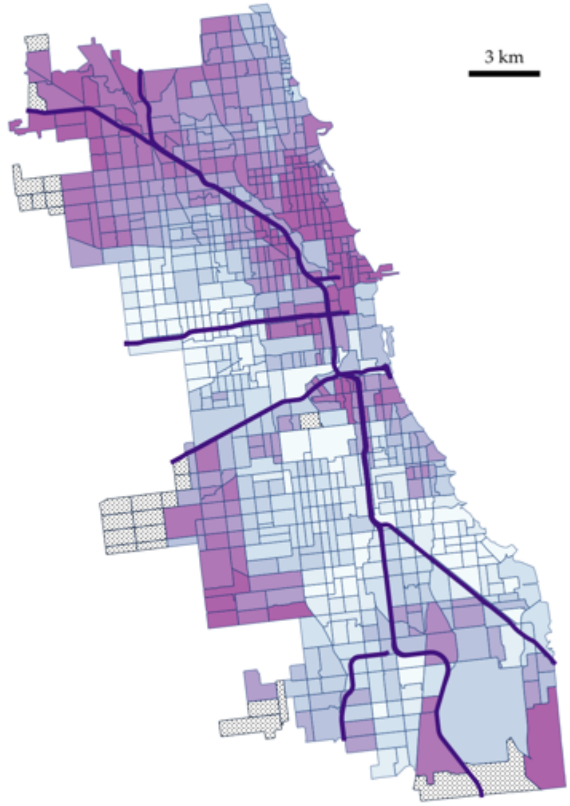
C.1 Maps of change in primary and secondary outcomes, 1950-1990

Figure C1: Δ share Black residents



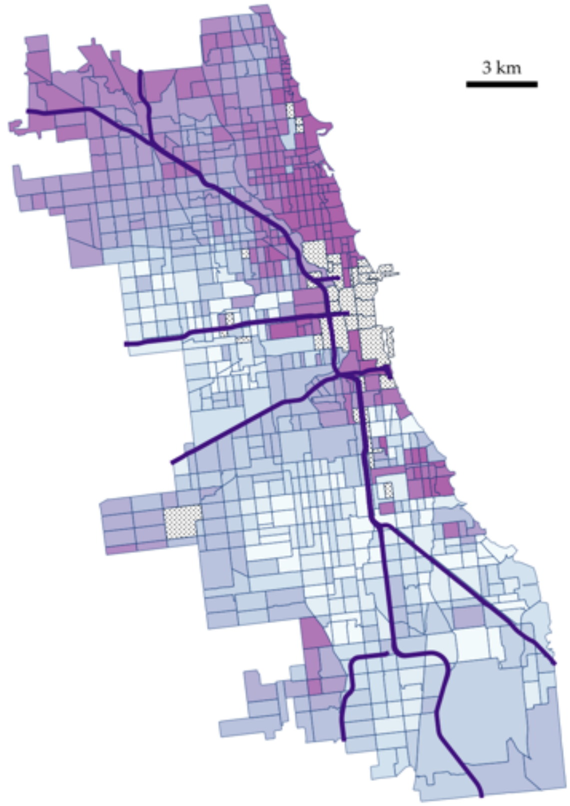
Note: The figure plots the change in the outcome variable (share of Black residents) between 1950 and 1990 for each census tract in the city. Census tracts are grouped into deciles based on the change in exposure to Black residents, with darker colors indicating larger increases in value. The purple lines show the expressways route as of 1990. Missing data is shown in dotted gray.

Figure C2: Δ land value



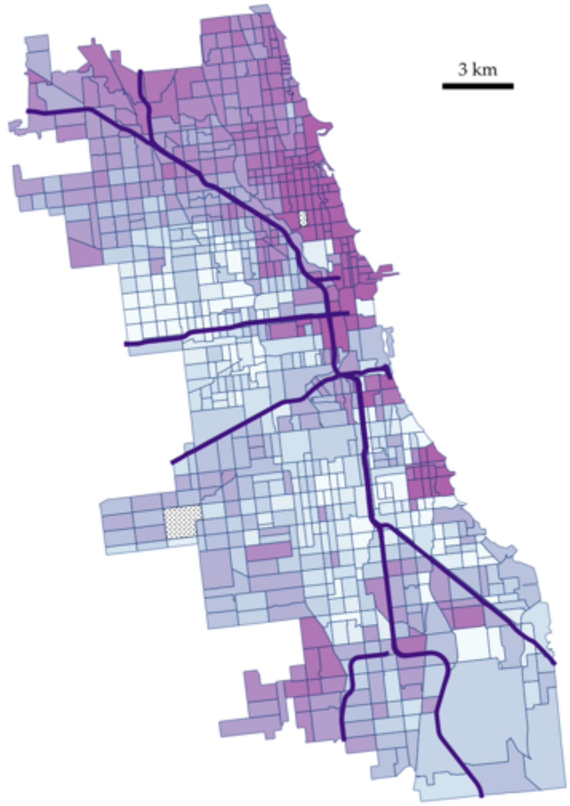
Note: The figure plots the change in the outcome variable (land value) between 1950 and 1990 for each census tract in the city. Census tracts are grouped into deciles based on the change in exposure to Black residents, with darker colors indicating larger increases in value. The purple lines show the expressways route as of 1990. Missing data is shown in dotted gray.

Figure C3: Δ house value



Note: The figure plots the change in the outcome variable (house value) between 1950 and 1990 for each census tract in the city. Census tracts are grouped into deciles based on the change in exposure to Black residents, with darker colors indicating larger increases in value. The purple lines show the expressways route as of 1990. Missing data is shown in dotted gray.

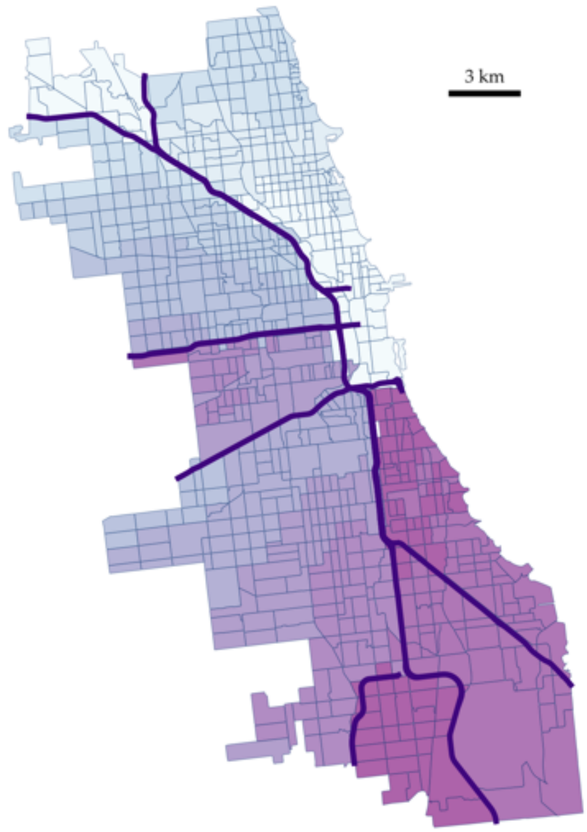
Figure C4: Δ college share



Note: The figure plots the change in the outcome variable (college share) between 1950 and 1990 for each census tract in the city. Census tracts are grouped into deciles based on the change in exposure to Black residents, with darker colors indicating larger increases in value. The purple lines show the expressways route as of 1990. Missing data is shown in dotted gray.

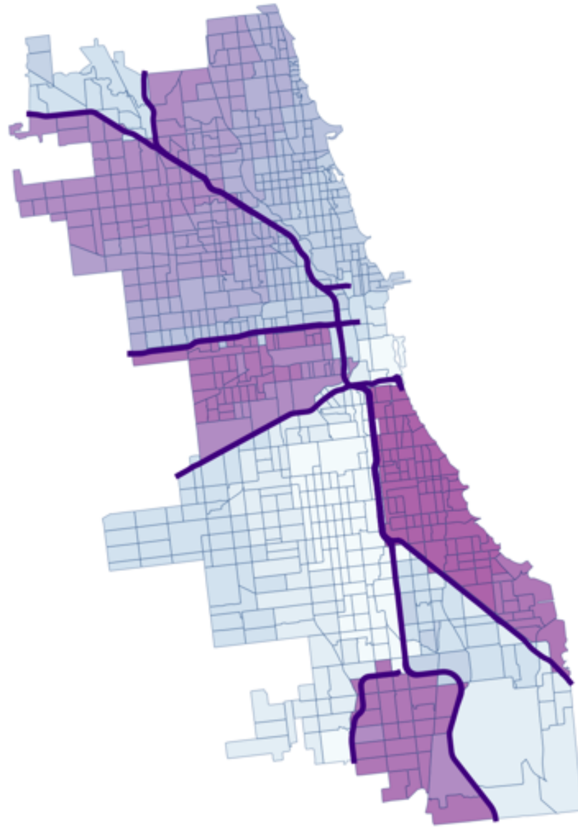
C.2 Deciles of changes in distribution of exposure to Black measure and its IV

Figure C5: Change in exposure to Black residents, 1990 vs. 1950



Note: The figure plots the overall change in exposure ΔS_i for each neighborhood in the city. The overall change includes both the change in exposure due to the spatial resorting of people between 1950 and 1990 and the change due to the development of the road network. Census tracts are grouped into deciles based on the change in exposure to Black residents, with darker colors indicating larger increases in exposure. The purple lines show the expressways route as of 1990.

Figure C6: Instrument ΔSMA, 1990 vs. 1950



Note: The figure plots the baseline instrument for the change in exposure to Black residents. The instrument isolates the variation that is due only to changes in traveling times through expressway construction. In the post-period, I assume infinitely high costs of crossing the expressway network. Census tracts are grouped into deciles, with darker colors indicating larger increases in exposure. The purple lines show the expressways route as of 1990.

C.3 Long-difference results: 1950 vs. 1980

Table C1: 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)	0.481***	0.465***	0.329***	0.394***	0.393***	0.393***	0.393***	0.136**	0.149**	0.209***	0.152**
	(0.053)	(0.052)	(0.055)	(0.050)	(0.049)	(0.103)	(0.118)	(0.067)	(0.066)	(0.069)	(0.065)
Dist expressway (km)		-0.039**	-0.222***	-0.251***	-0.250***	-0.250***	-0.250***	-0.281***	-0.283***	-0.289***	-0.279***
		(0.017)	(0.020)	(0.021)	(0.021)	(0.069)	(0.039)	(0.022)	(0.022)	(0.023)	(0.022)
ΔY (std)					0.033	0.033	0.033	0.039	0.047	-0.076	0.009
					(0.047)	(0.122)	(0.090)	(0.046)	(0.046)	(0.053)	(0.053)
Observations	764	764	764	727	727	727	727	727	722	648	727
Adjusted R^2	0.222	0.225	0.382	0.462	0.462	0.462	0.461				
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								1051	1048	823	466.6

The table reports the estimation results from regression (2) on the change in the share of Black residents. The regressors of interest are: ΔS (standardized) measures the change in exposure to Black areas in the city; *Dist expressway* measures the km distance from the closest expressway; ΔY measures the change in exposure to rich areas in the city. Region FE for being in the north, west, or south side of the city are always included. Tract controls are: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to water. Historical controls include: distance to railroads in 1898; HOLC grade, historical outcomes in levels, and the change in population density between 1920 and 1940. Column (6) shows standard errors assuming that census tract within the same grid cell are spatially correlated (for this exercise, I partitioned the city into 25 squares). Column (7) computes Conley (1999) standard errors to allow arbitrary spatial correlation of errors between tracts within 3 km from each other. Column (8) shows the IV results after instrumenting for the change in exposure to Black residents holding the distribution of races within the city fixed to the pre-period. Column (9) reports the IV results after removing the 5% of the sample that in 1920 already had a large concentration of Black residents (i.e., removes all area with more than 20% share in 1920). Column (10) reports the estimated IV coefficients after removing the 12% of the census tracts in the sample that are within 5 km of the CBD. Column (11) additionally instruments for the change in exposure to rich neighborhoods in the city, with an instrumental variable (ΔYMA) that is constructed similarly to ΔSMA. Supplementary detail is available in the main text. Standard errors clustered at census tract level in parentheses (unless specified differently). *** p<0.01, ** p<0.05, * p<0.1.

Table C2: 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)	-0.467***	-0.469***	-0.468***	-0.445***	-0.446***	-0.446***	-0.446***	-0.417***	-0.479***	-0.520***	-0.432***
	(0.049)	(0.049)	(0.051)	(0.052)	(0.052)	(0.141)	(0.097)	(0.068)	(0.066)	(0.071)	(0.067)
Dist expressway (km)		-0.006	0.097***	0.111***	0.112***	0.112	0.112*	0.116***	0.111***	0.139***	0.114***
		(0.024)	(0.028)	(0.028)	(0.028)	(0.086)	(0.058)	(0.028)	(0.028)	(0.027)	(0.028)
ΔY (std)					0.027	0.027	0.027	0.025	-0.002	0.198***	0.051
					(0.058)	(0.103)	(0.104)	(0.057)	(0.056)	(0.060)	(0.060)
Observations	742	742	742	720	720	720	720	720	715	641	720
Adjusted R^2	0.231	0.230	0.346	0.337	0.336	0.336	0.336				
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								1087	1052	841.7	442.2

The table reports the estimation results from regression (2) on the change in land value. The regressors of interest are: ΔS (standardized) measures the change in exposure to Black areas in the city; *Dist expressway* measures the km distance from the closest expressway; ΔY measures the change in exposure to rich areas in the city. Region FE for being in the north, west, or south side of the city are always included. Tract controls are: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to water. Historical controls include: distance to railroads in 1898; HOLC grade, historical outcomes in levels, and the change in population density between 1920 and 1940. Column (6) shows standard errors assuming that census tract within the same grid cell are spatially correlated (for this exercise, I partitioned the city into 25 squares). Column (7) computes Conley (1999) standard errors to allow arbitrary spatial correlation of errors between tracts within 3 km from each other. Column (8) shows the IV results after instrumenting for the change in exposure to Black residents holding the distribution of races within the city fixed to the pre-period. Column (9) reports the IV results after removing the 5% of the sample that in 1920 already had a large concentration of Black residents (i.e., removes all area with more than 20% share in 1920). Column (10) reports the estimated IV coefficients after removing the 12% of the census tracts in the sample that are within 5 km of the CBD. Column (11) additionally instruments for the change in exposure to rich neighborhoods in the city, with an instrumental variable (ΔYMA) that is constructed similarly to ΔSMA. Supplementary detail is available in the main text. Standard errors clustered at census tract level in parentheses (unless specified differently). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C.4 Long-difference results: 1950 vs. 2000

Table C3: 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)	0.518***	0.532***	0.343***	0.407***	0.435***	0.435***	0.435***	0.164**	0.179**	0.201***	0.159**
	(0.054)	(0.053)	(0.056)	(0.051)	(0.055)	(0.139)	(0.114)	(0.073)	(0.073)	(0.076)	(0.073)
Dist expressway (km)		0.043**	-0.147***	-0.170***	-0.167***	-0.167***	-0.167***	-0.195***	-0.197***	-0.207***	-0.195***
		(0.018)	(0.020)	(0.020)	(0.020)	(0.055)	(0.039)	(0.021)	(0.021)	(0.022)	(0.021)
ΔY (std)					0.122**	0.122	0.122	0.045	0.057	-0.083	0.061
					(0.050)	(0.128)	(0.097)	(0.053)	(0.053)	(0.062)	(0.061)
Observations	764	764	764	727	727	727	727	727	722	648	727
Adjusted R^2	0.239	0.242	0.416	0.497	0.500	0.500	0.499				
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								1336	1314	1141	615.2

The table reports the estimation results from regression (2) on the change in the share of Black residents. The regressors of interest are: ΔS (standardized) measures the change in exposure to Black areas in the city; *Dist expressway* measures the km distance from the closest expressway; ΔY measures the change in exposure to rich areas in the city. Region FE for being in the north, west, or south side of the city are always included. Tract controls are: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to water. Historical controls include: distance to railroads in 1898; HOLC grade, historical outcomes in levels, and the change in population density between 1920 and 1940. Column (6) shows standard errors assuming that census tract within the same grid cell are spatially correlated (for this exercise, I partitioned the city into 25 squares). Column (7) computes Conley (1999) standard errors to allow arbitrary spatial correlation of errors between tracts within 3 km from each other. Column (8) shows the IV results after instrumenting for the change in exposure to Black residents holding the distribution of races within the city fixed to the pre-period. Column (9) reports the IV results after removing the 5% of the sample that in 1920 already had a large concentration of Black residents (i.e., removes all area with more than 20% share in 1920). Column (10) reports the estimated IV coefficients after removing the 12% of the census tracts in the sample that are within 5 km of the CBD. Column (11) additionally instruments for the change in exposure to rich neighborhoods in the city, with an instrumental variable (ΔYMA) that is constructed similarly to ΔSMA. Supplementary detail is available in the main text. Standard errors clustered at census tract level in parentheses (unless specified differently). *** p<0.01, ** p<0.05, * p<0.1.

Table C4: Dep variable: Δ land value, log (standardized)

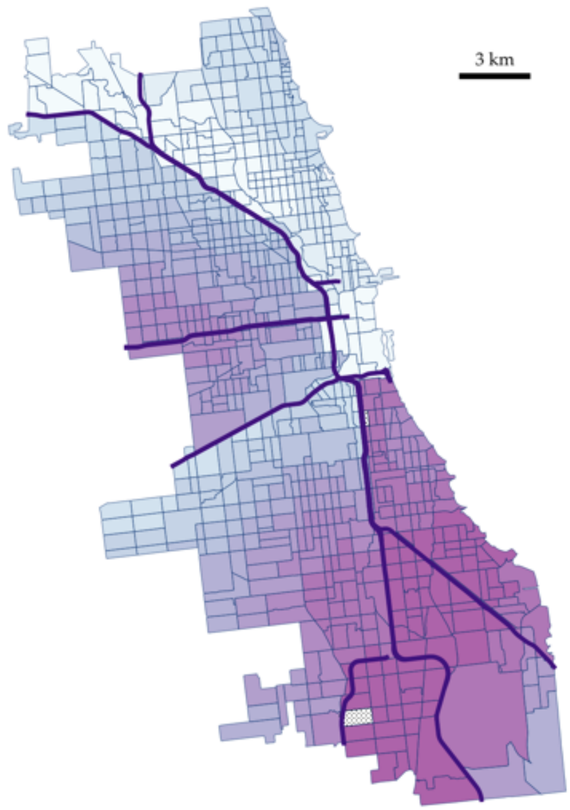
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS All	(6) Grid city se	(7) Conley se	(8) IV All	(9) IV Subs 1	(10) IV Subs 2	(11) IV Δ YMA
ΔS (std)	-0.479***	-0.533***	-0.354***	-0.351***	-0.352***	-0.352***	-0.352***	-0.273***	-0.323***	-0.366***	-0.278***
	(0.037)	(0.038)	(0.041)	(0.040)	(0.038)	(0.100)	(0.071)	(0.048)	(0.045)	(0.044)	(0.047)
Dist expressway (km)		-0.168***	0.015	0.026	0.026	0.026	0.026	0.035*	0.032*	0.056***	0.035*
		(0.018)	(0.019)	(0.018)	(0.018)	(0.054)	(0.034)	(0.018)	(0.018)	(0.018)	(0.018)
ΔY (std)					-0.007	-0.007	-0.007	0.014	-0.013	0.238***	0.029
					(0.048)	(0.103)	(0.090)	(0.048)	(0.047)	(0.043)	(0.049)
Observations	742	742	742	720	720	720	720	720	715	641	720
Adjusted R^2	0.511	0.571	0.707	0.727	0.727	0.727	0.726				
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								1422	1362	1199	596.7

The table reports the estimation results from regression (2) on the change in land value. The regressors of interest are: ΔS (standardized) measures the change in exposure to Black areas in the city; $Dist\ expressway$ measures the km distance from the closest expressway; ΔY measures the change in exposure to rich areas in the city. Region FE for being in the north, west, or south side of the city are always included. Tract controls are: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to water. Historical controls include: distance to railroads in 1898; HOLC grade, historical outcomes in levels, and the change in population density between 1920 and 1940. Column (6) shows standard errors assuming that census tract within the same grid cell are spatially correlated (for this exercise, I partitioned the city into 25 squares). Column (7) computes Conley (1999) standard errors to allow arbitrary spatial correlation of errors between tracts within 3 km from each other. Column (8) shows the IV results after instrumenting for the change in exposure to Black residents holding the distribution of races within the city fixed to the pre-period. Column (9) reports the IV results after removing the 5% of the sample that in 1920 already had a large concentration of Black residents (i.e., removes all area with more than 20% share in 1920). Column (10) reports the estimated IV coefficients after removing the 12% of the census tracts in the sample that are within 5 km of the CBD. Column (11) additionally instruments for the change in exposure to rich neighborhoods in the city, with an instrumental variable (ΔYMA) that is constructed similarly to ΔSMA. Supplementary detail is available in the main text. Standard errors clustered at census tract level in parentheses (unless specified differently). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C.5 Local exposure measure: 20 km cutoff

Here, I replicate the same analysis presented in the main text, using more localized measures of exposure to Black residents. To compute both ΔS_i and the IV (ΔSMA_i), I set weights in such a way that locations further than 20 km away from each origin location effectively receive weights close to zero). Specifically, in each period t, the pairwise weights are calculated as: $w_{ijt} = e^{-0.25\,\tau_{ijt}}$, where τ_{ijt} corresponds to the shortest distance between i and j (and viceversa), in the road network at time t.[83] In the next section, I repeat the same but using a cutoff distance of 10 km.

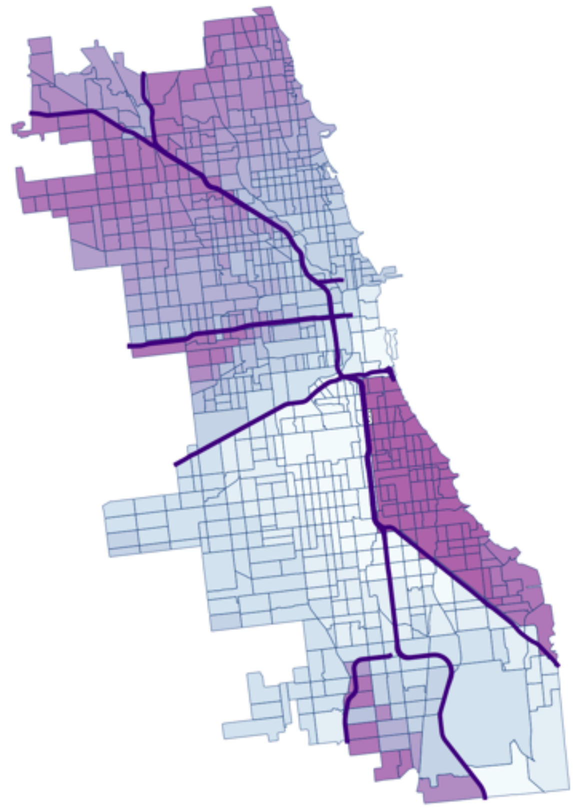
Figure C7: Change in exposure to Black residents (20 km cutoff)



Note: The figure plots the overall change in exposure to Black residents (ΔS_i) for each neighborhood in the city. The overall change includes both the change in exposure due to the spatial resorting of people between 1950 and 1990 and the change due to the development of the road network. Weights are set in such a way that locations further than 20 km away from each origin location receive close to zero weights. Census tracts are grouped into deciles based on the change in exposure to Black residents, with darker colors indicating larger increases in exposure. The purple lines show the expressways route as of 1990.

[83] To compute the shortest path (using Dijkstra's algorithm) between each location and every other location in the city, I use the QGIS plugin QNEAT3.

Figure C8: Instrument ΔSMA (20 km cutoff)



Note: The figure plots the baseline instrument for the change in exposure to Black residents. The instrument isolates the variation that is due only to changes in traveling times through expressway construction. In the post-period, I assume infinitely high costs of crossing the expressway network. Weights are set in such a way that locations further than 20 km away from each origin location receive close to zero weights. Census tracts are grouped into deciles, with darker colors indicating larger increases in exposure. The purple lines show the expressways route as of 1990.

Table C5: 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 20 km (std)	0.812***	0.815***	0.693***	0.808***	0.827***	0.827***	0.827***	0.245**	0.269**	0.441***	0.202*
	(0.035)	(0.035)	(0.040)	(0.040)	(0.039)	(0.092)	(0.078)	(0.103)	(0.106)	(0.096)	(0.105)
Dist expressway (km)		0.017	-0.084***	-0.119***	-0.115***	-0.115***	-0.115***	-0.217***	-0.213***	-0.206***	-0.223***
		(0.016)	(0.019)	(0.018)	(0.018)	(0.038)	(0.028)	(0.025)	(0.025)	(0.024)	(0.026)
ΔY 20 km (std)					0.102**	0.102	0.102	-0.054	-0.048	-0.187***	0.040
					(0.046)	(0.102)	(0.075)	(0.055)	(0.056)	(0.060)	(0.062)
Observations	790	790	790	751	751	751	751	751	738	663	751
Adjusted R^2	0.476	0.476	0.526	0.673	0.675	0.675	0.675	0.558	0.564	0.654	0.537
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								196	184.4	169.3	82.89

The table reports the estimation results from regression (2) using local measures of exposure. Detail on the specifications and the controls are at the bottom of Table 1. *** p<0.01, ** p<0.05, * p<0.1

Table C6: 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 20 km (std)	-0.533***	-0.552***	-0.554***	-0.477***	-0.376***	-0.376***	-0.376***	-0.125	-0.212**	-0.252***	-0.052
	(0.043)	(0.043)	(0.046)	(0.045)	(0.045)	(0.115)	(0.083)	(0.087)	(0.091)	(0.096)	(0.088)
Dist expressway (km)		-0.127***	-0.038	0.009	0.043*	0.043	0.043	0.094***	0.078***	0.092***	0.103***
		(0.023)	(0.026)	(0.024)	(0.022)	(0.057)	(0.049)	(0.025)	(0.027)	(0.025)	(0.026)
ΔY 20 km (std)					0.459***	0.459***	0.459***	0.546***	0.506***	0.758***	0.386***
					(0.079)	(0.145)	(0.139)	(0.072)	(0.076)	(0.068)	(0.081)
Observations	766	766	766	744	744	744	744	744	731	656	744
Adjusted R^2	0.382	0.417	0.493	0.564	0.608	0.608	0.608	0.587	0.602	0.625	0.565
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								228.5	176.1	175.4	92.65

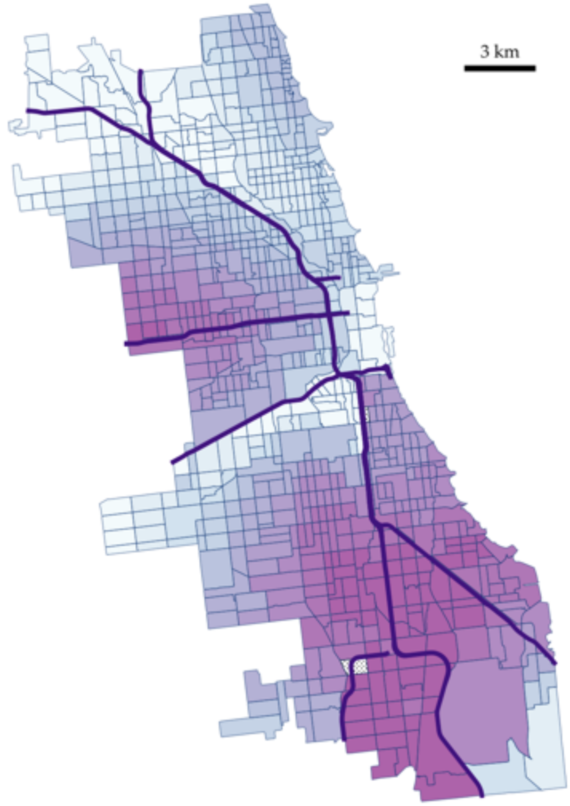
The table reports the estimation results from regression (2) using local measures of exposure. Detail on the specifications and the controls are at the bottom of Table 1. *** p<0.01, ** p<0.05, * p<0.1

C.6 Local exposure measure: 10 km cutoff

Here, I repeat again the same analysis as in the previous section, using a 10 km cutoff. That is, in computing the change in exposure to Black residents in the city and its instrument for each census tract, weights are set in such a way that locations further than 10 km away from each origin location effectively receive weights close to zero. Specifically, in each period t, the pairwise weights are calculated as: $w_{ijt} = e^{-0.5\,\tau_{ijt}}$, where τ_{ijt} corresponds to the shortest distance between i and j (and viceversa), in the road network at time t.[84]

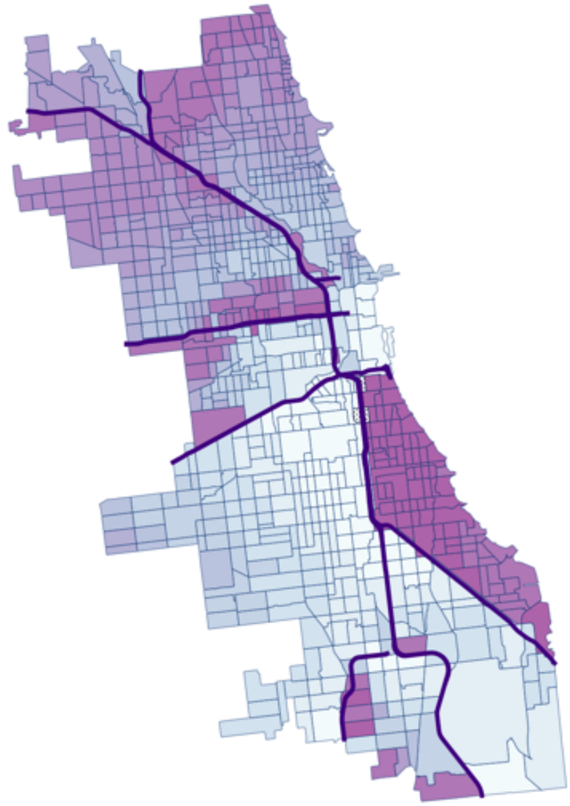
[84] To compute the shortest path (using Dijkstra's algorithm) between each location and every other location in the city, I use the QGIS plugin QNEAT3.

Figure C9: Change in exposure to Black residents (10 km cutoff)



Note: The figure plots the overall change in exposure to Black residents (ΔS_i) for each neighborhood in the city. The overall change includes both the change in exposure due to the spatial resorting of people between 1950 and 1990 and the change due to the development of the road network. Weights are set in such a way that locations further than 10 km away from each origin location receive close to zero weights. Census tracts are grouped into deciles based on the change in exposure to Black residents, with darker colors indicating larger increases in exposure. The purple lines show the expressways route as of 1990.

Figure C10: Instrument ΔSMA (10 km cutoff)



Note: The figure plots the baseline instrument for the change in exposure to Black residents. The instrument isolates the variation that is due only to changes in traveling times through expressway construction. In the post-period, I assume infinitely high costs of crossing the expressway network. Weights are set in such a way that locations further than 10 km away from each origin location receive close to zero weights. Census tracts are grouped into deciles, with darker colors indicating larger increases in exposure. The purple lines show the expressways route as of 1990.

Table C7: 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 10 km (std)	0.881***	0.881***	0.840***	0.858***	0.855***	0.855***	0.855***	0.279**	0.316**	0.400***	0.200
	(0.026)	(0.026)	(0.028)	(0.028)	(0.029)	(0.060)	(0.049)	(0.139)	(0.147)	(0.140)	(0.147)
Dist expressway (km)		0.003	-0.031*	-0.070***	-0.071***	-0.071**	-0.071**	-0.199***	-0.191***	-0.187***	-0.215***
		(0.013)	(0.017)	(0.016)	(0.016)	(0.026)	(0.025)	(0.035)	(0.037)	(0.037)	(0.037)
ΔY 10 km (std)					-0.016	-0.016	-0.016	-0.191***	-0.182***	-0.304***	-0.051
					(0.039)	(0.080)	(0.062)	(0.063)	(0.066)	(0.084)	(0.078)
Observations	790	790	790	751	751	751	751	751	738	663	751
Adjusted R^2	0.670	0.670	0.682	0.771	0.771	0.771	0.770	0.626	0.641	0.706	0.577
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								42.56	39.09	38.38	19.54

The table reports the estimation results from regression (2) using local measures of exposure. Detail on the specifications and the controls are at the bottom of Table 1. *** p<0.01, ** p<0.05, * p<0.1

Table C8: 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 10 km (std)	-0.566***	-0.571***	-0.593***	-0.505***	-0.365***	-0.365***	-0.365***	-0.346**	-0.525***	-0.536***	-0.100
	(0.033)	(0.034)	(0.036)	(0.037)	(0.038)	(0.095)	(0.040)	(0.155)	(0.154)	(0.193)	(0.154)
Dist expressway (km)		-0.114***	-0.061**	-0.014	0.032*	0.032	0.032	0.037	-0.005	0.003	0.086**
		(0.021)	(0.024)	(0.023)	(0.019)	(0.045)	(0.045)	(0.039)	(0.040)	(0.049)	(0.040)
ΔY 10 km (std)					0.655***	0.655***	0.655***	0.663***	0.583***	0.743***	0.344***
					(0.073)	(0.145)	(0.126)	(0.086)	(0.087)	(0.119)	(0.104)
Observations	766	766	766	744	744	744	744	744	731	656	744
Adjusted R^2	0.454	0.482	0.542	0.594	0.680	0.680	0.680	0.680	0.673	0.702	0.612
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								25.87	27.61	17.64	13.01

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The table reports the estimation results from regression (2) using local measures of exposure. Detail on the specifications and the controls are at the bottom of Table 1. *** p<0.01, ** p<0.05, * p<0.1

C.7 Additional evidence

Table C9: Dep variable: Δ house value (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)	0.000	-0.037	-0.056	-0.079*	-0.062	-0.062	-0.062	0.015	0.036	0.048	-0.002
	(0.031)	(0.035)	(0.045)	(0.047)	(0.046)	(0.076)	(0.083)	(0.066)	(0.068)	(0.064)	(0.066)
Dist expressway (km)		-0.090***	0.018	0.026	0.042*	0.042	0.042	0.050**	0.051**	0.069***	0.050**
		(0.022)	(0.021)	(0.022)	(0.022)	(0.038)	(0.038)	(0.022)	(0.022)	(0.020)	(0.022)
ΔY (std)					0.342***	0.342***	0.342***	0.348***	0.360***	0.371***	0.398***
					(0.065)	(0.106)	(0.091)	(0.063)	(0.065)	(0.050)	(0.069)
Observations	733	733	733	700	700	700	700	700	695	637	700
Adjusted R^2	0.403	0.420	0.524	0.567	0.589	0.589	0.589				
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								1234	1199	1099	440.4

The table reports the estimation results from regression (2) on the change in house value. The regressors of interest are: ΔS (standardized) measures the change in exposure to Black areas in the city; *Dist expressway* measures the km distance from the closest expressway; ΔY measures the change in exposure to rich areas in the city. Region FE for being in the north, west, or south side of the city are always included. Tract controls are: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to water. Historical controls include: distance to railroads in 1898; HOLC grade, historical outcomes in levels, and the change in population density between 1920 and 1940. Column (6) shows standard errors assuming that census tract within the same grid cell are spatially correlated (for this exercise, I partitioned the city into 25 squares). Column (7) computes Conley (1999) standard errors to allow arbitrary spatial correlation of errors between tracts within 3 km from each other. Column (8) shows the IV results after instrumenting for the change in exposure to Black residents holding the distribution of races within the city fixed to the pre-period. Column (9) reports the IV results after removing the 5% of the sample that in 1920 already had a large concentration of Black residents (i.e., removes all area with more than 20% share in 1920). Column (10) reports the estimated IV coefficients after removing the 12% of the census tracts in the sample that are within 5 km of the CBD. Column (11) additionally instruments for the change in exposure to rich neighborhoods in the city, with an instrumental variable (ΔYMA) that is constructed similarly to ΔSMA. Supplementary detail is available in the main text. Standard errors clustered at census tract level in parentheses (unless specified differently). *** p<0.01, ** p<0.05, * p<0.1.

Table C10: Dep variable: Δ college share (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)	-0.077	-0.119**	-0.078	-0.070	-0.023	-0.023	-0.023	0.031	0.019	-0.020	0.023
	(0.050)	(0.053)	(0.056)	(0.058)	(0.056)	(0.087)	(0.097)	(0.075)	(0.076)	(0.068)	(0.073)
Dist expressway (km)		-0.123***	-0.011	-0.008	0.003	0.003	0.003	0.009	0.008	0.036	0.009
		(0.020)	(0.022)	(0.023)	(0.023)	(0.062)	(0.052)	(0.024)	(0.024)	(0.022)	(0.023)
ΔY (std)					0.320***	0.320***	0.320***	0.330***	0.326***	0.413***	0.358***
					(0.070)	(0.095)	(0.082)	(0.068)	(0.070)	(0.048)	(0.069)
Observations	763	763	763	726	726	726	726	726	721	647	726
Adjusted R^2	0.401	0.433	0.502	0.525	0.548	0.548	0.548				
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								1346	1294	1111	550.4

The table reports the estimation results from regression (2) on the change in the share of college graduates. The regressors of interest are: ΔS (standardized) measures the change in exposure to Black areas in the city; *Dist expressway* measures the km distance from the closest expressway; ΔY measures the change in exposure to rich areas in the city. Region FE for being in the north, west, or south side of the city are always included. Tract controls are: a quadratic polynomial of distance to the central business district (CBD), land area, and distance to water. Historical controls include: distance to railroads in 1898; HOLC grade, historical outcomes in levels, and the change in population density between 1920 and 1940. Column (6) shows standard errors assuming that census tract within the same grid cell are spatially correlated (for this exercise, I partitioned the city into 25 squares). Column (7) computes Conley (1999) standard errors to allow arbitrary spatial correlation of errors between tracts within 3 km from each other. Column (8) shows the IV results after instrumenting for the change in exposure to Black residents holding the distribution of races within the city fixed to the pre-period. Column (9) reports the IV results after removing the 5% of the sample that in 1920 already had a large concentration of Black residents (i.e., removes all area with more than 20% share in 1920). Column (10) reports the estimated IV coefficients after removing the 12% of the census tracts in the sample that are within 5 km of the CBD. Column (11) additionally instruments for the change in exposure to rich neighborhoods in the city, with an instrumental variable (ΔYMA) that is constructed similarly to ΔSMA. Supplementary detail is available in the main text. Standard errors clustered at census tract level in parentheses (unless specified differently). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

D Appendix to the quantitative model

D.1 Calibration

D.1.1 Travel times calibration

Travel times are measured in minutes and depend on the road transportation network available in each period. I assume average travel speeds for each mode of transport. Travel times differ between low and high-educated individuals, because they are assumed to rely on different transportation modes. I consider high-educated individuals to move only by car in both periods. Low-educated individuals instead move exclusively by bus in 1940, but they move by bus with 0.75 probability and by car with 0.25 probability in 1990.

Data on average speed and transportation mode by income group come from different sources. For the pre-period data, the closest information comes from the 1956 Chicago Area Transportation Study, which had the purpose of analyzing travel behavior and anticipating future needs for transportation facilities. It reports an average speed of 9.98 km/h for buses and 17.86 km/h for cars. For the more recent period, the closest information comes from a 2013 RTA sub-regional report and TomTom data that estimate an average speed of 20.02 km/h for buses and 32.99 km/h for cars. The assignment of travel modes by income level comes from the 2001 National Household Travel Survey report (Hu and Reuscher, citeyearNHTS2001). It describes that 3/4 low-income families do not have a car. I hence compute an average speed that is a weighted sum of traveling by car (with probability 0.25) and traveling by bus (with probability 0.75). For 1940, data was difficult to find. I assume all high-educated people move by car, and all low-educated people move by bus. In this exercise, I am not considering travel modes that operate outside of the road network (like light rails and trains). Variation in travel times over time and across types hence only depends on changes in the road network and changes in the transportation technology.

D.1.2 Wages calibration

A special census administered in Chicago in 1934 allows to recover educational attainment by racial group. As a first step, I compute the median educational attainment at the city level, which corresponds to grades 5-8 completed. As a result, I define as low educated people that have completed at most grade 8 and I define as highly educated people that have completed grade 9 or more (i.e., with above median educational attainment). Then, I compute for each census tract in the city, the number of Black and white individuals that have below or above median educational attainment. At the city level, I find that in 1934 only 29% of the Black population above 18 completed grade 9 or above, as opposed to 40% of the residual non-Black category.[85] Since I could not find information on wage by race even at the city level, I rely on summary information from the 1940 census of population on wage by educational attainment by race.[86] Weighing the median wages by educational attainment

[85] By looking at native white with native white parents only, the share of individuals above 18 that have above median educational attainment corresponds to 60%.

[86] The information is retrieved here: `https://www.census.gov/library/publications/1946/demo/p46-5.html`. The table provides wage categories by education, separately for white and Black. I hence computed the median wage for each

by the share of each race-by-education group that I find for the city of Chicago, the calibrated wages in the pre-period (in $2010) are as follows: $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.

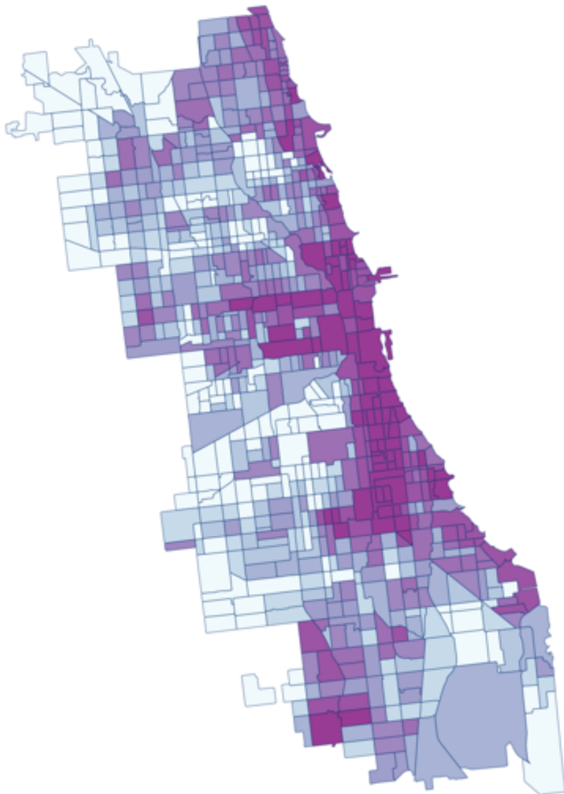
In 1990, median educational attainment in the city of Chicago corresponds to completing high school. I divide the sample into above educational attainment (at least some college) and below median (high school level or below). I then use country-wide summary information of income by years of school completed by race in 1990 to compute median wages by race with below or above median education.[87] Weighting median wages by educational attainment by the share of each-race-by-education group, the calibrated wages in the post-period (in $2010) are: $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.

educational attainment group available, and then I computed the median wages for above and below median education in Chicago weighing the values by the educational group categories found for the city of Chicago.

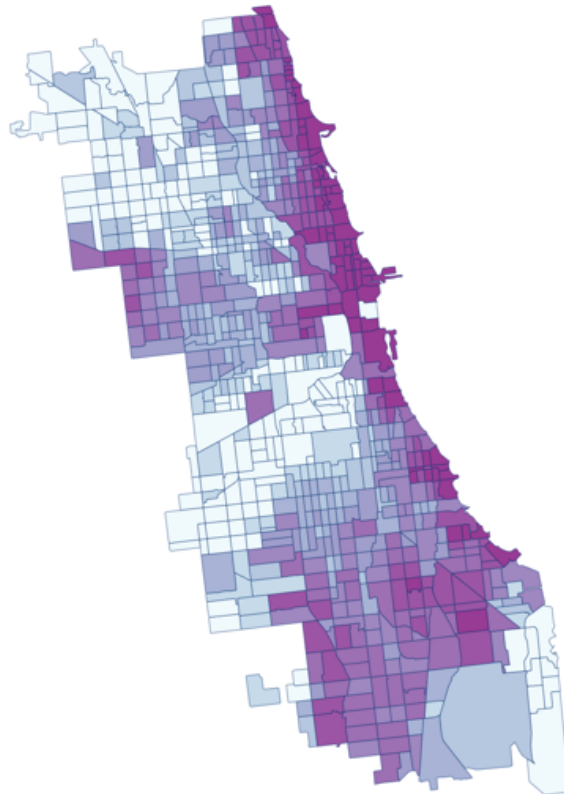
[87] 1990 data available at: `https://www2.census.gov/programs-surveys/demo/tables/educational-attainment/time-series/p20-462/tab08.pdf`. The table provides median income by completed years of schooling, separately for Black and white. The below or above median education wages are then computed by weighting the median values in this table by the share of Black and white population with the respective education level in the city of Chicago.

D.2 Inverted overall amenities by type

Figure D1: Recovered overall amenities (type BH)



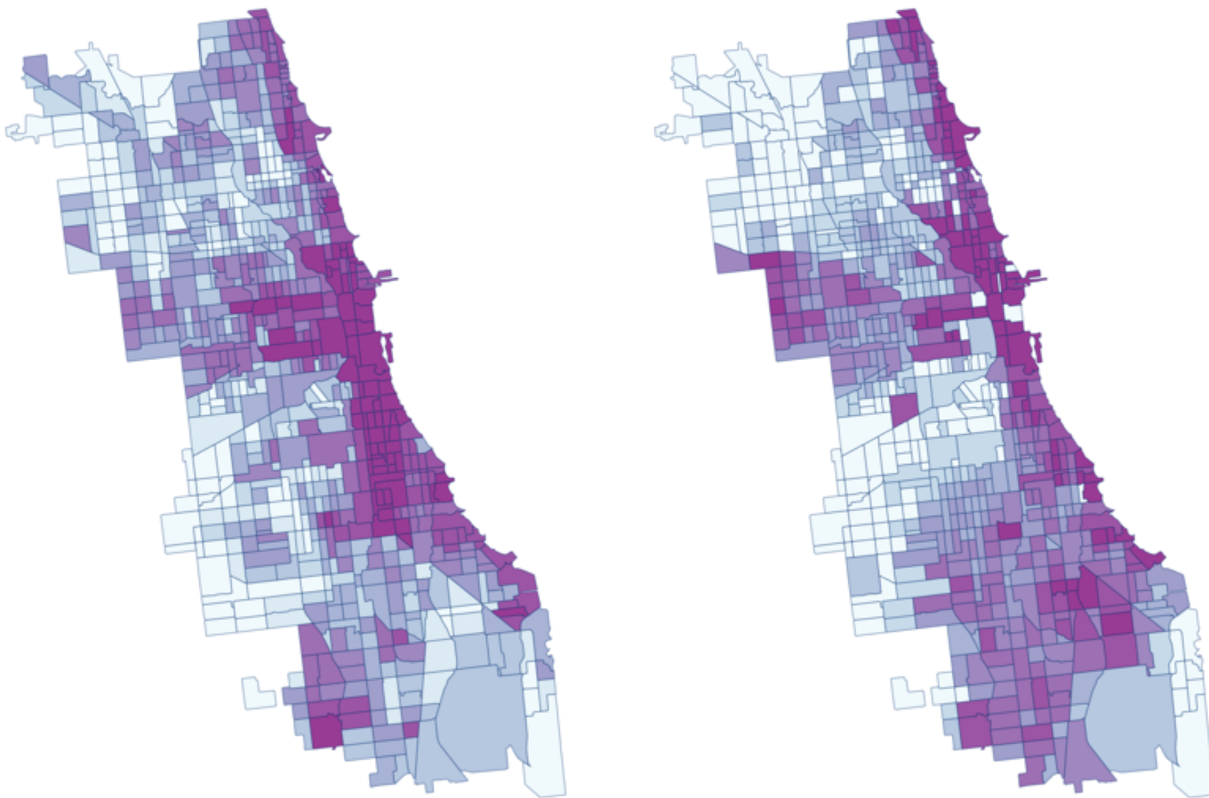
(a) 1940



(b) 1990

Note: The maps show deciles of the distribution of recovered overall amenities after inverting the model in each period, for type BH (Black with above median level of education). Darker colors correspond to higher amenity values.

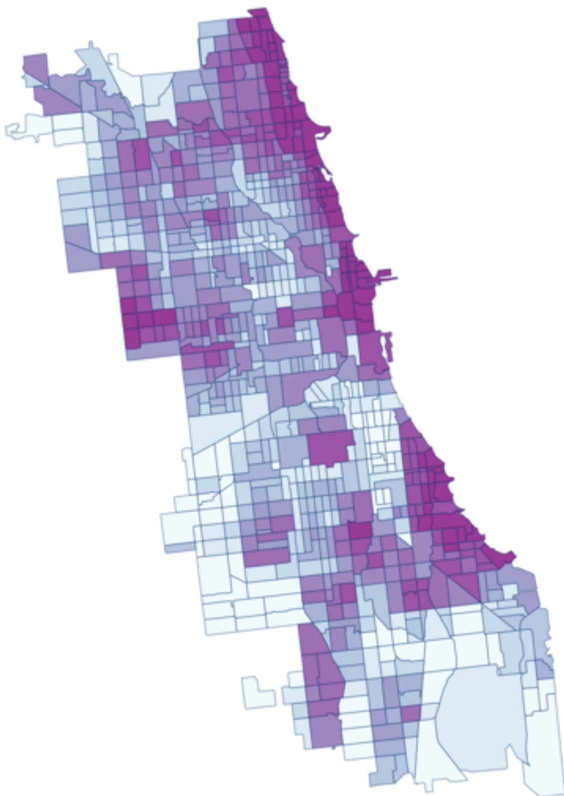
Figure D2: Recovered overall amenities (type BL)



(a) 1940 (b) 1990

Note: The maps show deciles of the distribution of recovered overall amenities after inverting the model in each period, for type BL (Black with below median level of education). Darker colors correspond to higher amenity values.

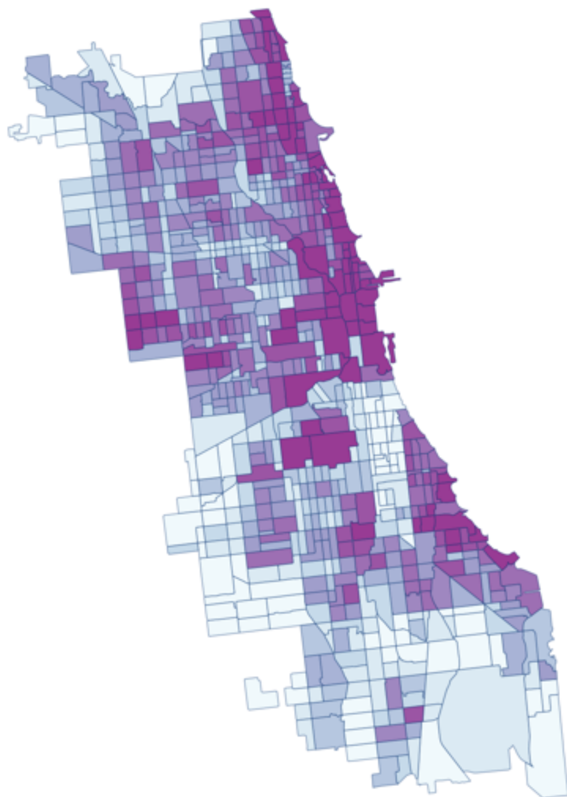
Figure D3: Recovered overall amenities (type WH)



(a) 1940 (b) 1990

Note: The maps show deciles of the distribution of recovered overall amenities after inverting the model in each period, for type WH (white with above median level of education). Darker colors correspond to higher amenity values.

Figure D4: Recovered overall amenities (type WL)



(a) 1940 (b) 1990

Note: The maps show deciles of the distribution of recovered overall amenities after inverting the model in each period, for type WL (white with below median level of education). Darker colors correspond to higher amenity values.

D.3 Equilibrium

An equilibrium of the model is characterized by the assignment of households of each type to neighborhoods and a vector of rental prices, such that land market clears in each location and no household has an incentive to deviate by moving to a different place. Given the model's parameters $\{\alpha, \epsilon, \kappa\, \lambda^o_{B,W}, \rho^o, g^o, \eta, \mu\}$, the vectors of exogenous location characteristics $\{T, B, K, \tau^{H,L}\}$, and 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 vectors $\{R_j, \pi^o_j\}$ and total city population scalars N^o.

The nine elements of the equilibrium vector are determined by the following system of nine equations: population mobility conditions for each type ($\times 4$), residential choice probability for each type ($\times 4$), and the land market clearing condition ($\times 1$).

The system of equations characterizing the equilibrium of the model consists of:

1. Population mobility conditions

$$\mathbb{E}[u^o] = \gamma \left[\sum_s T_s (R_s^{1-\alpha})^{-\epsilon} (B_s^o)^{\epsilon} (w^o / d_{sC}^{H,L})^{\epsilon} \right]^{1/\epsilon} = \bar{U}^o \tag{D1}$$

2. Residential choice probabilities

$$\frac{B_j^o T_j^{1/\epsilon}}{\bar{U}^o/\gamma} = \left(\frac{N_j^o}{N^o} \right)^{1/\epsilon} \frac{R_j^{1-\alpha}}{w^o / d_{jC}^{H,L}} \tag{D2}$$

3. Residential amenities depend on adjusted fundamentals ($\tilde{b}_j^o$), the disamenity of expressways (E_j^o), and neighborhoods' demographics (H_j, Ω_j^o)

$$\begin{aligned} \tilde{B}_j^o &= \tilde{b}_j^o H_j E_j^o \Omega_j^o \\ &= \tilde{b}_j^o \frac{N_j^H}{N_j} (1 - g^o e^{-\eta dist_j}) \left(\sum_{i \neq j} e^{-\rho^o \tau_{ji}^{H,L}} \frac{N_i^B}{K_i} \right)^{\lambda_B^o} \left(\sum_{i \neq j} e^{-\rho^o \tau_{ji}^{H,L}} \frac{N_i^W}{K_i} \right)^{\lambda_W^o} \end{aligned} \tag{D3}$$

4. Land market clearing condition

$$\phi_j = \frac{(1-\alpha)\bar{W}_j N_j}{R_j K_j^{1-\mu}} \tag{D4}$$

D.3.1 Iterative algorithm

Given model's parameters, recovered unobserved fundamentals, and initial conditions, I implement a standard iterative procedure (e.g., see Alhfeldt et al., 2015) to find an equilibrium of the model. The algorithm proceeds iteratively using an initial guess for location specific floorspace prices, population, and neighborhood demographics, denoted by $\{R_j^0, N_j^{0^B}, N_j^{0^H}, N_j^0\}$.[88] Given the starting values, exogenous location characteristics $\{T_j, K_j, \tau_{ji}^{H,L}, dist_j\}$, recovered unobserved fundamentals $\{\tilde{b}_j^o, \phi_j\}$, and model's parameters $\{\alpha, \epsilon, \kappa\, \lambda_{B,W}^o, \rho^o, g^o, \eta, \mu\}$, the model supports closed-form solutions for all the endogenous variables in the model. I use the equilibrium conditions of the model to solve for the new predicted values for floorspace prices and population $\{R_j^1, N_j^{1^B}, N_j^{1^H}, N_j^1\}$. The required equations are given by the following system of equilibrium conditions:

1. Residential amenities

$$\tilde{B}_j^{1^o} = \tilde{b}_j^o \frac{N_j^{0^H}}{N_j^0} (1 - g^o e^{-\eta dist_j}) \left(\sum_{i \neq j} e^{-\rho^o \tau_{ji}^{H,L}} \frac{N_i^{0^B}}{N_i^0} \right)^{\lambda_B^o} \left(\sum_{i \neq j} e^{-\rho^o \tau_{ji}^{H,L}} \frac{N_i^{0^W}}{N_i^0} \right)^{\lambda_W^o} \tag{D5}$$

[88] As initial guess, I used the values in the data, but one could equally use constant values.

2. Residential choice probabilities

$$\pi_j^{1^o} = \frac{T_j(R_j^0)^{-\epsilon(1-\alpha)}(B_j^{1^o})^{\epsilon}(w^o/d_{jC}^{H,L})^{\epsilon}}{\sum_s T_s(R_s^0)^{-\epsilon(1-\alpha)}(B_s^{1^o})^{\epsilon}(w^o/d_{sC}^{H,L})^{\epsilon}} = \frac{\Phi_j^{1^o}}{\Phi^{1^o}} \tag{D6}$$

3. Residential population

$$N_j^{1^o} = N^o \pi_j^{1^o} \tag{D7}$$

4. Updated total relevant populations

$$\begin{aligned} N_j^{1^B} &= N_j^{1^{BL}} + N_j^{1^{BH}} \\ N_j^{1^H} &= N_j^{1^{BH}} + N_j^{1^{WH}} \\ N_j^1 &= \sum_o N_j^{1^o} \end{aligned} \tag{D8}$$

5. Location-specific effective wages

$$\bar{W}_j^1 = (1/N_j^1)\sum_o (w^o/d_{jC}^{H,L})N_j^{1^o} \tag{D9}$$

6. Updated floorspace prices

$$R_j^1 = \frac{(1-\alpha)\bar{W}_j^1 N_j^1}{\phi_j K_j^{1-\mu}} \tag{D10}$$

An equilibrium is found when the new predicted values are equal to the starting values: $\{R_j^0, N_j^{0^B}, N_j^{0^H}, N_j^0\} = \{R_j^1, N_j^{1^B}, N_j^{1^H}, N_j^1\}$. If the new predicted values are not equal to the starting values, I update the endogenous variables of the model using a weighted average of the starting values and the new predicted values, as follows:

$$\begin{aligned} R_j^0 &= 0.5R_j^0 + 0.5R_j^1 \\ N_j^{0^B} &= 0.5N_j^{0^B} + 0.5N_j^{1^B} \\ N_j^{0^H} &= 0.5N_j^{0^H} + 0.5N_j^{1^H} \\ N_j^0 &= 0.5N_j^0 + 0.5N_j^1 \end{aligned} \tag{D11}$$

The algorithm continues to solve the system until the endogenous variables converge to the counterfactual values.[89]

D.4 GMM estimation

I use the Generalized Method of Moments (GMM) with the moment conditions above to estimate the parameters of interest. The parameter vector is $\Lambda = [\lambda_{B,W}^o \ \rho^o \ g^o]'$. Combining the moment conditions

[89] The algorithm stops when the distance between the starting values and the updated values of the endogenous variables (in absolute terms) is smaller than 1×10^{-7}.

into a vector of moments, I get: $\mathbb{M}(\Lambda) = (1/N)\sum_{i=1}^{N} m(X_i, \Lambda) = 0$, with $m(X_i, \Lambda)$ being the moment function for observation i. The two-step efficient GMM estimation then solves:

$$\hat{\Lambda}_{GMM} = argmin\,(\mathbb{M}(\Lambda))'\,\mathbb{W}\,(\mathbb{M}(\Lambda)) \tag{D12}$$

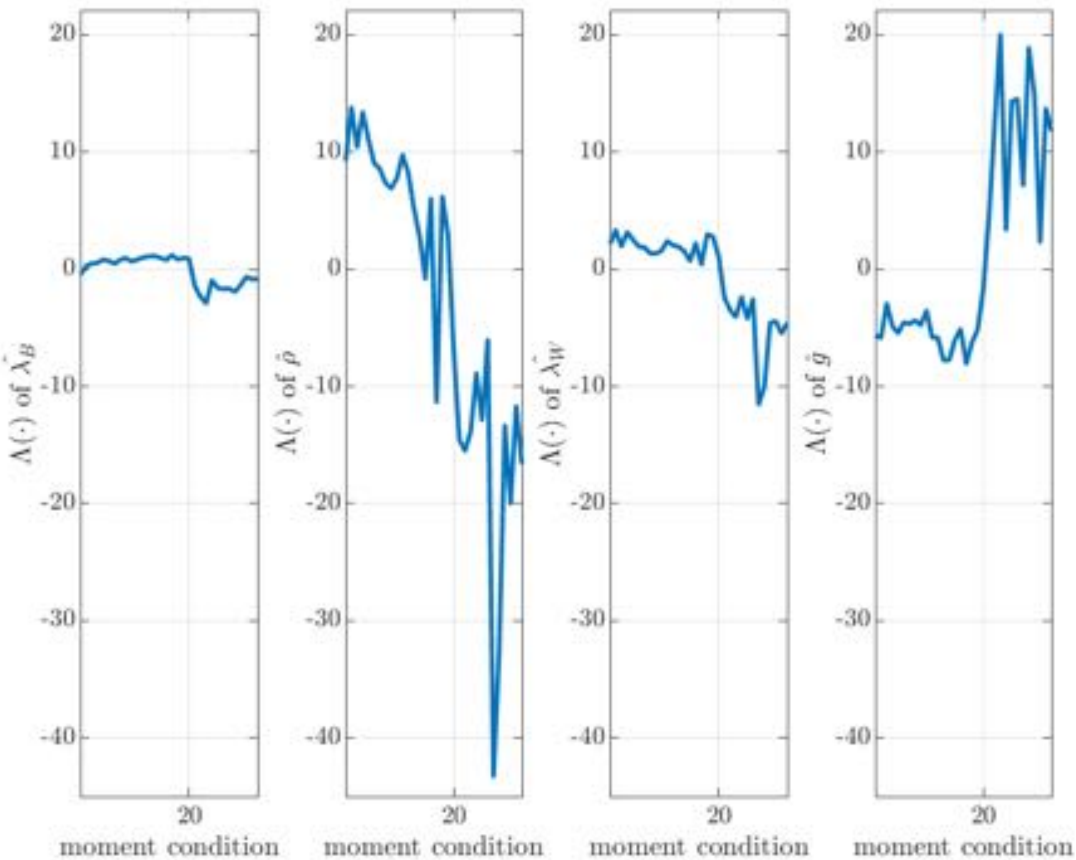
where $\mathbb{W}$ is the efficient weighting matrix. The GMM estimator chooses the values of the model's parameters to minimize the GMM objective function. This optimization routine searches over alternative parameter vectors and evaluates the moment function $m(X_i, \Lambda)$ for each parameter vector. In terms of implementation, I use the two-step GMM estimation in a standard procedure. First, I obtain a first estimate of $\hat{\Lambda}$ using the identity matrix as weighting matrix ($\mathbb{W} = I$). I then use the estimated parameters to compute the variance-covariance matrix of moments. Second, I use the estimate of the variance-covariance matrix of moments from step 1 as the weight matrix in step 2 of the estimation, to obtain a new (efficient) set of estimates. Finally, to compute the standard errors, I use numerical derivatives to get an estimate of the Jacobian matrix ($\hat{J}$).[90] Together with the estimates of the variance-covariance matrix of moments, standard errors are computed as: $se(\hat{\Lambda}) = (1/\sqrt{N})diag\left(\hat{J}'\hat{\Sigma}^{-1}\hat{J}\right)^{-1}$.

D.4.1 Sensitivity measure (Andrews et al., 2017)

I explore the sensitivity of the estimated parameters to the orthogonality conditions following Andrews et al. (2017). The sensitivity matrix is $\Lambda^S = -(J'WJ)^{-1}J'W$ where J is the Jacobian matrix and W is the weighting matrix. Below, I report the results separately for each type.

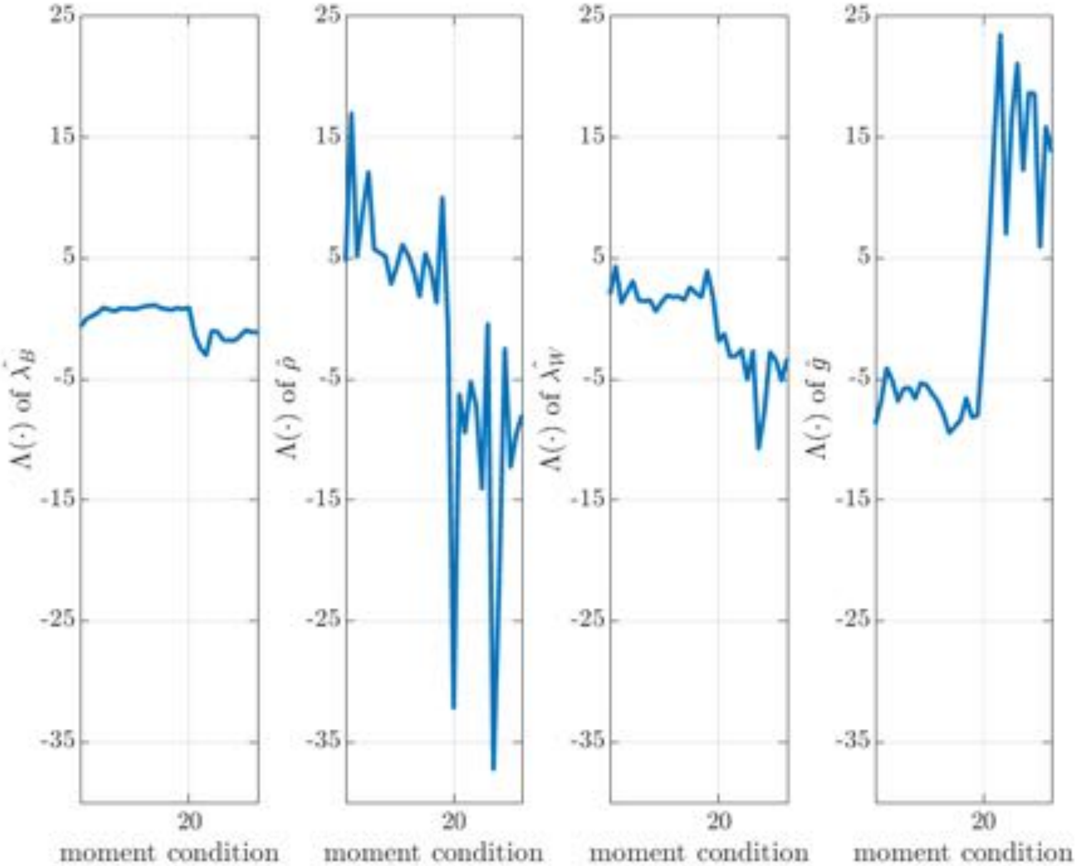
[90] I estimate the derivative of the moment function $m(X_i, \Lambda)$ at the estimated parameter given a small perturbation.

Figure D5: Sensitivity measures of estimated parameters (type BL)



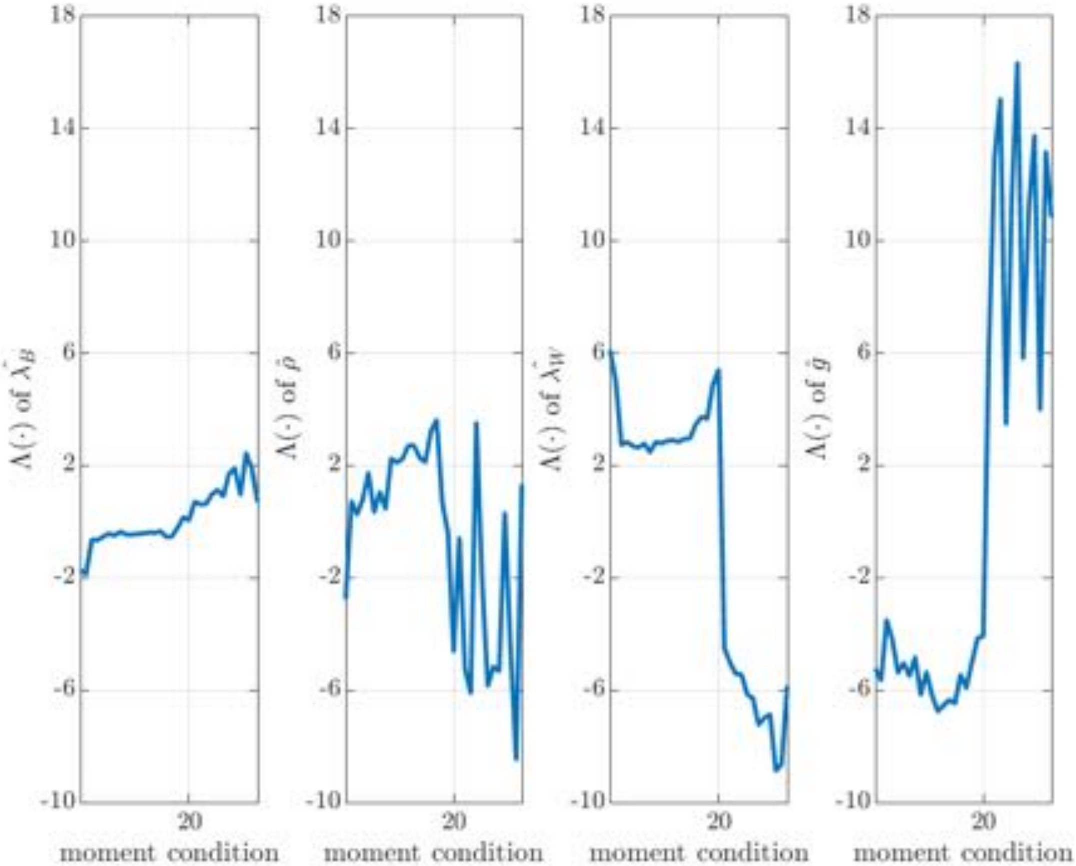
Note: The figures reports the values of the sensitivity matrix from Andrews et al. (2017) for each of the estimated parameters. The x-axis orders the moment conditions as follows: the first 30 correspond to the 30-quantiles of distances from the Black Belt; the latter 30 correspond to the 30-quantiles of distances from the CBD.

Figure D6: Sensitivity measures of estimated parameters (type BH)



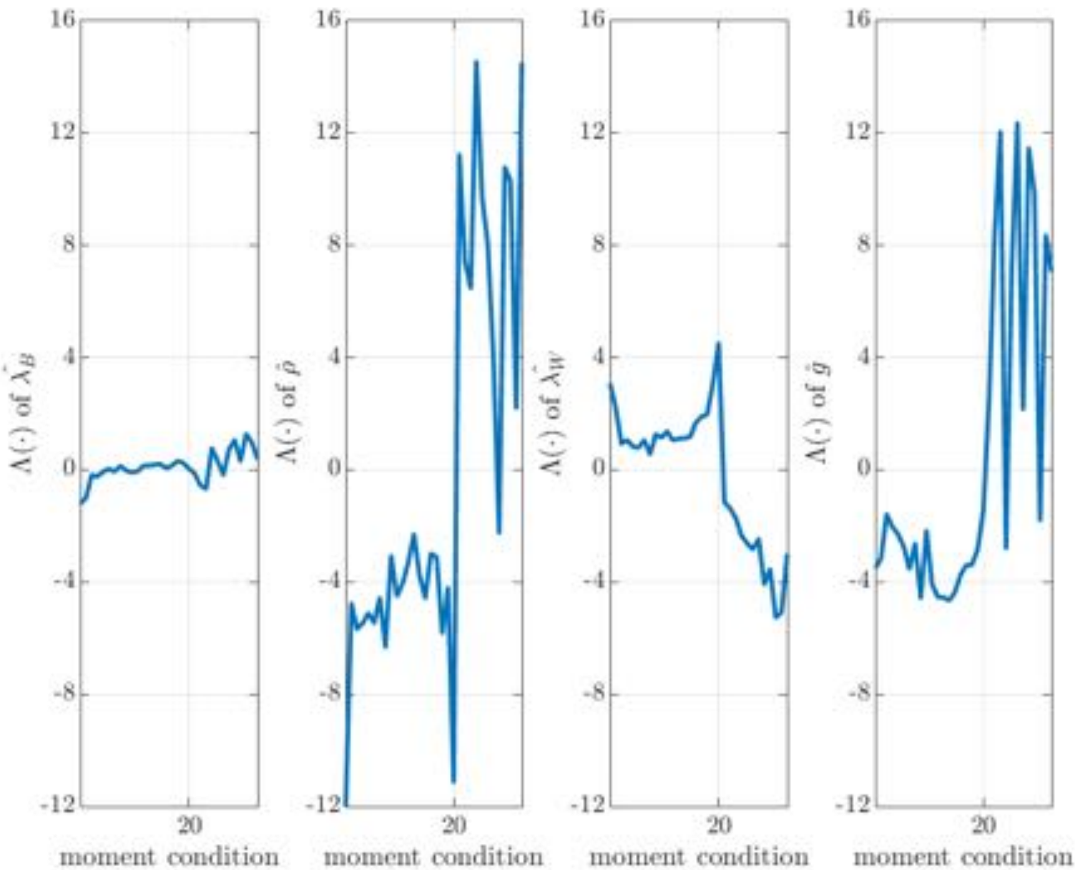
Note: The figures reports the values of the sensitivity matrix from Andrews et al. (2017) for each of the estimated parameters. The x-axis orders the moment conditions as follows: the first 30 correspond to the 30-quantiles of distances from the Black Belt; the latter 30 correspond to the 30-quantiles of distances from the CBD.

Figure D7: Sensitivity measures of estimated parameters (type WL)



Note: The figures reports the values of the sensitivity matrix from Andrews et al. (2017) for each of the estimated parameters. The x-axis orders the moment conditions as follows: the first 30 correspond to the 30-quantiles of distances from the Black Belt; the latter 30 correspond to the 30-quantiles of distances from the CBD.

Figure D8: Sensitivity measures of estimated parameters (type WH)



Note: The figures reports the values of the sensitivity matrix from Andrews et al. (2017) for each of the estimated parameters. The x-axis orders the moment conditions as follows: the first 30 correspond to the 30-quantiles of distances from the Black Belt; the latter 30 correspond to the 30-quantiles of distances from the CBD.

D.4.2 GMM objective functions and parameter space

I check how the GMM objective functions behave in the parameter space, by reporting the estimation results of the optimization routines from alternative initial values. The results are reported for a set of 10 alternative initial values, each drawn from a uniform distribution on the respective parameter space. For each of the randomly chosen set of initial values, reported in Table D1 below, the corresponding solutions of the GMM optimization procedure are reported in Table D2. The objective functions are well-behaved. The optimization routines for white residents (both low and high-educated) always return the same set of solutions, irrespective of the initial values chosen - corresponding to the baseline estimates reported in the main text. For Black high-educated individuals, the optimization routine stops at the baseline set of estimates 9/10 of the times. The remaining 1/10 of the times (corresponding to randomization 3 in the table below) finds an alternative configuration of the model's parameters as solution. It stops at a corner value for λ_W, and it shows more extreme and noisier values for the other parameters. Similarly, the optimization routine for Black low-educated individuals finds 9/10 of the times the baseline set of parameters, and the remaining one time (corresponding as before to randomization 3) stopping at an alternative set of parameters as solution. Also in this case, the alternative configuration stops at a corner solution for λ_W. Furthermore, it shows lower rate of spatial decay, and large disamenity parameter.

Table D1: Set of random initial values for GMM estimation

	initial value(λ_B)	*initial value*(ρ)	*initial value*(λ_W)	*initial value*(g)
rand 1	0.251066014	0.625533007	0.307984706	0.417022005
rand 2	1.16097348	1.08048674	-0.922221305	0.720324493
rand 3	-0.999656876	0.000171562	0.648987434	0.000114375
rand 4	-0.093002282	0.453498859	0.305967178	0.302332573
rand 5	-0.559732328	0.220133836	0.261103406	0.146755891
rand 6	-0.722984216	0.138507892	-0.008995537	0.092338595
rand 7	-0.441219366	0.279390317	-0.386054098	0.186260211
rand 8	0.036682181	0.518341091	0.857812899	0.345560727
rand 9	0.190302423	0.595151211	-0.101035979	0.396767474
rand 10	0.616450202	0.808225101	-0.199518175	0.538816734

Note: The table reports alternative initial values for each of the parameters of interest, used for the computation of the GMM optimization routine. For each parameter, I randomly selected 10 values within the respective range: $\lambda_{B,W} \in [-1, 2]$; $\rho \in [0, 1.5]$; $g \in [0, 1]$.

Table D2: GMM objective function search over the parameter space

	λ_B	*(s.e.)*	ρ	*(s.e.)*	λ_W	*(s.e.)*	g	*(s.e.)*	frequency
BH (baseline)	0.1795	*0.0145*	0.7474	*0.1672*	-0.1238	*0.0404*	0.2286	*0.0986*	9/10
BH (alternative)	-0.0258	*0.6605*	0.0042	*0.0489*	2.0000	*21.8331*	0.4466	*0.0823*	1/10
BL (baseline)	0.1537	*0.0152*	0.6737	*0.1807*	-0.1463	*0.0424*	0.2152	*0.1013*	9/10
BL (alternative)	0.2605	*0.0768*	0.0759	*0.0121*	-1.0000	*0.3247*	0.4059	*0.0906*	1/10
WH (baseline)	0.0443	*0.0089*	0.2908	*0.0478*	0.2679	*0.0174*	0.2044	*0.0437*	10/10
WL (baseline)	0.0746	*0.0122*	0.2285	*0.0605*	0.2508	*0.0262*	0.2630	*0.0582*	10/10

Note: The table reports the GMM estimates together with the frequency at which they are obtained after randomly varying the initial values of the GMM optimization routine.

D.4.3 Additional GMM results

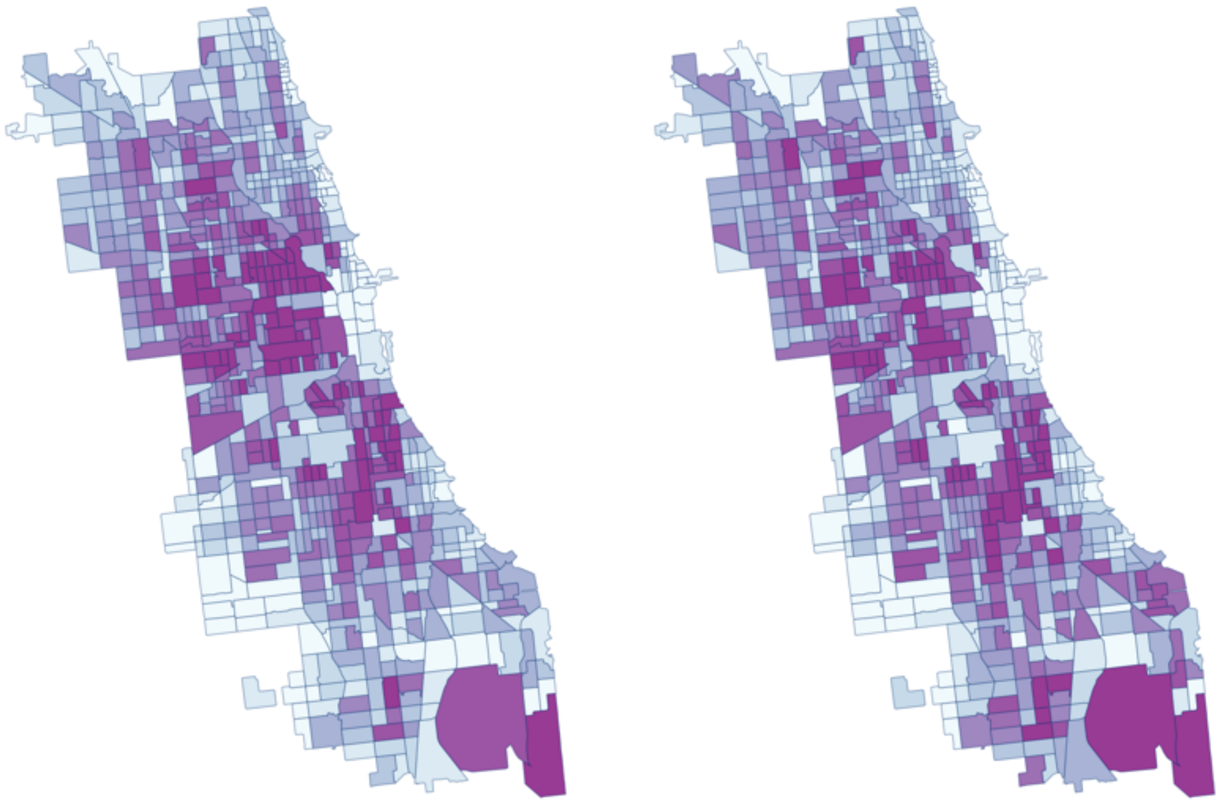
Table D3: Interpretation of magnitudes for ρ^o

	Racial externalities $(1 \times e^{-\rho^o \tau})$				Commuting costs $(1 \times e^{\kappa \tau})$
	BL	BH	WL	WH	
0 min	1.000	1.000	1.000	1.000	1.000
1 min	0.510	0.474	0.796	0.748	0.990
2 min	0.260	0.224	0.633	0.559	0.980
3 min	0.133	0.106	0.504	0.418	0.970
4 min	0.068	0.050	0.401	0.312	0.961
5 min	0.034	0.024	0.319	0.234	0.951
7 min	0.009	0.005	0.202	0.131	0.932
10 min	0.001	0.001	0.102	0.055	0.905
15 min	0.000	0.000	0.032	0.013	0.861
20 min	0.000	0.000	0.010	0.003	0.819
30 min	0.000	0.000	0.001	0.000	0.741

The table reports the reduction in residential externalities with travel time by type, compared to the reduction in utility from commuting with travel time. Travel time measured in minutes. Results are based on GMM estimates $\rho^{BL} = 0.674$, $\rho^{BH} = 0.747$, $\rho^{WL} = 0.229$, $\rho^{WH} = 0.291$, and calibrated $\kappa = 0.010$.

D.4.4 Over-identification checks

Figure D9: Recovered density of development (structural residual)



(a) 1940

(b) 1990

Note: The maps show deciles of the distribution of recovered density of development computed after inverting the the land market clearing condition in each period. Darker colors correspond to higher values of the variable.

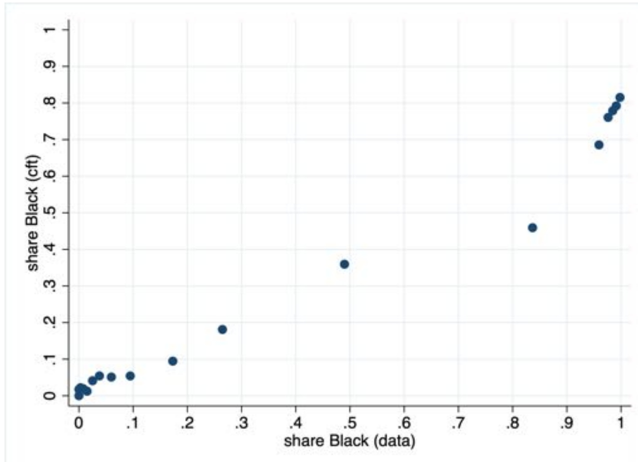
Table D4: Relation between ϕ (model) and observed data

	1940		1990	
	(1)	(2)	(3)	(4)
Dep. variable: Density of development $ln(\phi)$				
ln(# housing units)	0.7654***	0.7654***	0.5184***	0.5184***
	(0.0565)	(0.0839)	(0.1426)	(0.1148)
Adj-R^2	0.4870	0.4870	0.1002	0.1002
Dep. variable: $ln(\phi)$				
Share land for residential use (zoning)			1.8064***	1.8064***
			(0.1918)	(0.5056)
Adj-R^2			0.2124	0.2124
Clustered standard errors	Census tract	Grid 25	Census tract	Grid 25
Observations	767	767	766	766

Note: The table reports the estimates of OLS regressions of the (log) number of housing units (top panel) from the respective census year and of the share of land for residential use (bottom panel) on the (model-derived) density of development measure (ϕ), corresponding to the ratio of floorspace to land area. Columns (1) and (3) use standard errors clustered at the census tract level. Columns (2) and (4) use standard errors more conservatively clustered at the grid level after partitioning the city into 25 equally-sized squares. The regression outputs in 1990 lose one observation because one location shifts to zero reported residential population in 1990 (the location corresponds to the Midway airport). *** p<0.01, ** p<0.05, * p<0.1.

D.5 Counterfactual analyses

Figure D10: Model fit: share Black data vs. simulation



Note: The figure plots a binned scatterplot of the relation between share Black (1990 data) and the counterfactual share Black variable obtained from simulating the shock induced by the construction of expressways using the estimated parameters, but holding the location fundamentals fixed to the pre-period (see Section 7.5 in the main text for details).