The Problem Has Existed over Endless Years: Racialized Difference in Commuting, 1980–2019*

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Abstract

How have the longer journeys to work faced by Black commuters evolved in the United States over the last four decades? Black commuters spent 49 more minutes commuting per week in 1980 than White commuters; this difference declined to 22 minutes per week in 2019. Two factors account for the majority of the difference: Black workers are more likely to commute by transit, and Black workers make up a larger share of the population in cities with long average commutes. Increases in car commuting by Black workers account for nearly one quarter of the decline in the racialized difference in commute times between 1980 and 2019. Today, commute times have mostly converged (conditional on observables) for car commuters in small- and mid-sized cities. In contrast, differential job access today drives persistent differences of commute times, particularly in large, congested, and expensive cities.

JEL Codes: J15, R14, R40, J71

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1 Introduction

In 1955, Rosa Parks and five other Black women physically desegregated buses in Montgomery, AL when they refused to give up their seats to White passengers. Parks's arrest sparked action in the local Black community, bringing local leaders together to form the Montgomery Improvement Association (MIA) and lead a boycott of the buses until a more just solution was achieved.[1] The year-long boycott involved many Black bus commuters: only 36% of commuters in the most segregated Black census tracts of central Montgomery commuted by car in the 1960 Census.[2] MIA organizers faced many challenges coordinating carpooling services for the boycotters. Montgomery was very segregated, with Black residents heavily concentrated in neighborhoods away from the mostly White neighborhoods that were closer to the jobs in the city center. Black women in particular were likely to work in domestic service, which entailed commuting to White households scattered throughout the segregated city. Meanwhile, the police sought to intimidate carpool drivers and boycott leaders by pursuing early versions of "driving while Black" policing strategies (Jefferson-Jones 2020). During a speech to the boycotters, Dr. Martin Luther King, Jr. said that Black commuters "have been inflicted with the paralysis of crippling fears on buses" and that "[this] problem has existed over endless years."

The challenges faced by the MIA highlight how home location, work location, and the means of getting between the two collectively shape the time a worker spends commuting each day. Kain (1968) observed that the segregation of Black workers into certain center-city neighborhoods, job suburbanization, and lower rates of car ownership generated worse employment outcomes for Black households via increased *spatial mismatch* between home and work locations. Since then, each factor has evolved considerably. Residential segregation has declined after peaking in 1970, with some Black families now having access to a wider array of neighborhoods (Blair 2017; Sander, Kucheva, and Zasloff 2018). Occupational segregation has likewise declined with Black workers having greater opportunities in a wider array of occupations and industries, though employment suburbanization has also continued (see, e.g., Bahn and Cumming 2020). Today,

1. In fighting for their civil rights within transportation, the women entered a longstanding battleground. The landmark Supreme Court case enshrining segregation, Plessy v. Ferguson, was filed by Homer Plessy over segregated railcars (Plessy v. Ferguson, 163 U.S. 537 (U.S. Supreme Court 1896)). Fights in this arena have continued and expanded; for example, the Los Angeles Bus Riders Union filed suit over greater investment in White suburbs relative to communities of color in Greater Los Angeles (*Labor/Community Strategy Center et al. v. Los Angeles Metropolitan Transportation* 1996).

2. By contrast, 90% of commuters in the most segregated White tracts commuted by car (see Appendix).

85% of Black workers now commute by car, a far cry from the transit and walking dependence common among Black commuters in 1950s Montgomery. Given these substantial improvements, how has commuting evolved for Black workers, and are commuting outcomes in American cities equitable by race?

The short answer is no. While the *racialized difference* in commute times has declined from 49 minutes per week in 1980, Black commuters today still spend 22 more minutes per week commuting than White commuters.[3] In this paper, we investigate the factors behind this partial convergence and examine the mechanisms operating on individual commuters, neighborhoods, and cities that collectively obligate Black commuters into spending more time commuting.

We quantify the racialized difference in commute times conditional on working and decompose what portion of its evolution worked through channels observable in our data.[4] Two factors explain more than half of the aggregate difference in commute times: Black workers are more likely to live in cities with longer average commutes and to commute by transit. Black workers also hold demographic and job characteristics associated with shorter commutes; these differences partly offset the other factors and lower the racialized difference by 3% in 1980 and by 22% today. Income does not explain this difference (in fact, it is *positively* correlated with commute time). While the racialized difference in commute times is larger among those with low incomes and among transit users, it persists even for those with high incomes and who commute by car.

Of the total decline in the racialized difference in commute times from 1980 to 2019, we attribute 22% to changes in travel mode. Car usage increased for all commuters, with mode shares partially converging from 88% of White commuters and 76% of Black commuters in 1980 to 92% and 85%, respectively, by 2019. Commute times of White drivers increased more than those of Black drivers, amplifying the effect of mode on overall convergence in commute times. A further 13% of the convergence was attributable to changes in industry, occupation, and income: Black workers hold employment characteristics that are associated with relatively short commutes in general. Intriguingly, demographics and

3. Throughout this paper, we use the language of "racialized difference" to refer to the longer journeys to work reported by Black commuters relative to White commuters. We use this wording—rather than a passive term like "gap"—to highlight that this material outcome is a manifestation of social processes of racialization, the "process that naturalizes social difference" (Chun and Lo 2015).

4. We use "channels" to describe the role of observable characteristics in the manifestation of a racialized difference in commuting. These characteristics are not "controls" that must be accounted for to uncover the effects of racism because the labor and housing markets underlying these characteristics are themselves racialized (Bayer et al. 2017; Bohren, Hull, and Imas 2022; Neumark 2018).

commuting zone (CZ) of residence play almost no role in the decline. The remainder of the overall decline (63%) flows through other channels.

We investigate several dimensions of heterogeneity to identify channels that could explain racialized difference in commuting. First, we conduct a bounding exercise and show that racialized difference is not generated by differential selection into the labor market.[5] Next, we ask whether driving or high incomes eliminate the difference. While convergence in commute times has been greater among car commuters, it remains incomplete for drivers and for high earners. Among transit users, there has been no net convergence in commute times since 1980. Racialized difference in commuting is also present throughout the house price distribution; Black workers are not taking longer commutes as compensation for more affordable housing. Instead, spatial differences in home and workplace appear key. We incorporate within-CZ residential and workplace geographies available since 2000. Though coarse, residential and (especially) place-of-work PUMAs account for some racialized difference, especially in large cities.

We then quantify the variation in racialized difference across cities, estimating the *residual racialized difference* (RRD)—the average commute time difference that does not arise through observable channels—for each city and decade. The RRD has declined since 1980 in most cities; among cities with fewer than 500,000 employed workers, the average RRD today is near zero. The RRD is strongly correlated with city population, suggesting that a large population is now necessary (but not sufficient) for a city to generate a racialized difference in commute times.

We develop several city-level measures of job accessibility and relate them to RRD. We construct time-varying measures of local labor market access for the White and Black populations and aggregate these to measure city-by-racialized-group market access from ZIP-code level data on residential and workplace locations. In the largest cities, relative market access of Black residents deteriorated over our study period, with almost no change, on average, across other large and medium-sized cities. Differential market access thus undercut the convergence in commute times for Black and White workers. Other trends worked in the opposite direction: notably, declines in statistical segregation are associated with smaller values of RRD and account for a sizeable share of the total decline in RRD. Similarly, changes in inputs to travel speed—freeway construction, declining transit use, and indicators of faster travel speeds—are likewise associated with a

5. In fact, if long commutes disproportionately push Black workers out of the labor market, as Kain (1968) hypothesized, then our estimates may understate the racialized difference in commute times.

declining RRD. Lastly, high housing price growth is a driver of persistent positive RRD: in expensive cities, access to job-rich areas is rationed by housing markets.

Racialized commuting outcomes were a pervasive feature of U.S. geography 40 years ago, present across much of the country regardless of city size or travel mode. The dramatic decline since 1980 belies nuanced forces that are increasingly city specific: for car commuters in small- and mid-sized cities, there has been almost complete convergence, conditional on observed characteristics. Today, the racialized difference in commute times arises primarily in very large cities with unequal job access, and distances too long (or congestion too intense) for a car to offer a short commute. The reductions in residential and employment segregation need not fully translate into more equitable job access—as Kain (1992) observed, Black households often relocated to suburbs on the opposite side of the city from suburbanizing employment in cities like Dallas. The evolution of the racialized difference in commuting reflects both meaningful gains for many Black workers and durable barriers to convergence.

This paper offers several contributions to literatures within urban economics and inequality. First, we comprehensively quantify the Black-White difference in commute times for all U.S. CZs and describe its evolution over the last 40 years. While the consequences of spatial mismatch on racial differences in employment outcomes has been studied at length, there has been little recent attention on the complementary study of inequitable commuting outcomes.[6] While commuting mode—and particularly automobile access—impacts spatial mismatch (e.g., Gautier and Zenou 2010; Gobillon, Selod, and Zenou 2007; Ong 2002; Ong and Miller 2005; Raphael and Stoll 2001; Taylor and Ong 1995), differences in commuting time itself are also indicative of spatial patterns of adversity.[7] In fact, a growing literature examines gendered differences in commuting times (e.g., Black, Kolesnikova, and Taylor 2014; Gutierrez 2018; Hu 2021; Liu and Su 2020). We therefore focus on differences in commuting time as an outcome, and consider home and work location, mode, and selection into the labor market as potential explanations for these differences.

To this end, we use decomposition methods from the literature on gender and race wage differences to explore individual and city-level explanations of the difference in

6. Gabriel and Rosenthal (1996), Johnston-Anumonwo (1997), Johnston-Anumonwo (2001), McLafferty (1997), Petitte and Ross (1999), and Zax (2003) examine unequal urban commuting outcomes before 2000.

7. The increase in automobile use by Black commuters, though, has expanded the potential for unequal treatment by law enforcement; see, e.g., Feigenberg and Miller (2021). Indeed, Martin Luther King, Jr., faced his first arrest for purportedly driving five miles over the speed limit (King 2010).

commuting times (Chamberlain 2016; DiNardo, Fortin, and Lemieux 1995). Like that literature, we account for the role that observable individual demographic and occupation characteristics play in explaining racialized or gendered difference. Blau and Kahn (2017) find that individual characteristics explain very little of the gender wage gap in more recent years, and Altonji and Blank (1999), in a summary of the racial wage gap literature, note that the convergence of individual characteristics over time contributes to the decrease in the gap. The unexplained portion of the gap is traditionally interpreted as a measure of discrimination; however, it may also account for unmeasured productivity or compensating differentials. Our focus on the production of racialized difference in commuting follows calls for understanding the structural bases of racialized material difference (Darity Jr, Hamilton, and Stewart 2015).

We hypothesize that spatial stratification within cities provides a basis for racialized commuting differences to arise. Existing work on neighborhood sorting contextualizes commuting differences, arguing that transportation rather than housing prices dictates urban patterns of income sorting (Glaeser, Kahn, and Rappaport 2008; LeRoy and Sonstelie 1983). To this point, Aliprantis, Carroll, and Young (2019) observe that in cities without high-income Black neighborhoods, high-income Black households locate in Black neighborhoods with socioeconomic status similar to low-income White neighborhoods. In large cities with large Black populations and high-income Black neighborhoods, this result does not hold. Race—through possible channels of psychological costs and benefits, White flight, and racial discrimination—rather than financial constraints (wealth, housing prices) is driving income and racial neighborhood sorting.

Our use of commuter market access terms (e.g., Ahlfeldt et al. 2015) to measure the evolution of differential job access by race furthers this conclusion. We complement a growing literature on Black suburbanization and neighborhood change as it relates to the spatial organization of Black and White households within cities (Card, Mas, and Rothstein 2008; Blair 2017; Wiese 2005; Zax 1990) and the related literature on sorting in schools (e.g., Caetano and Maheshri 2017). Two recent papers are particularly relevant. Bartik and Mast (2021) document some convergence in the neighborhood income levels and poverty rates experienced by White and Black households, a change coming largely from the migration of some Black households to suburban neighborhoods (rather than rising incomes in mostly Black central-city neighborhoods). Indeed, about one-third of African Americans lived in the suburbs before 1980; by 2000, nearly two-thirds did (Wiese 2005). Relatedly, Miller (2018) determines that job suburbanization has decreased Black employment, showing that Black workers are less likely to work in jobs further from city centers even among relocating firms. In addition to these disemployment effects, our results indicate that racialized differences in mode use and the spatial relationship between work and home form another nexus of inequality: commuting.

The rest of the paper proceeds as follows. Sections 2 and 3 describe our data, showcase descriptive statistics that motivate our analysis, and develop our methodology. Section 4 reports decomposition results and examines heterogeneity. Section 5 investigates city-level determinants of racialized difference.

2 Data

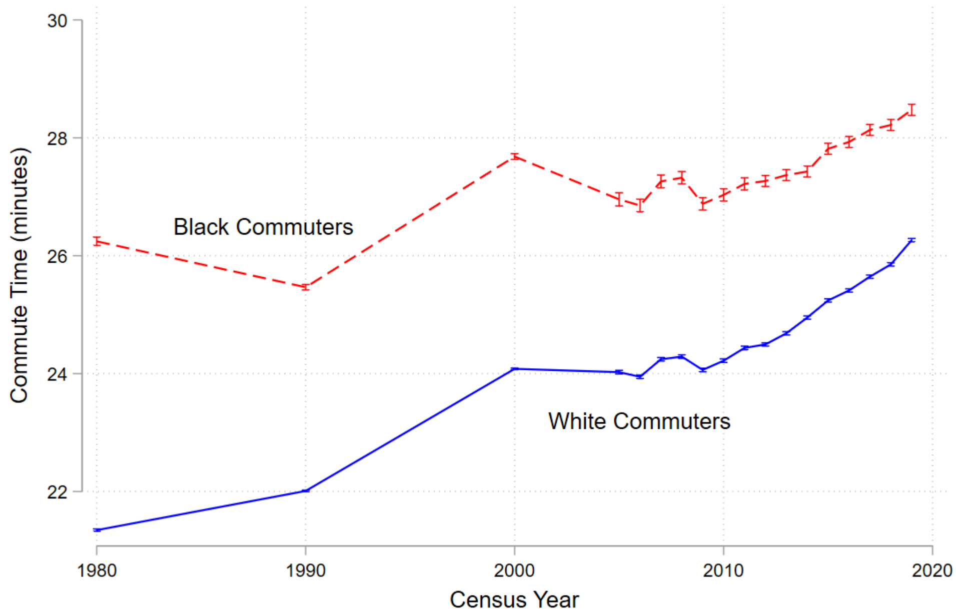
We study commuting time in the United States from 1980–2019 as reported in response to the Census Journey to Work questionnaire. Beginning in 1980, the Census asked long-form respondents to give their usual travel time and primary mode for the one-way journey from home to work in the prior week. Our primary data source is the IPUMS Census and American Community Survey (ACS) public use microdata from 1980, 1990, 2000, and 2005–2019 (Ruggles et al. 2021). We limit our sample to commuters in most specifications, i.e., those in the labor force actively working outside the home. For a limited set of mode share data, we also use 1960 and 1970 Census microdata.

We use slightly modified 1990 commuting zones as our base geography and follow Autor and Dorn (2013) and Dorn, Hanson, et al. (2019) to assign observations to commuting zones. We combine five pairs of commuting zones that reflect larger metropolitan areas. Denoted by their largest constituent cities, they are: New York City and Newark; Dallas and Fort Worth; Philadelphia and Wilmington, DE; Charlotte and Gastonia-Rock Hill, NC; and Hickory and Morganton, NC. We adjust observation weights so that the sum of weights is equivalent to the average employed population for each of the following groups of years (year bins): 1980, 1990, 2000, 2005–2011, and 2012–2019.[8] For 2000 and later, we use the Census public use microdata areas (PUMAs) to control for residential location in some specifications (pre-2000 PUMAs do not provide much additional geographic resolution).

We normalize key variables to ensure consistency over time. We top-code travel time to the minimum top-coded value of 99 minutes. To consistently reflect changes in the

8. Travel time is reported for only about one-half of eligible respondents in the 1980 Census, so weights are doubled. The year bins 2005–2011 and 2012–2019 respectively include seven and eight years of a 1% sample of the population, and are thus downweighted by a factor of seven and eight.

Figure 1: Average (Unconditional) Commute Times by Race



classifications of transportation modes over time, we use the following mode categories: Walking (walked only), Bicycle, Bus (bus or streetcar), Subway (includes elevated), Railroad (typically commuter rail), Auto (includes motorcycles, taxi, and carpooling), and Other. For nominally denominated variables, we adjust to real using the CPI. We also use a variety of other individual covariates from the Census/ACS data; we introduce these as needed below and provide details in the Appendix.

We rely on the definitions of race used in the data. These have evolved over time, though our results are not sensitive to these details. For our primary analyses, we denote as "Black" those observations that are recorded as "Black alone or in combination." However, prior to 2000, the Census did not record responses on multiple races, and so Black is assigned only to those who list Black as their primary race. The share of respondents who list Black along with other races increases substantially after 2010. As a comparison group, we use respondents whose primary race is White or White alone.[9]

Figure 1 shows the overall evolution in average commute times for Black and White commuters. In 1980, the average commute among Black workers was 26.2 minutes, while

9. We experimented with using the entire non-Black commuting population as a comparison group; this makes little difference in our main results. When we use CZ-level aggregates (e.g., commuting population), we calculate them from the entire commuting population regardless of race.

the average commute among White workers was 21.3 minutes. By 2019, the average commute among White workers was 26.3 minutes while the average commute among Black workers 28.5 minutes.[10]

We supplement these data with various other data sources that we use to construct the variables included in the CZ-level specifications. This is primarily tract-level data taken from the IPUMS National Historical Geographic Information System (NHGIS) (Manson et al. 2021) corresponding to decennial Census data (1980, 1990, 2000), ACS data (2006-2010, 2014-2018), and ZIP Code Business Pattern data (1994, 2000, 2010, 2018).

3 Methodology & Background

Racialized difference in commuting conceptually owes to some combination of three factors: racialized difference in residential location, work location, and commute speed. Racialized difference in each factor may arise for independent reasons. While workers in general may prefer to locate near their workplaces, they may be differently able to realize these preferences due to (in)ability to pay, discriminatory practices by sellers and landlords, and preferences for other amenities. Within a city, commute speeds vary due to the mode of commuting, time of day, infrastructural differences, and patterns of traffic congestion. We structure our inquiry through the lens of this constellation of residential, workplace, and commuting factors.

We borrow this lens from the spatial mismatch framework, developed in the early 1960s to understand the postwar transformations of urban structure and its relation to the underemployment of Black workers (Kain 1965; 1968). Such changes to urban structure were (and continue to be) characterized by trends towards workplace and White residential suburbanization (Boustan and Margo 2009a; 2009b), especially along freeways as automobile adoption continued (Baum-Snow 2007; Fischel 2004; Jackson 1987); the second great migration of Black southerners to northern and western cities (Boustan 2016; Wilkerson 2010); and the intentive segregation of Black residents primarily to congested center-city districts (Hirsch 2009; Rothstein 2017; Trounstine 2018).

With many Black households constrained to living far from potential workplaces, and

10. We multiply these differences by ten commutes to get our headline weekly commute differentials. Figure A1 shows the distribution of commute times. In 1980, there were relatively more Black commuters in the 30, 45, and 60 minute commute time bins than White commuters, and fewer between 0 and 15 minutes. This pattern is visible in the 2012–19 histogram, though the distributions are more similar. There are also substantially more Black than White commuters with commutes of 90 minutes or longer.

lower automobile access and limited transit restricting mobility, differential job access and the resulting underemployment of Black workers served as tinder for riots, protest, and other demands for change (Kerner Commission 1968). The Kerner Commission concluded:

> Providing employment for the swelling [segregated Black] population will require society to link these potential workers more closely with job locations. This can be done in three ways: By developing incentives to industry to create new employment centers near [Black] residential areas; by opening suburban residential areas to [Black residents] and encouraging them to move closer to industrial centers; or by creating better transportation between [segregated Black] neighborhoods and new job locations (pg. 217).

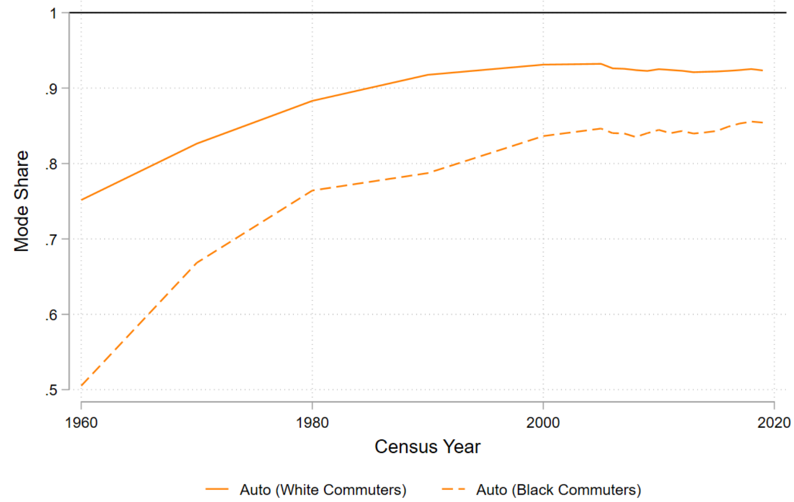
These prescriptions were taken up to varying degrees. The Fair Housing Act (1968) provided protections to Black would-be purchasers and tenants against private discrimination. Civil rights legislation likewise outlawed discrimination in private employment, and legislation from the Community Redevelopment Act (1977) to the Empowerment Zones and Enterprise Communities Act (1993) and Tax Cuts and Jobs Act (2017) provided incentives for private investment in marginalized neighborhoods. While federal outlays for transportation between center cities and suburbs has primarily taken the form of freeways, rising incomes and the falling real automobile costs have given more Black families the ability to purchase an automobile (or two), potentially speeding such commutes.

The transformation in commuting modes over time is shown in Figure 2. This figure reports the share of Black and White commuters using cars, transit, or walking (and other modes) in each year from 1960–2019. The solid lines denote the share for White commuters and dashed lines the corresponding share for Black commuters. Figure 2a shows the rise of automobile commuting. Among Black commuters, the share of drivers in 1960 was only about 50%, rising to 76% in 1980 and to just over 85% in 2019. About 76% of White commuters used private vehicles in 1960, rising to 88% in 1980 and 92% in 2019. The Black-White difference in commuting by private automobile thus declined by nearly three-quarters since 1960, from 26 percentage points (pp) in 1960 to 12pp in 1980 and about 7pp today.

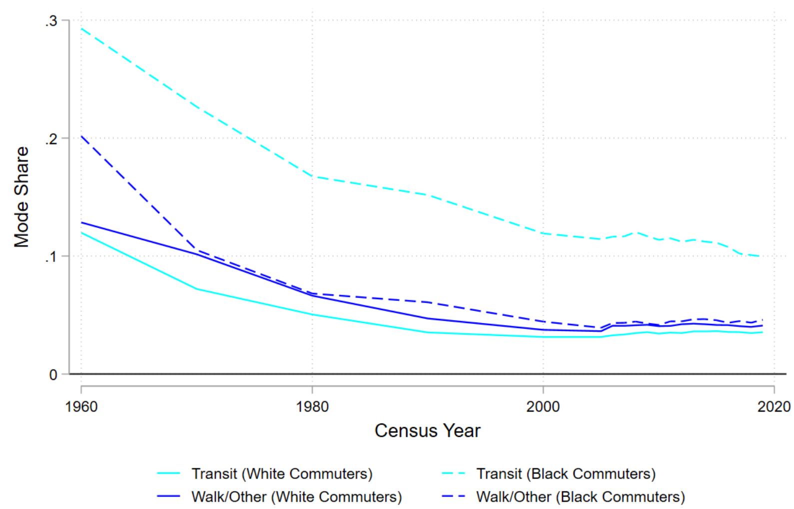
The increase in automobile share came at the expense of transit share, in particular from buses and streetcars. Figure 2b shows the decline in the share of commuters using buses and streetcars, falling from 24% of Black commuters in 1960 down to just over 12% in 1980 and about 6% in 2019. Among White commuters, the decline had largely taken

Figure 2: Commute Share by Mode

(a) Unconditional Auto Share



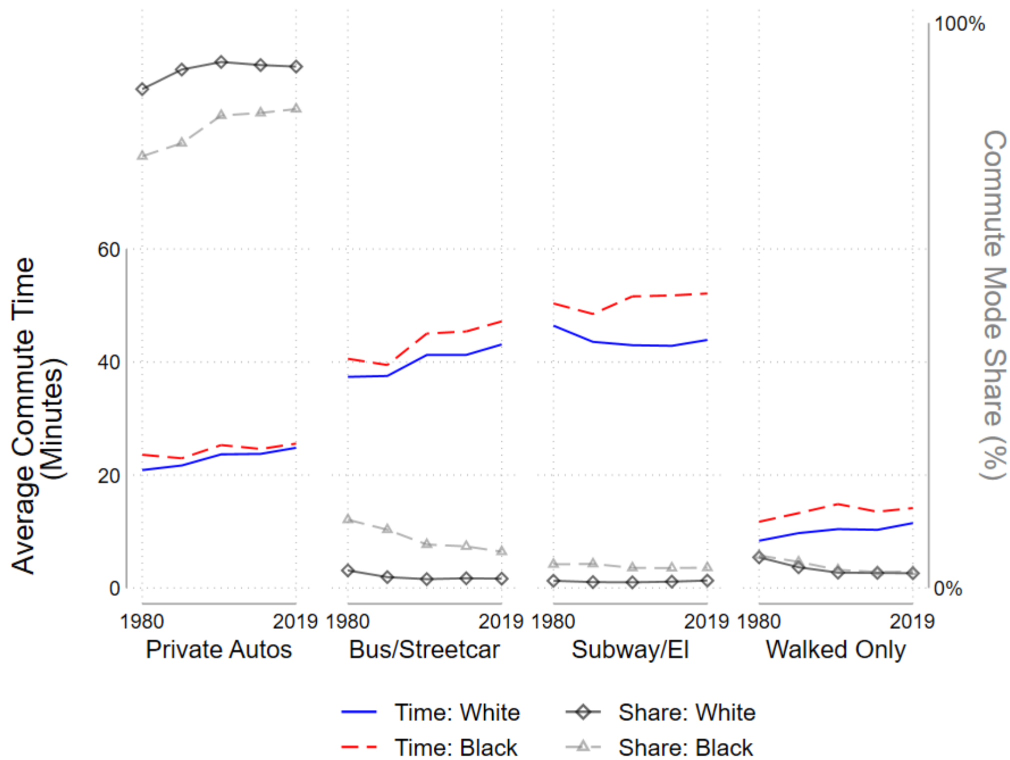
(b) Unconditional Transit and Nontransit/Nonauto Share



place before the census started asking in 1960: only 8% of White commuters used transit in 1960, and the declines continued from there. There was a slight uptick in subway usage among White commuters over the last 40 years (after falling between 1960 and 1980) and a slight decline for Black commuters.

There was also a large decline in the share of commuters that walk to work (see Figure A2b). In 1960, nearly 17% of Black commuters and 11% of White commuters walked to work, with some urban waterfront neighborhoods serving primarily walking commuters.

Figure 3: Unconditional Commute Times and Shares by Travel Mode



By 1980, as waterfront employment fell (Levinson 2006), walking had mostly converged to about 6% for both Black and White commuters, and fell further to about 3% for both groups by 2019. Conversely, bicycle use increased slightly, as did the "Other" category, which includes commutes via modes not elsewhere categorized (this residual category includes bicycles before 1980). These large shifts in commute share reflect substantial suburbanization over the latter half of the 20th century largely driven by expansion of the Interstate Highway System (Baum-Snow 2007), which also had the effect of spatially separating residential location and place of work (Baum-Snow 2020).

The rising automobile share—especially for Black workers—likely maps onto changes in commute times, which are typically shorter for cars than transit. Figure 3 reports the evolution of average one-way commute times by mode and year bin. Average travel time is shown by solid blue lines for White commuters and dashed red lines for Black commuters. While Black commuters face longer travel times than White workers within most modes,[11] those differences are largely swamped by differences in mode. All three transit modes have longer average commutes than driving, while the small share of bicycling and walking commuters experience shorter average commutes. Travel times are generally trending upward for most modes, with the possible exception of subway.

Within mode, disparate home and workplace location still imply longer commutes for Black workers, and declines in this spatial mismatch would imply convergence. This pattern is tentatively visible in some modes—most notably, private automobiles. For transit modes, however, differences in average commute times have been static or increasing. In most cities, transit ridership is quite low and likely concentrated among low-income commuters with few other options, suggesting that non-spatial processes may be at work. Commute time divergence is particularly notable for subway commuters, as average times for White subway commuters have fallen since 1980 while those for Black subway commuters have risen. Subway commuters are concentrated in just a few very large cities, where gentrification and other particular processes may be at work.

Altogether, the descriptive statistics suggest a few hypotheses. First, increasing automobile ownership has provided most Black workers with the means to overcome some degree of spatial mismatch. Yet within modes, differential job access likely results in longer commutes for Black workers. Lastly, slower transit implies that poor job access produces long commutes for Black workers who cannot or do not drive, especially in larger cities where spatial mismatch may already decrease Black employment.

3.1 Decomposition

For our baseline measure of the racialized difference in commute times between Black and White workers, we specify for commuter i in commuting zone c in year bin t:

$$\ln(\tau_{ict}) = \beta_t \mathbb{1}[\text{Black}_{ict}] + \lambda_t + \epsilon_{ict}. \tag{1}$$

Here τ is the reported travel time for a one-way commute, λ_t are year dummies, ϵ is the error term, and the subscript t on coefficients indicates that they are time varying across year bins. We cluster standard errors by commuting zone throughout the paper.

We extend the baseline model to account for differences across commuting zones and by a variety of individual characteristics that may relate to home and work locations as

11. The exceptions are railroad and other, which together contain 3% of commuters. Railroad trips are primarily from suburbs to downtown job centers in the handful of cities with commuter rail.

well as mode and speed. We estimate:

$$\ln(\tau_{ict}) = \beta_t^* \mathbb{1}[\text{Black}_{ict}] + x_{ict}' \mu_t + \lambda_{ct} + \epsilon_{ict}, \tag{2}$$

where x are individual and job characteristics and λ_{ct} are commuting zone-by-year bin fixed effects. We denote the coefficient on $\mathbb{1}[\text{Black}]$ as β^* to differentiate from β in Equation 1. We divide $\{x_{ct}, \lambda_{ct}\}$ variables into five thematic groups:

- *Commuting Zone*: indicators for each commuting zone of residence.
- *Demographics and Education*: sex; a quadratic in age; and indicators for education (less than high school, high school, college graduate, and masters or higher), marital status, head of household, and number of children (zero, one or two, and three or more).
- *Access to Car and Group Quarters Residence*: indicators for car in household if household is not in group quarters and for household residence in group quarters.
- *Transportation Mode*: indicators for usual primary commuting mode. These are private motor vehicle (including motorcycle, taxi, and carpool), bus or streetcar, subway or elevated; railroad (commuter rail), bicycle, walked only, and other.
- *Work and Income*: log income (set to 0 if zero income); indicators for zero income, industry, and occupation (1990 IPUMS basis).

Characteristics are interacted with year-bin to allow for time-varying correlation with commute time.

The coefficients β_t and β_t^* provide unconditional and conditional regression-based measures of the racialized difference in commute times. However, there are two significant caveats in their interpretation. The first is conceptual: β^* reflects both the racialized difference that manifests through channels that we do not observe and collider bias from any racialization of characteristics we do observe. For this reason, we interpret the response of the estimates to these covariates as a way to understand the channels through which the racialized difference manifests. Second, the measures may reflect selection into the workforce and into employment (we do not observe commute times for those who do not commute). This selection issue is precisely the spatial mismatch hypothesis: long commutes may differentially cause some Black workers to be unemployed or withdraw from the labor force. We later use a bounding exercise to address selection.

We use a decomposition framework to clarify the contribution of observables both within and across time (Kitagawa 1955). Consider the following two-equation model:

$$\begin{aligned} \ln(\tau_{ict}) &= \alpha_t^W + x'_{ict}\mu_t^W + \lambda_{ct} + \epsilon_{ict}^W && \text{if } \mathbb{1}[\text{Black}_{ict}] = 0 \\ \ln(\tau_{ict}) &= \alpha_t^B + x'_{ict}\mu_t^B + \lambda_{ct} + \epsilon_{ict}^B && \text{if } \mathbb{1}[\text{Black}_{ict}] = 1 \end{aligned}$$

where B indexes the sample if $\mathbb{1}[\text{Black}_{ict}] = 1$ and W indexes the sample if $1[\text{Black}_{ict}] = 0$. The mean unconditional racialized difference, Δ, can be decomposed into explained and unexplained components (Fortin, Lemieux, and Firpo 2011):

$$\Delta = \underbrace{\Big((\alpha^B - \alpha^W) + \bar{x}^{B'}(\mu^B - \mu^W)\Big)}_{\Delta^{\text{Unexplained}}} + \underbrace{\Big((\bar{x}^B - \bar{x}^W)\mu^W + \sum(p_c^B - p_c^W)\lambda_c\Big)}_{\Delta^{\text{Explained}}}.$$

Here, $\bar{x}^k$ is the group-k average of x and p_c^k is the share of the overall population of k that lives in c; time subscripts are suppressed for brevity.

To estimate the decomposition, we assume that the coefficients in a single-regression model provide valid counterfactuals, leading to a regression-compatible framework that can be easily implemented with our large dataset (Fortin 2008). Specifically, we estimate Equation 2 under the implicit restriction that $\mu^B = \mu^W = \mu$.[12] Under this assumption:

$$\begin{aligned} \Delta &= \Big(\alpha^B - \alpha^W\Big) + \Big((\bar{x}^{B'} - \bar{x}^{W'})\mu + \sum(p_c^B - p_c^W)\lambda_c\Big) \\ \Delta &= \beta^* + \Delta^{\text{Explained}} \end{aligned}$$

and $\beta^* = \Delta^{\text{Unexplained}}$ is the portion of Δ unexplained by observables. The role of each thematic group of characteristics is simply then the linear combination of those characteristics and their covariates. This identifies the role of each group in explaining $\Delta_t^{\text{Explained}}$:

$$\begin{aligned} \Delta_t^{\text{Explained}} = \Delta_t^{\text{Demographics \& Education}} &+ \Delta^{\text{Car Access \& Group Quarters}} + \Delta_t^{\text{Transit Mode}} \\ &+ \Delta_t^{\text{Work \& Income}} + \Delta_t^{\text{Commuting Zone}} \end{aligned}$$

We follow Gelbach (2016) to avoid bias from inferring the shares of β explained from the sequential inclusion of controls.

12. We consider race-specific coefficients on income and housing in Section 4. Because μ is a weighted average of μ^B and μ^W, the regression-compatible approach is a reweighting of the more general two-equation model. In the two-equation model, it is common to assume that majority-group coefficients provide a valid counterfactual. See Zax (2003) for an application to 1990 commuting outcomes.

3.2 City-Level Heterogeneity

We use a two-step approach to explore the CZ-level relationship between racialized difference in commute times and urban spatial structure. The first step is to estimate CZ-by-year-bin-specific models to produce a panel of CZ-specific racialized difference. As these condition on observables, we call them estimates of the residual racialized difference (RRD). The second step is to regress the RRD on city-level characteristics:

$$\ln(\tau_{ict}) = \beta^*_{ct}\mathbb{1}[\text{Black}_{ict}] + x'_{ict}\mu_{ct} + \lambda_{ct} + \epsilon_{ict} \tag{3}$$

$$\hat{\beta}^*_{ct} = z'_{ct}\gamma + D_c + T_t + e_{ct}. \tag{4}$$

The first equation is similar to Equation 2 except here we estimate a separate β^*_{ct} for each CZ and year-bin combination, allowing for local heterogeneity in the role that individual controls play. The second equation lets us study the role of CZ-level factors on the racialized difference in commute times.[13]

Our CZ-level measures fall into three groups. First, we use aggregate spatial patterns of residence and employment to measure market access by racialized group. Alongside this direct measure, we construct indices of two potential correlates: residential segregation and residential decentralization. Second, we use measures of transportation investment and outcomes to assess the differential ability of cities to overcome spatial mismatch through faster commuting. Last, we use measures of house prices, which are theoretically linked to commute times in standard spatial economic models.

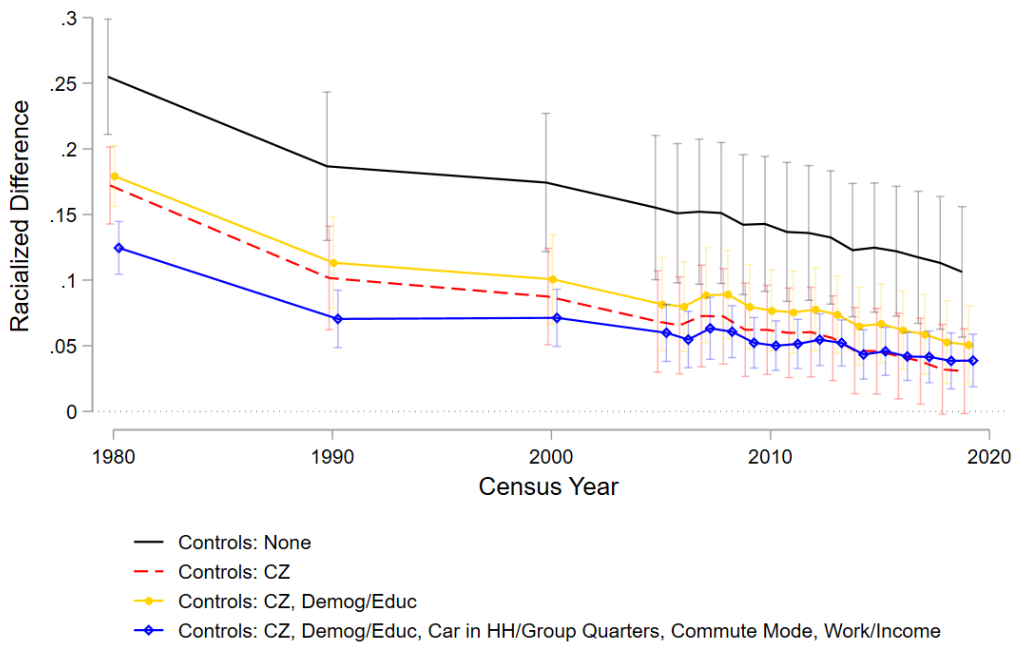
Equation 4 includes CZ and year-bin fixed effects to limit the role of confounding factors in explaining the relationship between these city-level variables and RRD. However, it is unlikely that the fixed effects completely eliminate confounding variation. We instead see the value in this exercise of highlighting likely channels for future research.

4 Decomposing Racialized Difference in Commuting

Figure 4 depicts estimates of β_t from Equation 1. The black line in Figure 4 includes only year dummies and provides baseline measures of the racialized difference in commute times, Δ_t. The 1980 difference of 26 log points implies 30% longer unconditional average commutes for Black commuters than White commuters. The difference declines over the

13. This two-step approach is conceptually equivalent to adding CZ-level controls to Equation 2, so the portion of Δ explained by this second step is approximately a subset of $\Delta^{\text{Unexplained}}$. See Appendix A1.

Figure 4: Estimates of the Racialized Difference in Commuting Time



next forty years, falling to roughly 12 log points (13%) in 2012–19. The majority of the partial convergence between 1980 and 2019 occurs before 1990.

The red, blue, and yellow lines lines in Figure 4 consecutively add observable characteristics to the model, as in Equation 2. We note that these characteristics—like commute mode, residential location, and demographic and job characteristics—are best thought of as *channels* rather than as 'controls' accounting for alternative, non-racial explanations. Racialization, the process by which social difference is naturalized (Chun and Lo 2015), permeates the markets and policies underlying all of these determinants of commute time. For example, labor markets feature direct discrimination resulting in lower wages for Black workers (Neumark 2018). Of course, wage differentials are only partly accounted for by discrimination, with "pre-market" factors like educational attainment accounting for a substantial portion of the remainder (Bayer and Charles 2018; Bohren, Hull, and Imas 2022)—but schooling itself remains heavily segregated (Erickson 2016; Logan and Burdick-Will 2016). No factor is necessarily upstream of racialization.

The red line of Figure 4 introduces CZ-by-year fixed effects to account for the different distribution of the Black and White commuters across commuting zones with longer (e.g., New York City) and shorter (e.g., Salt Lake City) average commutes. Estimates of β_t^* compare only people living in the same commuting zone at the same time. Accounting for this first-order channel reduces estimates of the difference to 18 log points (20%) in 1980 and 5 log points (5%) in 2012–19. In recent years, point estimates are only marginally different from zero. Most convergence again occurs between 1980 and 1990. The yellow line in Figure 4 incorporates demographic and household characteristics, including car availability. Accounting for these characteristics *increases* estimates of the difference relative to the estimates that reflect CZ-by-year fixed effects, with larger impacts more recently.

The blue line in Figure 4 represents the most saturated model, additionally including commuting mode, income, and job characteristics. The conditional racialized difference falls from 13 log points (14%) in 1980 to 5 log points (5%) in 2019. Relative to the specifications with fewer controls, these estimates show less of a trend, and are notably flat since 1990. This suggests that these factors are becoming increasingly important in understanding differences in commute time.[14] Mode and work characteristics contribute in opposite directions: accounting for commute mode substantially decreases the conditional difference, while accounting for work characteristics mildly increases it.

Decomposition results, shown in Table 1, quantify the contributions of different groups of observable characteristics. Column 1 reports the total racialized difference, Δ_t (the black line in Figure 4). Column 2 reports the part of Δ_t that is not explained by observable characteristics, $\Delta_t^{\text{Unexplained}}$ (the blue line in Figure 4). The remaining columns of Table 1 characterize the contribution of the various groups of observable characteristics to Δ_t. Because we follow the partial decomposition method of Gelbach (2016), estimates in Columns 2–7 of each row of Table 1 sum to Δ_t in Column 1. Table 1 also includes a *Components of Change* calculation that presents the portion of the change in Δ between 1980 and 2012–19 that is explained by each group of characteristics.

City (CZ) of residence plays an important role in explaining the level of unconditional racialized difference but plays no role in convergence. A disproportionate share of Black workers live in CZs with relatively long commutes, and Δ_t^{CZ} consistently explains 6–7 log points of Δ_t. Because this has been constant, it makes up an increasing share of Δ_t over time, from 25% in 1980 to 51% in 2019. But there is essentially no convergence on this front. This suggests there has not been substantial net migration of Black commuters to faster cities from slower cities, relative to White commuters.

Transportation mode explains both a significant part of the level of Δ_t as well as its decline over time. Mode accounts for 27% of the racialized difference in 1980 and 32% in

14. See Table A1 for point estimates similar to Figure 4.

Table 1: Decomposing the Racialized Difference in Commute Time Due to Observable Individual Characteristics

	Δ_t	$\Delta_t^{\text{Unexplained}}$	$\Delta_t^{\text{Explained}}$				
			Δ_t^{CZ}	$\Delta_t^{\text{Demog.}}$	$\Delta_t^{\text{Car \& GQ}}$	$\Delta_t^{\text{Tr. Mode}}$	$\Delta_t^{\text{Work/Inc.}}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Decomposition							
$1[\text{Black}] \times t_{1980}$	0.255	0.125	0.063	-0.007	0.009	0.068	-0.002
		48.9%	24.6%	-2.7%	3.4%	26.6%	-0.8%
$1[\text{Black}] \times t_{1990}$	0.187	0.070	0.065	-0.009	0.007	0.060	-0.007
		37.8%	34.7%	-4.6%	3.7%	31.9%	-3.5%
$1[\text{Black}] \times t_{2000}$	0.174	0.071	0.069	-0.008	0.005	0.048	-0.011
		40.9%	39.8%	-4.4%	2.8%	27.4%	-6.4%
$1[\text{Black}] \times t_{2005-11}$	0.147	0.056	0.063	-0.009	0.005	0.047	-0.015
		38.0%	42.8%	-6.2%	3.5%	31.9%	-10.0%
$1[\text{Black}] \times t_{2012-19}$	0.123	0.046	0.063	-0.008	0.003	0.039	-0.019
		37.2%	51.0%	-6.5%	2.2%	31.8%	-15.7%
Components of Change							
$\frac{\Delta^k_{1980}-\Delta^k_{2012-19}}{\Delta_{1980}-\Delta_{2012-19}}$	-	59.8%	0.0%	1.2%	4.5%	22.0%	12.9%

Data: Commuters 18 years of age and older in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone. The number of observations is 47,952,072. Column 1 is the unconditional racialized difference in commute time. Columns 2–7 report the contribution of a group of variables to the level and the share of Δ_t. Demographics include sex, educational attainment, age, marital and household status, and number of children in household. Car & GQ are indicators for car in the household and group quarters. Work and income controls are log income, an indicator for zero income, and indicators for industry and occupation. Standard errors clustered by commuting zone. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

2012–19, though in levels $\Delta_t^{\text{Tr. Mode}}$ falls by nearly half. Figure 2 indicates substantial but incomplete convergence in the modes used by Black and White commuters. The partial convergence in mode explains 22% of the overall decline in the racialized difference in commute time.

In contrast, neither demographics, the presence of a car, nor group quarters status explain much in levels or changes of Δ_t, as indicated by $\Delta_t^{\text{Demog.}}$ and $\Delta_t^{\text{Car \& GQ}}$.[15] This indicates that non-race observable demographic factors play little role in explaining unconditional racialized difference in commute times, at least on average. The presence of a car in the household also has limited explanatory power, although it is highly correlated with car as a transportation mode.

15. It may seem odd to link presence of car and group quarters status. However, 'car in household' is only reported for households not in group quarters in our data, so it is not possible to decouple them.

Work-related factors, including income, do not matter much in 1980, but are increasingly important over time and account for -15% of the difference in unconditional commute times by 2012–19. As suggested by Figure 4, the negative sign on $\Delta_t^{\text{Work/Inc.}}$ indicates that including these characteristics *increases* $\Delta_t^{\text{Unexplained}}$. Of the variables that drive $\Delta_t^{\text{Work/Inc.}}$, the contribution of log-income declines in magnitude from -0.009 in 1980 to -0.003 in 2012–19. In contrast, occupation accounts for 0.010 in 1980, but only -0.005 by 2012–19. Altogether, Black commuters today hold jobs and earn incomes that are associated with relatively short commutes. Divergence in job-related factors contributes somewhat to convergence in commute times: changes in work and income covariates explain about 13% of the decline in Δ since 1980.

The demographic and work characteristics offered by the Census are only imperfect correlates of key factors in our framework: residence and workplace locations. For example, racial segregation persists after conditioning on household income (Reardon, Fox, and Townsend 2015). This imperfect accounting may well play a role in the high proportion of racialized difference unexplained by observed factors, which amounts to 39%–52% of the racialized difference in each year. Similarly, changes to unobserved factors account for the majority (nearly 63%) of its decline since 1980.

4.1 Labor Market Selection Does Not Drive Racialized Difference

The results presented in Figure 4 and Table 1 are, by necessity, conditioned on employment: commute times (and job characteristics) are not observed for those not working. Kain's original spatial mismatch hypothesis held that high unemployment rates among Black workers might owe in part to long potential commutes. Thus, our results—in particular, our results on convergence—may reflect shifting selection out of the workforce or out of employment. There is conflicting evidence about how adjusting for employment status might impact β and β^* of Equations 1 and 2. Raphael and Stoll (2001) find that car ownership can be important for closing differences in employment levels by race, and Black, Kolesnikova, and Taylor (2014) show that women are less likely to work in long commute cities, suggesting that commuting mode (and time) impact the marginal worker's entry decision. On the other hand, Gabriel and Rosenthal (1996) use plausibly excludable household income variables to control for selection into labor force participation; however, such controls seem to matter little for their results. While our results likely understate the true difference, it is useful to get a sense of the bias, as well as the role selection might play in convergence.[16]

We implement a conservative approach to estimating the potential for bias when outcomes are bounded. Following Horowitz and Manski (1998), we assume that unemployed workers and those not in the labor force face very long commutes. Specifically, we estimate the following variants of Equation 1 and Equation 2:

$$\ln(\tau^*_{ict}) = \beta_t \mathbb{1}[\text{Black}_{ict}] + \lambda_t + \epsilon_{ict} \tag{5}$$

$$\ln(\tau^*_{ict}) = \beta^*_t \mathbb{1}[\text{Black}_{ict}] + x^{\text{NILF}\prime}_{ict} \mu_t + \lambda_{ct} + \epsilon_{ict} \tag{6}$$

where we have replaced τ_{ict} with τ^*_{ict} and x_{ict} with x^{NILF}_{ict}, where

$$\tau^*_{ict} = \begin{cases} \tau_{ict} & \text{if } \tau \text{ is observed} \\ \tau^{\text{NILF}}_{ct} & \text{else} \end{cases}$$

and x^{NILF}_{ict} is the subset of observable characteristics observed for unemployed workers and those not in the labor force (these include all variables in Δ^{CZ}_t, $\Delta^{\text{Demog.}}_t$, and $\Delta^{\text{Car \& GQ}}_t$).

We explore bounds under two possible values of τ^{NILF}_{ct}. The maximal value of τ_{ict} in our data is 99 minutes (after harmonizing topcodes), so as an extreme bounding exercise we set $\tau^{\text{NILF}}_{ct} = 99$. We also consider a slightly less extreme bounding scenario, where we set τ^{NILF}_{ct} to the 95th percentile commuting time in the year bin-by-CZ to which the observation belongs ($\tau^{\text{NILF}}_{ct} = Q_{0.95}(\tau_{i \in ct})$).

Results, presented in Table 2, suggest that our headline results are not overly impacted by selection on commuting times. Columns 1–3 report baseline and selection-adjusted results for Equation 5. Results with unconditional bounds are somewhat smaller than baseline in 1980, somewhat larger between 1990 and 2011, and very similar in 2012–19. Columns 4–6 report baseline and selection-adjusted results for Equation 6, which control for characteristics observed for all adults (CZ, demographics, car in household and group quarters status). Results with conditional bounds are somewhat smaller than baseline in 1980, and somewhere larger thereafter.[17] In terms of convergence, the selection-adjusted results show convergence taking place mostly after 2000, while our baseline results show slower but continuous change over the entire period.

16. We show in the Appendix that our estimates likely understate the true difference using a selection-model inspired derivation.

17. These results include all adults. To ensure that the similarity between selection-adjusted and baseline results is not driven by older adults who are mostly out of the labor force, we perform a similar exercise on prime age adults. Results, shown in Appendix Table A3, are quite similar to those in Table 2.

Table 2: Effects Using Manski-style Bounds (All Workers)

	$\ln(\tau_{ict})$					
	No Controls			All Observed Controls if NILF		
	Baseline	$\tau_{ct}^{\text{NILF}} = Q_{0.95}(\tau_{i\in ct})$	$\ln(\tau^{\text{NILF}}) = \ln(99)$	Baseline	$\tau_{ct}^{\text{NILF}} = Q_{0.95}(\tau_{i\in ct})$	$\ln(\tau^{\text{NILF}}) = \ln(99)$
	(1)	(2)	(3)	(4)	(5)	(6)
$1[\text{Black}] \times t_{1980}$	0.255***	0.221***	0.219***	0.179***	0.126***	0.144***
	(0.022)	(0.019)	(0.015)	(0.012)	(0.010)	(0.012)
$1[\text{Black}] \times t_{1990}$	0.187***	0.193***	0.211***	0.113***	0.123***	0.156***
	(0.029)	(0.021)	(0.016)	(0.018)	(0.011)	(0.011)
$1[\text{Black}] \times t_{2000}$	0.174***	0.204***	0.218***	0.101***	0.144***	0.179***
	(0.027)	(0.023)	(0.016)	(0.017)	(0.009)	(0.008)
$1[\text{Black}] \times t_{2005--11}$	0.147***	0.155***	0.165***	0.082***	0.106***	0.132***
	(0.027)	(0.021)	(0.014)	(0.017)	(0.009)	(0.008)
$1[\text{Black}] \times t_{2012--19}$	0.123***	0.119***	0.118***	0.064***	0.081***	0.098***
	(0.025)	(0.021)	(0.015)	(0.015)	(0.009)	(0.008)
Year Bin×CZ FEs	-	-	-	Y	Y	Y
Demog. & Edu. Controls	-	-	-	Y	Y	Y
Car & GQ Controls	-	-	-	Y	Y	Y
Observations	47,952,072	86,708,936	86,708,936	47,952,072	86,708,936	86,708,936

Data: Commuters (Columns 1, 4) or all people (Columns 2, 3, 5, 6) 18 years of age and older in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone. Demographics include sex, educational attainment, age, marital and household status, and number of children in household. Car & GQ are indicators for car in the household and group quarters. Standard errors clustered by commuting zone. See text for description of bounding exercise. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

This conclusion does not imply that long commuting times do not play a role in spatial mismatch or labor force participation. Rather, these bounding results indicate that, to a first order, commuting-time driven selection into the labor market does not drive our estimates of racialized difference in realized commuting times.

4.2 Do Differences Reflect Modal Choice?

Mode is a central determinant of commute times. As shown in Table 1, mode explains 27%–32% of the unconditional racialized difference in commute times, 22% of its decline from 1980–2019, and as much as 65% of the difference conditional on CZ. We estimate mode-specific models to investigate heterogeneity in the roles of observable characteristics across mode. This approach implicitly allows mode-specific coefficient estimates, reducing the concern that, e.g., differences in mode-specific fixed effects between cities as different as New York City and Houston are confounding the aggregate difference.

Figure 5a shows the racialized difference for commuters using private automobiles (inclusive of carpooling), motorcycles, or taxis. Given the high share of commuters that use automobiles, this figure is broadly similar to Figure 4. Controlling for just CZ and year, the difference declines from 13 log points in 1980 to zero by 2019. However, once demographics and job characteristics are included, a positive and significant difference is again present in recent years. This suggests patterns in residential and workplace locations lead to longer commutes for Black workers with similar observable characteristics and income as White workers, even when all drive to work.

The difference for Black and White transit commuters, however, does not decline between 1980 and 2019. Figure 5b shows that the racialized difference in transit (bus, subway, and railroad) commute times falls somewhat between 1980 and 1990, but then increases substantially through the mid-2000s before mildly decreasing by 2019. In addition to differential patterns in residential and workplace location, this may reflect a decline in quality of transit service for Black commuters relative to White commuters (McKenzie 2013).[18] Given the large declines in transit share among Black commuters (and smaller declines among White commuters) shown in Figure 2b , the difference may also indicate poorer quality service to increasingly marginalized commuters.

4.3 Do Differences Reflect Variation in Income?

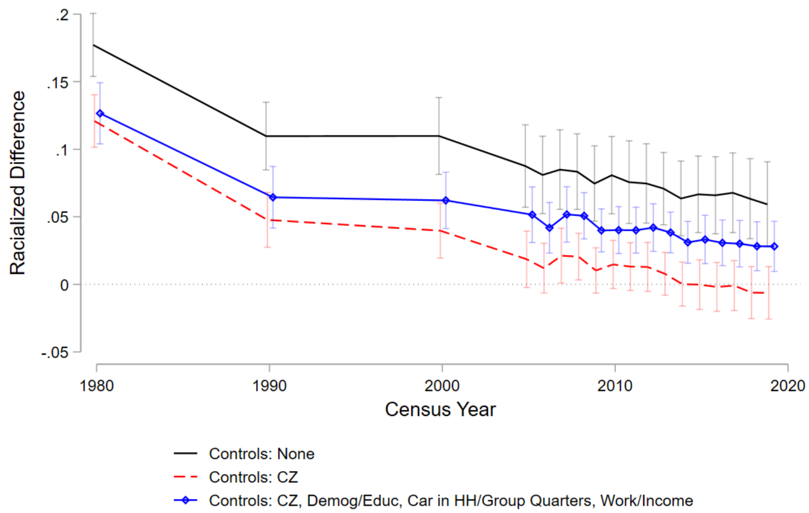
Income is included as an observed characteristic contributing to $\Delta_t^{\text{Work/Inc.}}$ in our primary specifications, where it does not play a large role. However, its role in the production of the racialized difference may vary across income levels: do high-earning Black workers overcome inequitably long commutes? To study this heterogeneity, Figure 6 plots estimates of $\mathbb{1}[\text{Black}]$ interacted with twenty equally sized bins of the national income distribution. Across income groups, Black commuters face substantially longer commutes. The black lines represent 1980, and the blue lines 2012–2019. Solid lines include commuting zone fixed effects, while dotted lines add all observable characteristics.

The difference is widest at the lower end of the income distribution; it is unconditionally nearly 36 log points (43%) at the 10th income percentile in 1980. Roughly one third of this difference is generated through channels captured by observable characteristics—accounting for these, the difference is 20 log points (22%) at the 10th income percentile in 1980. Workers in this income range likely face greater challenges in covering the expense

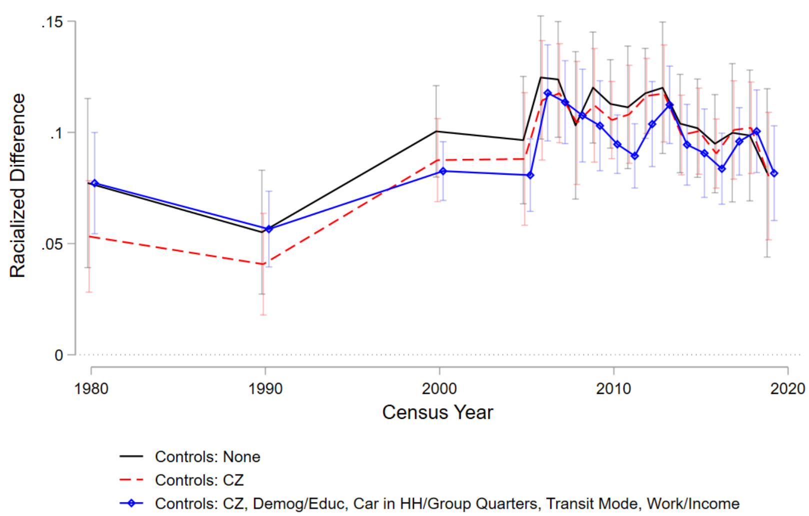
18. Figure A4 differentiates bus and subway commuters. The racialized difference for subway commuters grew steadily larger until around 2007, from whence it has declined somewhat. For bus commuters, the racialized difference was relatively steady until 2006, when it jumped up. It has only recently declined.

Figure 5: Racialized Difference in Commute Time by Mode

(a) Racialized Difference Conditional on Mode = Car



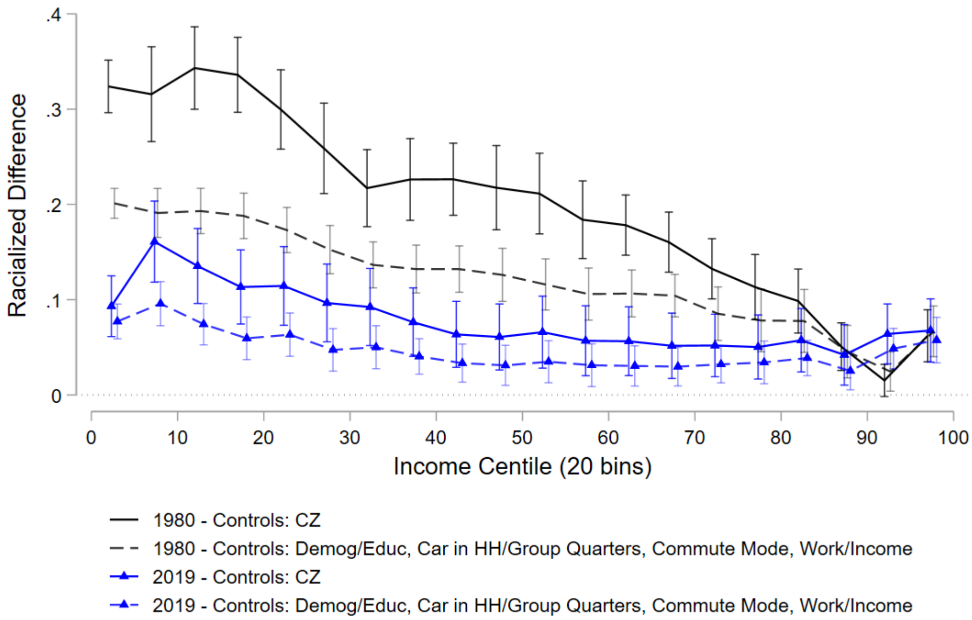
(b) Racialized Difference Conditional on Mode = Transit



of a car, potentially accounting for the relatively large role that observable characteristics play among low-income Black workers. Both the conditional and unconditional estimates of the racialized difference decline slowly across the middle part of the income distribution. At high incomes (above the 90th percentile), the racialized difference in 1980 is still present, but is typically less than 10 log points.

This pattern persists to some degree in 2012–2019, although levels are lower and the

Figure 6: Racialized Difference in Commute Times are Larger at Lower Incomes but Also Present at High Incomes



gradient with income is flatter. The unconditional difference is 16 log points (17%) at the 10th income percentile and 10 log points (11%) conditional on observables, substantially reduced from 1980—again, in line with the convergence in car-commuting rates and the role of mode in overall convergence. The difference declines by about half up to the middle of the income distribution, where it then levels out before increasing slightly at the top of the income distribution.

While income plays a role in shaping commuting possibilities, our finding of a large racialized difference in commute times cannot be fully explained by the racialized differences in income.[19] The relationship between income and commute time is potentially complex: "short commutes" may be a normal good, and higher wages may incentivize workers to pursue short commutes. Indeed, estimates of the value of time suggest that it is increasing, creating more incentive for sorting into short-commute locations (Su 2019). On the other hand, long commutes may come bundled with amenities that the rich value more than a short commute. In line with this, we find a positive correlation between income and commute time in our data. In our estimates of Equation 2, the coefficients on

19. Lacking data, we cannot investigate the role of wealth, itself a site of even greater racialized difference between Black and White individuals and households (Kuhn, Schularick, and Steins 2020).

income vary between 0.049–0.055. The differential findings here—White workers have relatively short commutes, but richer workers have relatively long commutes—highlight the importance of investigating racialization *per se*.

4.4 Are Housing Prices Capitalizing Commuting Differences?

In the standard monocentric city model, otherwise identical workers are compensated for longer commutes with lower housing prices, inducing a negative relationship between housing prices and commutes in equilibrium. In such a setting, all workers are equally well off; differences in commute time do not translate to differences in utility. This would suggest that differences in commuting do not lead to differences in household welfare. This section asks whether long commutes faced by Black workers are due to a trade-off with more affordable housing.

We provide two tests to determine whether Black commuters are compensated, on average, for their longer commutes with lower housing prices. First, we compare commutes within quantiles of the housing price distribution. Unlike in the income distribution figure in the prior section, we calculate these quantiles for each CZ (and year bin) separately in order to provide more local comparisons. Note two limitations to this exercise: we do not combine renters and owners, and housing prices are only reported within binned categories prior to the 2008 ACS.

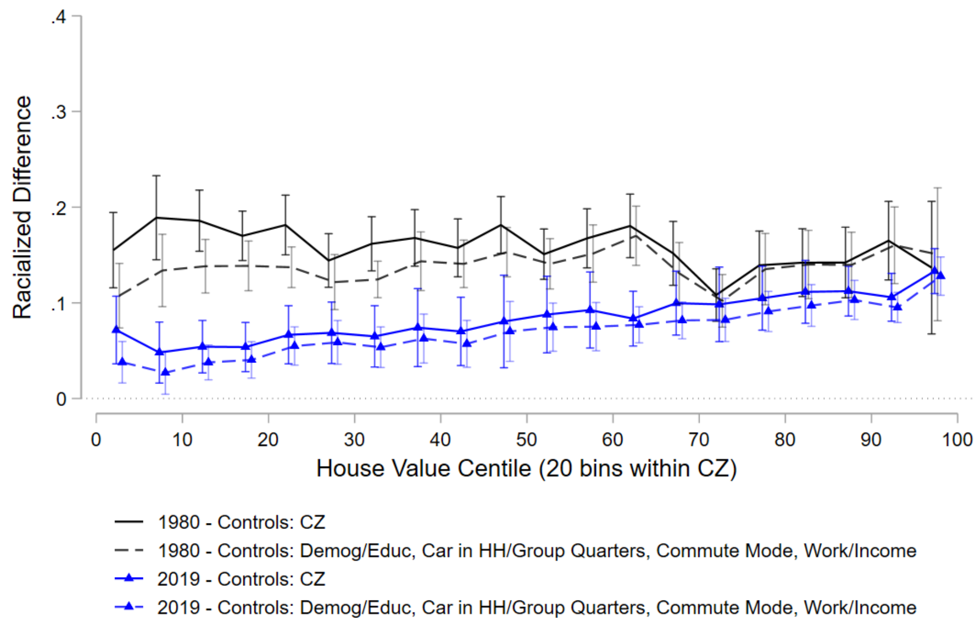
Figure 7 shows these comparisons within twenty equally sized bins of housing prices in 1980 and 2012–19. All models include CZ fixed effects; dotted lines additionally include the full battery of controls. In 1980, there is little variation across the housing price distribution. Black commuters are consistently commuting 10%–20% longer than White commuters *living in houses of the same value*. Adding controls barely alters the difference. By 2012–19, the difference had declined to 5%–10%, but did not disappear. Racialized difference in commute times is larger among those in more expensive housing.[20]

Second, we test whether housing price *gradients* differ by race. In the standard monocentric model, regressing the unit cost of housing on travel time should give a negative coefficient, *ceteris paribus*. Finding a zero or positive coefficient for a sub-group of the population would suggest that other factors are constraining housing location decisions.

To test this, we first create a rough quality- and quantity-adjusted measure of housing

20. Figure A5 provides similar results for rental prices. Differences are larger in 1980 for renters than homeowner, roughly 20%–30% when accounting for CZ and 15%–20% when controlling for other observables. Levels are smaller in 2012–19, but still persist between 5% and 15%.

Figure 7: Racialized Difference in Commute Times are Present Conditional on Housing Prices



prices to proxy for the unit cost of housing, $\ln(\tilde{P}_{ict})$.[21] We then regress adjusted housing price on commuting time and its interaction with race:

$$\ln(\tilde{P}_{ict}) = \xi^W \ln(\tau_{ict}) + \xi^\Delta \ln(\tau_{ict})\mathbb{1}[\text{Black}_{ict}] + x'_{ict}\mu_t + (\lambda_{ct} + \alpha_{ct}\mathbb{1}[\text{Black}_{ict}]) + \epsilon_{ict}. \quad (7)$$

Here, ξ^W is the price-travel time correlation for White commuters (this is akin to an elasticity, but we do not claim causal identification). For Black commuters, $\xi^B = \xi^W + \xi^\Delta$ is the price-travel time correlation. This specification includes CZ-by-year bin-by-race specific intercepts and CZ-by-year bin indicators for each transit mode.

Results for each year bin, in Table 3, indicate that White commuters always face a negative price-time correlation. However, the correlation for Black commuters is significant and positive in 2000 and 2012–19. In all years except 1980, the correlation for Black commuters is significantly less negative than for White commuters. The result in 1980 could indicate a more equitable housing market, but more likely reflects poorer data quality for that Census year. Regardless, the positive correlation between housing prices and com-

21. We regress reported housing price on house characteristics (total number of rooms, number of bedrooms, and decade of construction) within each of the smallest geographic groups in Census/ACS microdata by year bin (county groups in 1980, PUMAs thereafter), so $\ln(\tilde{P}_{ict}) = \ln(P_{ict}) - z_{ict}\hat{\gamma}_{gt}$ for $g \in c$.

Table 3: Housing Price-Travel Time Correlations for Black Commuters are Sometimes Positive

	Log Adjusted Housing Value				
	1980	1990	2000	2005–11	2012–19
	(1)	(2)	(3)	(4)	(5)
$\ln(\tau_{ict})$ (ξ^W)	-0.025***	-0.014***	-0.012***	-0.016***	-0.010***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
$1[\text{Black}] \times \ln(\tau_{ict})$ (ξ^Δ)	0.008+	0.011*	0.017***	0.019***	0.017***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)
$\xi^B = \xi^W + \xi^\Delta$	-0.017***	-0.003	0.005*	0.003	0.007**
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)
Year Bin × CZ × 1[Black] FEs	Y	Y	Y	Y	Y
Year Bin × CZ × Transit Mode FEs	Y	Y	Y	Y	Y
N	1817823	5662646	6038066	9138148	12701532

Data: Commuters 18 years of age and older in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone who live in an owner-occupied unit. The dependent variable, log adjusted housing value, is quality and quantity adjusted, as described in the text. All specification include year bin-by-CZ specific fixed effects that vary by race and by transit mode. Observations weighted by adjusted person sample weights. Standard errors clustered by commuting zone. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

mute times in recent years is another piece of evidence that the longer commutes of Black workers are not compensated by lower housing prices.

4.5 Are Differences Present at Finer Geographies?

Residential and workplace location are primary mechanisms by which differential commutes emerges. We provide two additional exercises to determine how accounting more completely for these spatial channels alters estimates of racialized difference.

Starting in 2000, the Census provides PUMAs that are of a fine enough spatial scale to approximate subregions of CZs. Incorporating PUMA fixed effects controls for meso-scale regional differences and sorting within CZs.[22] Because PUMA vintages prior to 2000 contain much less geographic resolution, we do not report results that include them. Note that PUMAs must contain at least 100,000 residents and thus provide the most nuance in larger cities. We also incorporate place-of-work PUMAs (POWPUMAs) in an additional set of models. Specifically, we interact POWPUMAs with residential PUMAs and year bins to provide a rough control for origin and destination pairs. Though coarse, this

22. As an example, Los Angeles County contains over half the population of its CZ and features 60–70 PUMAs during the period 2000–2019. We do not geo-normalize PUMAs across years.

compares commute trips that start and end in broadly comparable locations, implicitly accounting for commute distance.

Table 4 reports aggregate and mode-specific estimates of β_t^* from Equation 2. Panel A excludes finer geographic controls, Panel B includes PUMA-by-year bin fixed effects for 2000 and later, and Panel C includes POWPUMA-by-PUMA-by-year bin fixed effects for 2000 and later. All specifications condition on the full battery of controls, except that Columns 2–5 do not include (collinear) controls for mode.

Combining all commuters, Column 1 of Table 4 shows a clear downward trend in racialized difference regardless of geographic controls. PUMA fixed effects have little effect on their own, suggesting that Black workers in general do not live in PUMAs with inherently long commutes. The POWPUMA-by-PUMA fixed effects decrease point estimates by roughly one-quarter. The similarity of estimates across the panels indicates that accounting for commuting geography at this coarse level does not substantively explain the racialized difference in commute times over the period 2000–2019 among commuters as a whole. To the extent that these measures capture internal urban spatial processes, like the movement of many Black households to suburbs over the last forty years (Bartik and Mast 2021; Wiese 2005), our results suggest that these processes have a limited role in explaining the decline of $\Delta_t^{\text{Unexplained}}$.

Columns 2–5 of Table 4 repeat this exercise but condition the sample by mode (as in Section 4.2). The results for car commuters (Column 2) are similar to the overall results, but suggest a higher degree of convergence. Column 3 in Panel A shows a mild increase in the racialized difference for bus commuters over time, reaching 11 log points by 2012–19. Controlling for PUMA of residence decreases estimates by about 30%, but additionally controlling for POWPUMA has little additional impact. PUMA geographies are most salient among subway (and elevated rail) commuters (Column 4). These commuters see a near doubling in racialized difference over time, from 5 log points in 1980 to 10 log points in 2012–19 in Panel A. Among subway commuters, Panels B and C reveal that commuting geography plays a very substantial role in determining the difference. Controlling for PUMA of residence, the difference is a positive but small 3.3 log points in 2012–19. Rapid transit generally serves fixed areas in bigger cities where commuting geography is more finely measured—and subway riders in particular are primarily in New York City, which is large enough to contain 55 PUMAs across the five boroughs. Despite this, they do not fully account for differences in commute time, particularly for bus commuters. Column 5 examines walking commuters. Racialized difference in commute time

Table 4: Racialized Difference in Commute Time by Mode and with Residential PUMA Controls

	All Modes (1)	Car (2)	Bus (3)	Subway (4)	Walk (5)
A. With year-bin×CZ FEs					
1[Black] × t_{1980}	0.125***	0.127***	0.086***	0.048***	0.247***
	(0.010)	(0.011)	(0.015)	(0.011)	(0.014)
1[Black] × t_{1990}	0.070***	0.064***	0.061***	0.050***	0.221***
	(0.011)	(0.012)	(0.014)	(0.011)	(0.016)
1[Black] × t_{2000}	0.071***	0.062***	0.085***	0.094***	0.247***
	(0.011)	(0.011)	(0.017)	(0.017)	(0.018)
1[Black] × $t_{2005--11}$	0.056***	0.045***	0.103***	0.114***	0.167***
	(0.010)	(0.009)	(0.014)	(0.017)	(0.018)
1[Black] × $t_{2012--19}$	0.046***	0.034***	0.105***	0.103***	0.137***
	(0.009)	(0.008)	(0.014)	(0.018)	(0.014)
N	47,952,072	44,355,720	753,980	395,747	1,684,740
B. With year-bin×PUMA FEs (2000 and later only)					
1[Black] × t_{2000}	0.071***	0.066***	0.067***	0.022***	0.223***
	(0.006)	(0.006)	(0.012)	(0.006)	(0.012)
1[Black] × $t_{2005--11}$	0.056***	0.051***	0.077***	0.037***	0.167***
	(0.006)	(0.006)	(0.007)	(0.011)	(0.009)
1[Black] × $t_{2012--19}$	0.040***	0.033***	0.071***	0.033***	0.127***
	(0.005)	(0.004)	(0.007)	(0.009)	(0.010)
N	36,797,278	34,256,647	519,761	301,847	1,129,933
C. With year-bin×PUMA×POW-PUMA FEs (2000 and later only)					
1[Black] × t_{2000}	0.059***	0.053***	0.064***	0.016**	0.222***
	(0.004)	(0.004)	(0.010)	(0.007)	(0.013)
1[Black] × $t_{2005--11}$	0.038***	0.032***	0.066***	0.024**	0.168***
	(0.004)	(0.004)	(0.006)	(0.010)	(0.010)
1[Black] × $t_{2012--19}$	0.030***	0.022***	0.063***	0.027***	0.127***
	(0.004)	(0.004)	(0.006)	(0.008)	(0.010)
N	36,772,267	34,242,801	518,955	301,491	1,126,620

Data: Commuters 18 years of age and older in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone. Columns 2–5 further restricts the sample by commute mode. Each column in each panel is a different specification. The dependent variable is log travel time top-coded at 99 minutes. Each column includes demographic, car and group quarters, and work and income controls interacted with year bin, as well as commuting-zone-by-year-bin fixed effects. Column 1 of both panels includes transit mode controls. Panel B includes PUMA-by-year-bin fixed effects and only uses data from 2000 and later. Panel C further interacts these with Place-of-work (POW) PUMAs. Observations weighted by adjusted person sample weights. Standard errors clustered by commuting zone. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

for walkers is larger than for other modes, but has declined substantially over the last forty years. Because walking is slow, it mostly occurs within the commuting geographies we observe, limiting the impact of geographic controls.

Because our geographic controls provide different levels of nuance depending on city size, we estimate these models on commuters in three major subsets of cities: big transit

CZs, big non-transit CZs, and all other CZs.[23] Results (shown in Table A4) suggest notable heterogeneity in spatial processes within CZs (and, potentially, a differential ability of PUMAs to capture spatial processes in different types of CZs). Across all years, racialized difference is largest in big transit CZs, followed by big non-transit CZs. For other CZs and in recent years, racialized difference is very small, and nearly zero in some specifications. Black and White car commuters in smaller CZs now have very similar commute times. These results suggest that spatial processes in larger cities, often with substantial transit, are drivers of persistent racialized difference.

In our second exercise, we use tract-level average commute times and Black residential population shares to investigate whether finer-scale residential location explains differences in commute times. While not directly comparable to the other results presented in this section, it allows for tract-level fixed effects. These flexibly control for time-invariant tract-level factors (like distance to downtown or legacy subway access) that might explain commuting differences.

Specifically, we geonormalize census-tracts and calculate average commuting times, Black share of residential population, and transit share. Indexing census tracts by a, we estimate:

$$\ln(\bar{\tau}_{act}) = \beta_t^* s_{act}^{\text{Black}} + \bar{x}_{act}'\mu + \xi_a + \lambda_{ct} + u_{act}, \tag{8}$$

where $\bar{\tau}_{act}$ is the average commute time in a, s_{act}^{Black} is the Black residential population share in a, $\bar{x}_{act}$ is transit share, and ξ_a are tract fixed effects. CZ-by-year-bin-specific differences and changes in commute times are captured by λ_{ct}. We use observed tract-level travel times and, in some specifications, augment these with imputed values for tracts with missing times (see Appendix A2 for details).

Results are shown in Table 5. Unconditional results accord quite closely with Δ_t in Table 1, providing assurance that tract-level Black population share is a reasonable proxy for individual race in this specification. Columns 3–4 show models that include tract fixed effects and control for transit share. Estimates indicate a significant racialized difference between 4 and 9 log points (though 1990 is insignificant). These results do not exhibit a clear trend over time, though may be declining slightly. While smaller than $\Delta^{\text{Explained}}$ in Table 1, the persistent significance of these estimates suggests that residential location alone cannot substantially explain differences in commuting time. Together with

23. Big transit CZs are those with some meaningful heavy rail ridership: New York City, Boston, Chicago, Philadelphia, Washington, D.C., San Francisco, Atlanta, and Los Angeles. These cities contain about 95% of all subway and elevated commuters observations in our data. Big non-transit CZs are Dallas-Fort Worth, Houston, Miami, Phoenix, Seattle, Detroit, San Diego, and Minneapolis-St. Paul.

Table 5: Tract-Level Estimates of Racialized Difference in Commute Time

	Ave. commute time in tract ($\ln(\bar{\tau}_{act})$)			
	(1)	(2)	(3)	(4)
Share Black in Tract $\times t_{1980}$	0.245***	0.245***	0.064***	0.063***
	(0.042)	(0.042)	(0.016)	(0.016)
Share Black in Tract $\times t_{1990}$	0.179***	0.179***	0.021	0.021
	(0.046)	(0.046)	(0.014)	(0.014)
Share Black in Tract $\times t_{2000}$	0.197***	0.197***	0.087***	0.086***
	(0.047)	(0.047)	(0.013)	(0.012)
Share Black in Tract $\times t_{2006-10}$	0.116***	0.132**	0.059***	0.043***
	(0.034)	(0.047)	(0.011)	(0.011)
Share Black in Tract $\times t_{2014-18}$	0.100**	0.112*	0.065***	0.044***
	(0.037)	(0.049)	(0.013)	(0.012)
N	294906	346631	294686	346478
Data	Obs	Obs+Imp	Obs	Obs+Imp
Year Bin×CZ FEs	-	-	Y	Y
Year Bin×Share Transit in Tract	-	-	Y	Y
Tract FEs	-	-	Y	Y

Data: Average observed (Obs) and imputed (Imp) travel times, share Black, and share commuting by transit in 1980, 1990, 2000 Census data and 2006–10 and 2014–18 5-year ACS, from NHGIS, geonormalized to 2010 geographies. Imputation of travel time is described in Appendix A2. Each column is for a different specification. The dependent variable is log average travel time in a census tract. Standard errors clustered by commuting zone. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

the inability of mode to fully explain racialized difference, the interaction of these with workplace is likely paramount.

5 City-Level Heterogeneity and Spatial Stratification

We now turn to city- (CZ-)level correlates of racialized difference in commuting. This allows us to investigate the role of aggregate factors that have no analog in individual data. We again use the lens of spatial mismatch to focus our inquiry. Indeed, the spatial mismatch hypothesis was originally developed using data from 1950s–1960s Detroit and Chicago that captured three components: Black households lived in segregated center-city communities, employers were decentralizing to new suburban job sites, and relatively few urban Black households owned cars (Kain 1968). We develop measures of these phenomena, and relate them to the racialized difference in commute times by CZ.

First, we estimate CZ-specific measures of the *residual racialized difference* using CZ-by-year-bin models that condition on observable characteristics; this is β^{*}_{ct} in Equation 3. We refer to this measure as RRD. Because the RRD values are estimates, we exclude commuting zones with small numbers of total workers and small numbers of Black commuters to limit noise.[24] We weight all statistics and models by the number of Black commuters in that CZ and year bin to account for heteroskedasticity. This also imbues our estimates with an interpretation as being the average experience conditional on being a Black commuter. Appendix Table A5 reports summary statistics by year bin of the RRD across CZs,[25] while Appendix Table A6 shows the 1980 and 2012–19 values of the RRD for the 87 CZs with more than 200k workers in all year bins.

Figure 8 summarizes the evolution in RRD by city size over time. In 1980, RRD levels averaged about 0.1 (10 log points) for cities with fewer than one million employed workers, with higher levels for cities over one million. By 1990, RRD levels fell in cities with fewer than a half million workers, with smaller declines in large cities. Since 1990, RRDs have converged to near zero for cities with fewer than a million employed workers.

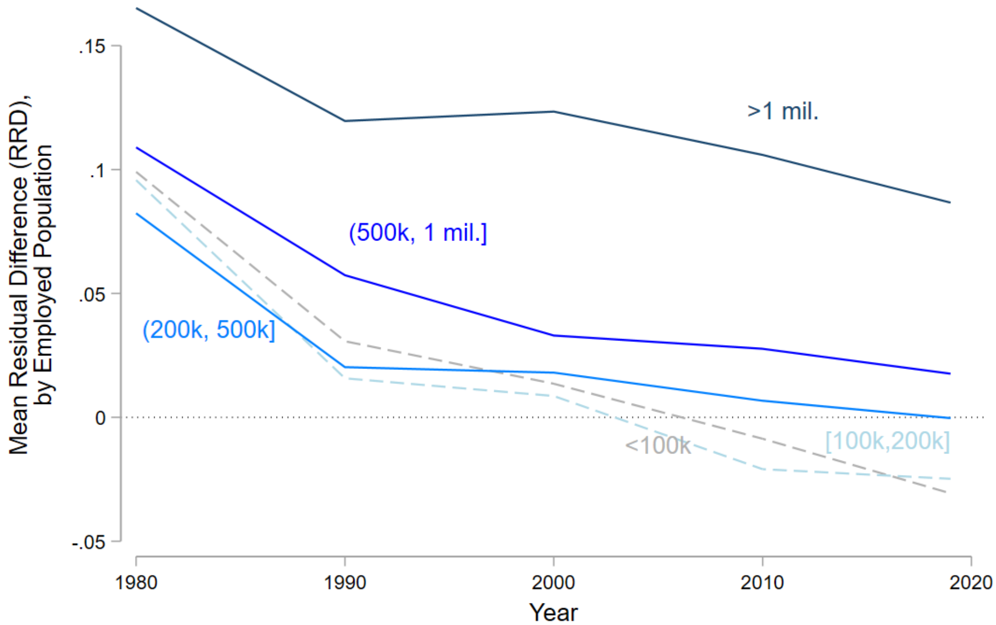
Large cities thus seem to be important for understanding obstacles to convergence. Indeed, part of the convergence in smaller cities is driven by continued growth in cities like Las Vegas and Atlanta, both of which moved into the largest size bin while experiencing below-average declines in RRD. The ingredients for the production of racialized commuting differences may be more prominent in larger cities: they may be more segregated, or employers may be more likely to co-locate near segregated, mostly-White neighborhoods in large cities. But even if segregation is similar in large and small cities, the factors driving spatial mismatch may have more bite in large cities due to the greater distances involved—or due to traffic congestion and transit dependence. By contrast, in small cities (or *fast* cities where long distances can be traversed quickly), patterns of segregation and unequal job access may not lead to commute time differences.

Table 6 presents panel estimates of various potential correlates of RRD. We concentrate on large and medium-sized cities, which we define as CZs with employed populations over 200,000. To ensure a balanced panel, cities must be above 200,000 in all observed years (results using all CZs are shown in Appendix Table A8). Because many

24. Specifically, we consider only commuting zones that satisfy two criteria in all five of the year bins: (i) Census data indicate there are at least 1,000 total employed persons, and (ii) there are greater than 50 unique Black commuter respondents.

25. Mean RRD values in Table A5 are similar to $\Delta^{\text{Unexplained}}$ estimated with heterogeneous effects of characteristics by CZ (see Appendix for details), but differ somewhat because they refer to a restricted set of CZs and weight by Black commuting population instead of total commuting population.

Figure 8: Residual Racialized Difference (RRD) by Employed Population



measures may be related city size even within this subset, we provide unconditional estimates (Panel A) and estimates in which we control for log population (Panel B); results are similar across panels. Estimates include CZ fixed effects, which control for the average level of the measure as well as for time-invariant features of the CZ, and year-bin fixed effects, which remove aggregate trends in the measure. These estimates therefore reflect the correlation between the *changes of the measure and changes in the RRD*. Column labels indicate the explanatory variables; the dependent variable is the RRD. To assess the salience of the relationship between the evolution of each measure and the RRD, the table also reports the mean value of each measure within the sample CZs in the earliest and most recent years. Details on the construction of these measures are in the Appendix.

The first two columns directly test the residential and/or workplace components of differential job accessibility. Column 1 relates the RRD to a (model-computed) measure of relative market access for Black and White workers. This measure is smaller when employment centers are located relatively far from where Black workers live and relatively near to where White workers live. For example, in cities like Dallas or Washington, job suburbanization has been most intense to the north and west, respectively, while Black

Table 6: Two-Way Fixed Effects Estimates of CZ-Level Correlates of the RRD for CZs Greater than 200k Employed Population in All Years

	Φ_{ct}^{Black} / Φ_{ct}^{White} (1)	Dissim-ilarity (2)	Centr-ality (3)	Ln Hwy Miles (4)	Transit Mode Share (5)	Ave. Car Time (6)	Ln House Value (7)	$\rho_{ct}(P,\tau)$ (8)
Panel A. No Controls								
Measure	-0.0960*	0.2123+	-0.0008	-0.0786**	0.4457*	0.0058+	0.0592***	-0.0774
	(0.0375)	(0.1151)	(0.0818)	(0.0281)	(0.1909)	(0.0032)	(0.0150)	(0.0534)
Panel B. Controlling for Log Population								
Measure	-0.1052***	0.2602*	0.0374	-0.0726**	0.4473*	0.0044	0.0570***	-0.0679
	(0.0301)	(0.1152)	(0.0723)	(0.0248)	(0.1699)	(0.0033)	(0.0165)	(0.0488)
Mean of Measure (earliest)	1.1910	0.7455	-0.0442	5.55	0.1034	23.3	12.0	-0.0561
Mean of Measure (most recent)	1.0874	0.6201	-0.0468	5.65	0.0805	27.1	12.5	-0.0953
Sample Years	’90-’19	’80-’19	’80-’19	’80-’00	’80-’19	’80-’19	’80-’19	’80-’19
N	348	435	435	255	435	435	435	435

Data: Estimated RRDs and CZ-level characteristics for CZs with greater than 50 unique Black commuter Census respondents and at least 200,000 total commuters in all five year bins. Each column in each panel is for a different specification. The dependent variable in each specification is the estimated RRD for each CZ-by-year-bin cell. The column title indicates the which CZ-level characteristics (“Measure”) is being used as the independent (right-hand-side) variable. All models include two-way fixed effects by CZ and year bin. Panel B further includes log commuting population as a control. Models are weighted by the Black commuting population in the CZ-by-year-bin cell. Standard errors clustered by commuting zone. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

suburbanization has concentrated in the opposite direction. Market access became relatively worse for Black workers between 1990 and 2019 on average, decreasing from 1.19 to 1.09. Multiplying this decline by the estimated coefficient in Panel A of Column 1 suggests the decline in relative market access is associated with 1 log point increase in the RRD (overall, RRD declined an average of 2.6 log points from 1990–2019).[26] In large dense cities like New York and San Francisco, or fast-growing large cities like Washington and Atlanta, worsening relative market access is associated with even larger increases in RRD of 2.5–3.7 log points. Those cities featured smaller than average declines in RRD, with San Francisco actually seeing an increase in RRD. Declining relative market access has thus limited the potential for convergence in commute times.

Column 2 regresses the RRD on dissimilarity, a measure of segregation that ranges between 0 (complete statistical integration) and 1. On average, segregation declined between 1980 and 2019, and multiplying by the coefficient from Panel A, this is associated with a decline of 2.7 log points in the RRD—38% of the 7 log point average decline in the 1980–2019 period. Together, the first two columns suggest that the relatively antipodal evolution of job accessibility for Black and White workers is an important component of

26. We do not have sub-CZ employment data for any year prior to 1990, and so this comparison focuses on the post-1990 evolution.

persistence and convergence. Declines in statistical segregation correspond to declines in the RRD, while worsening relative market access in some places matches up with relatively small declines (or even increases) in the RRD. Changes in market access are a likely partial explanation for the concentration of persistent racialized difference in large cities: the ten largest cities saw an average decline in relative market access of -0.185, while the average across other cities in the sample was a slightly positive 0.003.

Column 3 relates the RRD to the relative residential centrality of the city, a measure of urban form that is correlated with travel speed (Couture, Duranton, and Turner 2018). At the same time, a more centralized city may offer shorter commute *distances*, leaving the overall effect on commute length unclear. In any case, the relationship with the RRD is statistically and economically negligible after accounting for two-way fixed effects, with or without population controls. This is perhaps unsurprising: the overall average change is negligible relative to cross-city variation, reflecting the relative stability of the built environment.

Columns 4–6 relate the RRD to measures affecting travel speed. Column 4 considers infrastructure investment in highways over 1980–2000. CZs adding highway miles saw somewhat larger declines in RRD, with the mean change associated with a 0.8 log point decline in RRD—about 20% of the total over the period 1980–2000. Column 5 considers the evolution of transit use, a relatively slow mode as well as an indicator for the expense and challenge of owning and using a car in certain cities. Transit use declined over the period 1980–2019, with the mean change associated with a 1 log point decline in RRD—about 15% of the total decline over the period. Column 6 considers the average car commute time, a more direct measure of the changing ability of a car to offer a short commute. Places with relatively large increases in average car commutes did see somewhat smaller declines in RRD, although the estimated coefficients are not significant when controlling for population.

Columns 7 and 8 relate the RRD to measures of house prices. Column 7 uses the log of median house value. Cities with high house prices may be geographically extensive, while features that raise housing supply inelasticity—such as land unavailability due to coastal or mountainous location—may increase both house prices and commute times (Saiz 2010; Saiz and Wang 2021). Indeed, house prices are strongly correlated with the RRD, even accounting for population.[27] The average house price increase over the

27. Similar results hold when using a dynamic panel instrument for house prices as detailed in the Appendix and shown in Table A9.

period, from about $162,000 to roughly $268,000, is associated with an expected RRD increase of 3 log points—relative to a total decline of 7 log points. Column 8 relates the RRD to the within-CZ cross-tract correlation between house prices and commute times. A significantly negative correlation (like Washington's -0.35) reflects a higher likely expense in moving to a neighborhood with typically short commutes. House prices have, on average, become more correlated with commute time, although this correlation is not statistically significant after accounting for two-way fixed effects.

Overall, the results in Table 6 are consistent with mismatch of workplace and residential co-location playing a meaningful role in the evolution of the residual racialized difference in commuting across large cities. In particular, the market access term—which gets quite close to the original concept of spatial mismatch—lines up well with the chief pattern of persistence. Relative labor market access for Black workers has declined substantially in the largest cities, while staying unchanged, on average, in the smaller cities that have, on average, experienced near total convergence. Indeed, even some smaller cities with large residual racialized difference suggest the effects of market access: CZs like Sacramento and Poughkeepsie contain many commuters bound for San Francisco and New York. At the same time, the decline in statistical segregation means that some Black workers have found homes in the mostly-White neighborhoods that attract job centers, improving their access to relatively short commutes. Continued highway expansion and falling transit dependence have sped commutes for workers and reduced the racialized difference in commuting, while rising house prices (or their correlates) are associated with persistently high levels of racialized difference in commuting.

6 Conclusion

The Montgomery Bus Boycott lasted 382 days, ending after the Supreme Court ordered the buses of Montgomery to be integrated. The ensuing dozen years saw renewed federal commitment to the civil rights of Black Americans, including the Civil Rights Act of 1964 and the Fair Housing Act of 1968. In the aftermath of these hard-fought battles, the production of racialized difference in commute times was transformed: whereas Black workers spent 49 minutes per week longer commuting than White workers in 1980, the difference was 22 minutes by 2019. However, patterns of persistence point towards meaningful roadblocks to continued convergence: the racialized difference in commute times persists even when looking narrowly at commuters who drive, it persists across the income spectrum, and it persists particularly in large, segregated, congested, and expensive cities.

Rising automobile use among Black commuters is a leading contributor to the overall convergence in commute times. The difference in automobile use between Black and White commuters declines from 12pp to 7pp over the last four decades. About 37% of the decline in the racialized difference in commute times arises from the evolution of observable characteristics. This is mostly due to mode changes, with 22% of the total decline attributable to partial convergence in automobile use and, among drivers, partial convergence in travel times. Indeed, commute times have essentially converged for car drivers in all but the largest cities, conditional on observable characteristics.

Clearly, the car has been instrumental in securing these gains in relative commuting time by Black workers. However, this mechanism has both limits and costs. The limits are most apparent in the durable difference produced in large and congested cities with worsening job access for Black residents. The gentrifying San Francisco area saw a 2.3 log point increase in the residual racialized difference from 1980–2019, in contrast to an average decline of 7.8 log points nationwide. San Francisco may be exporting its commuting challenges to its neighbors: the rising RRD in nearby Sacramento may be partly explained by displaced Black workers commuting back to Bay Area jobs (Romem and Kneebone 2018). Even in freeway-heavy Dallas or Atlanta, jobs have suburbanized in one direction while Black workers have suburbanized in the opposite direction. In cities this large, freeways have not overcome long distances and traffic congestion to provide Black workers with shorter commutes.

Beyond these limits, car-based commuting has its own costs. Car commuters are subject to anti-Black discretionary policing tactics (Jefferson-Jones 2020). Livingston and Ross (2022) connect these strategies with high costs, financial and otherwise, for Black drivers: "By the turn of the twenty-first century, 'driving while Black' had become a well-traveled route to incarceration, or the raison d'être for gratuitous police violence. These hazards had also been supplemented by the menace of debt servitude as the costs of financing and maintaining a car ballooned." Black commuters have largely escaped the specific forms of oppression protested by the Black citizens of 1950s Montgomery. Widespread car access played a substantial role in these improvements, but inequitably long commutes still face Black drivers in many large cities and Black transit users everywhere.

Our results enrich the literature on changing racialized residential and workplace patterns by refocusing on commuting itself as an outcome of interest (Aliprantis, Carroll, and Young 2019; Bartik and Mast 2021; Miller 2018). The 21st century continues to see suburban growth of both jobs and Black communities (and other communities of color), but these processes do not necessarily overlap spatially (Kneebone and Holmes 2015). Job growth is often concentrated in particular suburbs that may not overlap with the suburbanization of communities of color; indeed, the two may be on opposite ends of the city, as in Dallas-Fort Worth or Washington, D.C. Time spent commuting represents a real cost to households: time spent in traffic or on the bus is time unavailable for other pursuits. The persistent production of the racialized difference in commute times is an ongoing process of spatial inequality whose costs are borne by Black commuters and their families.

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Appendix

A1 Additional Derivations

Footnote 13 argues that the two-step approach in Equations 3 and 4, which allows both β^* and all individual covariates to vary *at the CZ level*, contributes to decomposing the subset of $\Delta_{\{t\}}$ that is captured by $\Delta_{\{t\}}^{\text{Unexplained}}$. The following two subsections show that this is true under some additional assumptions.

CZ-specific control heterogeneity contributes to $\Delta^{\text{Unexplained}}$

First, rewrite differential outcomes by race to allow city-specific coefficients:

$$\begin{aligned}
\ln(\tau_{ict}) &= \alpha_{ct}^{W} + x_{ict}'\mu_{ct}^{W} + \tilde{\lambda}_{ct} + \epsilon_{ict}^{W*} && \text{if } \mathbb{1}[\text{Black}_{ict}] = 0 \\
\ln(\tau_{ict}) &= \alpha_{ct}^{B} + x_{ict}'\mu_{ct}^{B} + \tilde{\lambda}_{ct} + \epsilon_{ict}^{B*} && \text{if } \mathbb{1}[\text{Black}_{ict}] = 1.
\end{aligned}$$

Define $\mu_{ct}^{k} = \tilde{\mu}^{k} - \tilde{\mu}_{ct}^{k}$ for $k \in \{B, W\}$. Substituting in:

$$\begin{aligned}
\ln(\tau_{ict}) &= \alpha_{ct}^{W} + x_{ict}'(\tilde{\mu}^{W} - \tilde{\mu}_{ct}^{W}) + \tilde{\lambda}_{ct} + \epsilon_{ict}^{W*} && \text{if } \mathbb{1}[\text{Black}_{ict}] = 0 \\
\ln(\tau_{ict}) &= \alpha_{ct}^{B} + x_{ict}'(\tilde{\mu}^{B} - \tilde{\mu}_{ct}^{B}) + \tilde{\lambda}_{ct} + \epsilon_{ict}^{B*} && \text{if } \mathbb{1}[\text{Black}_{ict}] = 1.
\end{aligned}$$

Following Fortin (2008), we set $\tilde{\mu}^{k} = \tilde{\mu}$ and $\tilde{\mu}_{ct}^{k} = \tilde{\mu}_{ct}$ for $k \in \{B, W\}$ to retain regression compatibility. The difference in expected outcomes in a particular city c is (suppressing time variation):

$$\tilde{\Delta}_c = (\alpha_c^B - \alpha_c^W) + (\bar{x}_c^{B'} - \bar{x}_c^{W'})(\tilde{\mu} - \tilde{\mu}_c).$$

The overall difference between the two expected outcomes is now given by the sum of the weighted average of the city-specific differences and the weighted average of city-specific FEs (again suppressing time variation):

$$\Delta = \sum p_c \tilde{\Delta}_c + \sum (p_c^B - p_c^W)\tilde{\lambda}_c$$

where p_c is the share of the total population in c and p_c^k is as before.

Substituting $\tilde{\Delta}_c$ into Δ, we get:

$$\Delta = \sum p_c(\bar{x}_c^{B'} - \bar{x}_c^{W'})(\tilde{\mu} - \tilde{\mu}_c) + \sum p_c(\alpha_c^B - \alpha_c^W) + \sum (p_c^B - p_c^W)\tilde{\lambda}_c.$$

Noting that

$$\sum p_c(\bar{x}_c^{B'} - \bar{x}_c^{W'})\tilde{\mu} = (\bar{x}^{B'} - \bar{x}^{W'})\tilde{\mu} + \sum \left(s_W(p_c^W - p_c^B)\bar{x}_c^{B'} - s_B(p_c^B - p_c^W)\bar{x}_c^{W'} \right) \tilde{\mu},$$

where s_k are the overall share of k in the population, we see that

$$\begin{aligned}
\Delta = & \\
& (\bar{x}^{B'} - \bar{x}^{W'})\tilde{\mu} + \sum(p_c^B - p_c^W)\tilde{\lambda}_c && \tilde{\Delta}^{\text{Explained, Aggregate}} \\
& + \sum \left(s_W(p_c^W - p_c^B)\bar{x}_c^{B'} - s_B(p_c^B - p_c^W)\bar{x}_c^{W'} \right) \tilde{\mu} - \sum p_c(\bar{x}_c^{B'} - \bar{x}_c^{W'})\tilde{\mu}_c && \tilde{\Delta}^{\text{Explained, City Averages}} \\
& + \sum p_c(\alpha_c^B - \alpha_c^W) && \tilde{\Delta}^{\text{Unexplained}}.
\end{aligned}$$

City-level heterogeneity in non-race individual controls is represented by $\tilde{\mu}_c$, and thus its contribution to Δ is captured by $\tilde{\Delta}^{\text{Explained, City Averages}}$. This component also reflects the differential distributions of group-specific population characteristics.

To relate these to the decomposition in Section 3, we make additional assumptions to allow us to compare adding CZ-heterogeneous controls sequentially after those in the main paper (in contrast to Gelbach 2016). Specifically, suppose that $\tilde{\mu} = \mu$ and $\tilde{\lambda}_c = \lambda_c$ (that is, assume that including CZ-heterogeneous controls does not change the values of these estimates). Then $\tilde{\Delta}^{\text{Explained, Aggregate}} = \Delta^{\text{Explained}}$ and

$$\Delta - \Delta^{\text{Explained}} = \Delta^{\text{Unexplained}} = \tilde{\Delta}^{\text{Explained, City Averages}} + \tilde{\Delta}^{\text{Unexplained}}.$$

Thus, ignoring changes in μ and λ, CZ-level heterogeneity is a subset of $\Delta^{\text{Unexplained}}$.

Contribution of second step to $\Delta_{\{t\}}$

Define the CZ-specific RRD as $\tilde{\Delta}_c^{\text{RRD}} = \alpha_c^B - \alpha_c^W$ (recall that RRD is residual racialized difference). Suppose this has a linear representation, such that:

$$\tilde{\Delta}_c^{\text{RRD}} = \alpha_c^B - \alpha_c^W = a_0 + \gamma z_c + e_c$$

Recall that $\sum p_c \tilde{\Delta}_c^{\text{RRD}} = \tilde{\Delta}^{\text{Unexplained}}$, so we can quantify how any variable (or vector of variables) z_c contributes to $\tilde{\Delta}^{\text{Unexplained}}$ as:

$$\begin{aligned}
\tilde{\Delta}^{\text{RRD Explained}}(z_c) &= \sum p_c \gamma z_c \\
\tilde{\Delta}^{\text{RRD Unexplained}}(z_c) &= \sum p_c \left(\tilde{\Delta}_c^{\text{RRD}} - \gamma z_c \right)
\end{aligned}$$

where naturally $\tilde{\Delta}^{\text{RRD Explained}}(z_c) + \tilde{\Delta}^{\text{RRD Unexplained}}(z_c) = \tilde{\Delta}^{\text{Unexplained}}$ for any z_c and γ. As before, when $\tilde{\mu} = \mu$ and $\tilde{\lambda}_c = \lambda_c$, $\tilde{\Delta}^{\text{Unexplained}}$ is itself a subset of $\Delta^{\text{Unexplained}}$, so its subcomponents $\tilde{\Delta}^{\text{RRD Explained}}(z_c)$ and $\tilde{\Delta}^{\text{RRD Unexplained}}(z_c)$ are as well.[28]

This $\tilde{\Delta}^{\text{RRD Explained}}(z_c)$ embeds a differential response to a city-level variable, as we can expand $\tilde{\Delta}_c^{\text{RRD}}$ with race-specific coefficients:

$$\tilde{\Delta}_c^{\text{RRD}} = \alpha_c^B - \alpha_c^W = (a_0^B - a_0^W) + (\gamma^B - \gamma^W)z_c + (e_c^B - e_c^W),$$

where $\gamma^B - \gamma^W = \gamma$ is the value identified from our estimation model. This is not a difference in "endowments" or characteristics, but rather represents a differential response to aggregate variables. This does not "explain" the RRD in the same sense as individual covariates, but rather highlights channels through which racialized difference may arise. For this reason, we typically do not report magnitudes of $\tilde{\Delta}^{\text{RRD Explained}}(z_c)$ (with the exception of housing prices, for which we have a plausibly causal estimate).

Bias from Sample Selection

We briefly illustrate the bias that may result from selection into our sample of commuting times. Suppose that travel time, t_i^*, represents travel time for the population:

$$t_i^* = \beta D_i + e_i,$$

where $D_i = \mathbb{1}[\text{Black}_i]$. However, we only observe t_i^* if i is in the labor force. Denote LFP propensity as s_i^*, and suppose it follows:

$$s_i^* = \gamma D_i + a_i,$$

where a_i is a measure of access (and so increases the LFP propensity), and $s_i = 1[s_i^* > 0]$ is LFP for i. Finally, suppose a_i and e_i are distributed:

$$\begin{bmatrix} a_i \\ e_i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \cdot & \sigma^2 \end{bmatrix}\right)$$

28. Note, however, that an additional difference may arise between OLS estimates of Δ^k and average $\sum_c p_c \Delta_c^k$, because OLS estimates are variance weighted rather than weighted by population (Gibbons, Serrato, and Urbancic 2018). We ignore this concern to maintain simplicity of calculation and exposition.

Recall that a_i represents "access", so $\rho < 0$ (places with greater access have lower travel times on average).

Under these assumptions:

$$\mathbb{E}[t_i^*|s_i = 1] = \beta D_i + \rho\sigma\lambda(\gamma D_i),$$

where $\lambda(\cdot)$ is the inverse Mills ratio and so $\lambda(\cdot) > 0$. An estimate of racialized difference, say $\tilde{\beta}$, is the difference of these expectations evaluated at $D_i = 1$ and $D_i = 0$, and so:

$$\tilde{\beta} \rightarrow_p \beta + \rho\sigma(\lambda(\gamma) - \lambda(0)).$$

Maintaining the interpretation of a such that $\rho < 0$, this implies that our estimates of racialized difference will overstate the true value of β when Black LFP is higher than White LFP (that is, $\gamma > 0$ and so $\lambda(\gamma) - \lambda(0) < 0$) and that our estimates will understate the true value of β when Black LFP is smaller than White LFP (that is, $\gamma < 0$ and so $\lambda(\gamma) - \lambda(0) > 0$). Because $\lim_{x\to-\infty} \lambda(x) = \infty$ but $\lim_{x\to\infty} \lambda(x) = 0$, the bias is likely larger in the case that Black LFP is lower than White LFP.

In fact, Table A2 reveals that Black LFP is somewhat smaller that White LFP. Thus, we expect that our estimates understate the true effect.

A2 City-Level Heterogeneity Measures

Below we describe the full set of measures considered. Note that not all appear in the main text.

Population centrality

Centrality measures the population weighted average distance from census tract centroid to the commuting zone central business district (CBD). Given the variation in commuting zone total area, the population weighted average distance is standardized with respect to the average distance from all census tracts to the center. Centrality of a commuting zone is calculated as follows:

$$Ctr = \frac{\sum_{n=1}^{N} d(n, CBD)/N}{\sum_{n=1}^{N} (i_n/I) \cdot d(n, CBD)} - 1 \tag{A1}$$

where $d(n, CBD)$ is the distance from the centroid of census tract n to the CBD and i_n/I

is the weight assigned to tract n based on the proportion of population of type i in tract n with respect to the total population of type i within a given commuting zone. A number larger than zero indicates a population is more centrally located than would be expected on average. We consider the total population as well as Black and White populations separately.

Central business district longitude and latitudes are based on downtown location derived from Google Maps (Manduca 2021). This is a similar methodology to Holian and Kahn (2015), but with full coverage of all commuting zones considered. Population counts and census tract centroids are retrieved from the Decennial Census (1980, 1990, 2000) and the American Community Survey (2006-2010, 2014-2018) via NHGIS.

Population segregation

We employ a traditional Dissimilarity Index (Duncan and Duncan 1955; Massey and Denton 1988) but not such aspatial measures have shortcomings. Namely, they do not account for patterns of spatial organization that occur at multiple scales (Arcaya, Schwartz, and Subramanian 2018; Reardon et al. 2008). We acknowledge these shortcomings but present results in the main text using the Dissimilarity Index for ease of interpretation.

The Dissimilarity Index for a given commuting zone is constructed as follows:

$$Dissimilarity = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{w_i}{W} - \frac{b_i}{B}\right| \tag{A2}$$

where w_i and b_i represent the White and Black population count in tract i. W and B represent the total White and Black population in the commuting zone. Larger values indicate more White and Black separation. Population counts from the Decennial Census and ACS are used to construct both indexes.

Commute time and housing value

We measure the spatial relationship between housing values and commute time using a simple correlation between the average one-way commute time in minutes and the median housing value within a commuting zone using census tracts. The measure is constructed from the Decennial Census and ACS years using census tract level data retrieved from NHGIS: 1980, 1990, 2000, 2006-2010, 2014-2018. Note that for the ACS 5-year surveys, aggregate commute time is missing for roughly 25% of the tracts. We require the aggregate value to calculate average commute time. However, counts for binned commute times are available for all tracts. We impute the missing aggregate values by regressing the observed aggregate values on the set of binned counts along with commuting zone fixed effects. Coefficient estimates are used to construct the missing aggregate values. The R2 is 0.99 for the regression.

Market Access

We first define our target differential market access terms, and then show how to recover these. Index commuting zones by c, and let market access to jobs from a residential neighborhood $i \in c$ be denoted ϕ_{Ri}. Define residential market access as $\phi_{Ri} = \sum_s w_s^\theta \tau_{is}^{-\kappa\theta}$ and firm market access as $\phi_{Fj} = \sum_r b_r^\theta \tau_{rj}^{-\kappa\theta}$ for wages w, residential characteristics b, travel times τ, labor supply elasticity θ, and commuting elasticity κ.

Suppose we have known $\phi_{Ri}, \forall i \in c$. We define total measure of residential market access for a group k in c as:

$$\Phi_c^k = \sum_{i \in c} \pi_i^k \phi_{Ri},$$

where π_i^k is the fraction of total group-k population in c that resides in i. Differentials between two groups k and k' can be denoted by $\Phi_c^k - \Phi_c^{k'}$.

To calculate these market access terms, consider neighborhoods (ZIPs) indexed by i and j that reside within some c. Denote commute flows as L_{ij}, and residential population as $L_{Ri} = \sum_j L_{ij}$, workplace population as $L_{Fj} = \sum_i L_{ij}$, and distances between locations as $d_{ij} \geq 1$. The requirement that $d_{ij} \geq 1$ ensures $d_{ij}^{-\kappa} \in (0, 1]$ for $\kappa > 0$. Let θ and κ be common terms representing the the elasticity of labor supply and the marginal disutility of travel distance, respectively. (Note that we use an travel time elasticity rather than semi-elasticity.) Finally, let $\bar{s}_c$, $\bar{\tau}_c$, and $\bar{w}_c$ be CZ-specific average speed, average travel time, and average wage, respectively.

Proposition 1. *Consider a standard gravity model of commuting with the form* $L_{ij} \propto \gamma_i \delta_j k_{ij}$, $\forall i, j \in c$. *Given data* $\{L_{Ri}, L_{Fj}, d_{ij}\}_{i,j \in c}$, $\bar{\tau}_c$, $\bar{w}_c$, *and parameters* θ *and* κ, *there exist market access terms* $\{\phi_{Ri}, \phi_{Fj}\}_{i,j \in c}$ *and average speed* $\bar{s}_c$ *that are uniquely consistent with the data.*

Proof. Denote travel time as distance divided by speed: $\tau_{ij} = \frac{d_{ij}}{\bar{s}_c}$. The standard gravity model of commuting yields

$$\frac{L_{ij}}{L} = \pi_{ij} = \frac{b_i^\theta w_j^\theta \tau_{ij}^{-\kappa\theta}}{\sum_r \sum_s b_r^\theta w_s^\theta \tau_{rs}^{-\kappa\theta}} = \frac{b_i^\theta \tilde{w}_j^\theta d_{ij}^{-\kappa\theta}}{\sum_r \sum_s b_r^\theta \tilde{w}_s^\theta d_{rs}^{-\kappa\theta}}, \tag{A3}$$

where $\gamma_i = b_i^\theta = (u_i r_i^\beta)^\theta$ for some amenity u_i, housing price r_i, and housing expenditure share β; and where $\delta_j = \tilde{w}_j^\theta = (\varsigma w_j)^\theta$ for wages w_j. The third equality in Equation A3 holds because commute shares are invariant to speed and the level of wages (π_{ij} is homogeneous of degree zero in $\bar{s}_c$ and ς).

Aggregating Equation A3 by residence and workplace respectively yields:

$$\frac{L_{Ri}}{L} = \pi_{Ri} = \frac{b_i^\theta \tilde{\phi}_{Ri}}{\sum_r b_r^\theta \tilde{\phi}_{Rr}}, \quad \text{and} \quad \frac{L_{Fj}}{L} = \pi_{Fj} = \frac{\tilde{w}_j^\theta \tilde{\phi}_{Fj}}{\sum_s \tilde{w}_s^\theta \tilde{\phi}_{Fs}}, \tag{A4}$$

where $\tilde{\phi}_{Ri} = \sum_s \tilde{w}_s^\theta d_{is}^{-\kappa\theta}$ and $\tilde{\phi}_{Fj} = \sum_r b_r^\theta d_{rj}^{-\kappa\theta}$ are modified market access terms. These are level transformations of the true market access shares: Substitution yields $\phi_{Ri} = \frac{\tilde{\phi}_{Ri}}{\varsigma^\theta \bar{s}_c^{-\kappa\theta}}$ and $\phi_{Fj} = \frac{\tilde{\phi}_{Fj}}{\bar{s}_c^{-\kappa\theta}}$.

Proposition 1 in Tsivanidis (2022) establishes that $\{\tilde{\phi}_{Ri}, \tilde{\phi}_{Fj}\}_{i,j\in c}$ are the unique-to-scale solutions of the system:

$$\tilde{\phi}_{Ri} = \sum_s d_{is}^{-\kappa\theta} \frac{L_{Fs}}{\tilde{\phi}_{Fs}} \quad \text{and} \quad \tilde{\phi}_{Fj} = \sum_r d_{rj}^{-\kappa\theta} \frac{L_{Rr}}{\tilde{\phi}_{Rr}}, \tag{A5}$$

given $\{L_{Ri}, L_{Fj}, d_{ij}\}$, θ, and κ. Given these data, parameters, and values of $\{\tilde{\phi}_{Ri}, \tilde{\phi}_{Fj}\}_{i,j\in c}$, we only need values of ς and $\bar{s}_c$ to recover $\{\phi_{Ri}, \phi_{Fj}\}_{i,j\in c}$.

To proceed, define $\pi_{ij|i} \equiv L_{ij}/L_{Ri}$, and note that average time is

$$\bar{\tau}_c = \sum_{r\in c}\sum_{s\in c} \pi_{rs}\tau_{rs} = \sum_{r\in c} \pi_{Rr} \sum_{s\in c} \pi_{rs|r} \frac{d_{rs}}{\bar{s}_c} \tag{A6}$$

and that $\sum_{r\in c} \pi_{Rr} \sum_{s\in c} \pi_{rs|r} = 1$. Because $\pi_{ij} = \pi_{ij|i}\pi_{Ri}$, it follows that $\pi_{ij|i} = \tilde{w}_j^\theta d_{ij}^{-\kappa\theta}/\tilde{\phi}_{Ri}$. From Equation A4, $\tilde{w}_j^\theta = \frac{L_{Fj}\sum_s \tilde{w}_s^\theta \tilde{\phi}_{Fs}}{\tilde{\phi}_{Fj} L}$. Note that after some derivation

$$\sum_s \tilde{w}_s^\theta \tilde{\phi}_{Fs} = L \sum_r \pi_{Rr} \frac{\sum_s \tilde{w}_s^\theta d_{rs}^{-\kappa\theta}}{\sum_{s'} \tilde{w}_{s'}^\theta d_{rs'}^{-\kappa\theta}}$$

and so $\sum_s \tilde{w}_s^\theta \tilde{\phi}_{Fs} = L$. Thus, we can express $\tilde{w}_j^\theta = L_{Fj}/\tilde{\phi}_{Fj}$.

Substituting these derivations into Equation A6 gives:

$$\bar{\tau}_c = \sum_{r\in c} \pi_{Rr} \sum_{s\in c} \frac{L_{Fs} d_{rs}^{-\kappa\theta}}{\tilde{\phi}_{Rr}\tilde{\phi}_{Fs}} \frac{d_{rs}}{\bar{s}_c} = \bar{s}_c^{-1} \sum_{r\in c} \pi_{Rr} \sum_{s\in c} \frac{L_{Fs} d_{rs}^{1-\kappa\theta}}{\tilde{\phi}_{Rr}\tilde{\phi}_{Fs}}$$

And so $\bar{s}$ is

$$\bar{s}_c = \bar{\tau}_c^{-1} \sum_{r \in c} \pi_{Rr} \sum_{s \in c} \frac{L_{Fs} d_{rs}^{1-\theta}}{\tilde{\phi}_{Rr} \tilde{\phi}_{Fs}}.$$

To recover ς, note that average wage is

$$\bar{w}_c = \sum_s \pi_{Fs} w_s = \sum_s \pi_{Fs} \frac{\tilde{w}_s}{\varsigma} = \varsigma^{-1} \sum_s \pi_{Fs} \left(\frac{L_{Fs}}{\tilde{\phi}_{Fs}} \right)^{1/\theta} \tag{A7}$$

And so ς is

$$\varsigma = \bar{w}_c^{-1} \sum_s \pi_{Fs} \left(\frac{L_{Fs}}{\tilde{\phi}_{Fs}} \right)^{1/\theta}. \tag{A8}$$

□

One implementation note: It is standard to use κ as a semi-elasticity of commute time. To simplify Theorem 1, we instead define κ as an elasticity of commute time. To help facilitate cross-city comparison, we develop an adjusted local elasticity κ_c where we define

$$\kappa_c = \frac{\%\Delta U}{\%\Delta \tau_c} = \frac{\%\Delta U}{\Delta \tau / \bar{\tau}_c} = \bar{\tau}_c \frac{\%\Delta U}{\Delta \tau}.$$

The term $\frac{\%\Delta U}{\Delta \tau}$ is the semi-elasticity more frequently estimated in the quantitative spatial literature. The new elasticity κ_c will this be a bit higher in cities with longer average commutes. This provides a city-specific differential reflecting increasing marginal disutility of proportional travel time increases in longer-commute time cities. Thus, a change of travel time from 20 minutes to 40 minutes in a shorter-commute city will shift behavior less than a change in travel time from 30 minutes to 60 minutes in a longer-commute city.

The construction of the market access term requires granular employment and Black/White employed population counts. For employment counts, we use ZIP Code Business Patterns data (ZCBP) for 1994, 2000, 2010, and 2018 (Manson et al. 2021). Unfortunately data for 1980 and 1990 are unavailable. We thus match 1994 ZCBP to 1990 Census data. ZIP Code level Decennial Census (1990, 2000) and ACS (2006–2010, 2014–2018) data provide population counts. Note that the annual ZCBP data are produced using ZIP Codes, where as Census data rely on ZIP Codes for 1990 then uses ZIP Code Tabulation Areas (ZCTAs) for remaining years. ZCTAs are generalized representations of ZIP Code boundaries constructured by the Census Bureau.[29]

While the majority of ZIP Codes are stable over time and do coincide with ZCTAs, combining these two datasets presents some challenges. First, the number of ZIP Codes that do change over time is large enough to introduce measurement error into subsequent analysis. ZIP Codes may be decommissioned, merged, or split in any given year. Second, some ZIP Codes in the ZCBP represent large postal customers (e.g. a large company in one building) or PO boxes. Thus, they do not have associated spatial boundaries and are merely points in space. These ZIP Codes do not have corresponding ZCTAs as ZCTAs represent spatial boundaries with positive residential population. Third, ZIP Codes with positive employment and associated geography (not a large postal customer or PO box) that do not contain residential population (e.g. commercial office park) will not be contained within the Census data. This makes it difficult to know whether a ZIP Code in fact does not have residential population, or it is not properly crosswalked to consistent ZIP Code or ZCTA boundaries, a method which we describe below. We drop from the dataset ZCBP ZIP Codes and Census ZIP Codes/ZCTAs that we are unable to merge via the methods described below. This works out to 1,056, 50, 0, 0 ZCBP zipcodes for 1994, 2000, 2010, 2018 respectively. From the Census data we drop 212, 386, 0, 0 for 1990, 2000, 2006-2010, 2014-2018 respectively. Note that for the 2006–2010 and 2014–2018 ACS all ZCBP ZIP Codes merge so we set employment in the unmerged ZCTAs to zero and thus do not drop any ZCTAs.

We use a national ZIP Code crosswalk spanning 1990-2010 to create geographically stable "ZIP Code clusters" over 1990-2000 and 2000-2010 (Bailey and Suppan Helmuth 2020). This crosswalk facilitates the majority of merges between the ZCBP and Census datasets. To account for large customers and PO boxes, we use the 2020 UDS Mapper ZIP Code to ZCTA crosswalk (Snow 2020). For large postal customers or PO boxes this amounts to spatially joining the latitude and longitude of these ZIP Codes to the enclosing ZCTA. For older data with decommissioned ZIP Codes, this 2020 dataset is less helpful. Further, as stated by the creators of the crosswalk, not all large customers and PO box latitude and longitudes correspond to the location of the actual customers. We do not observe when this is the case and acknowledge potential for measurement error here. For ZCBP ZIP Codes that remain unmerged, we attach longitudes and latitudes and spatially join to ZCTAs shapefiles for their respective years. Longitudes and latitudes are provided

29. More details on the construction of ZCTAs can be found here https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html.

by https://www.unitedstateszipcodes.org (Zip Code Database 2021). These longitudes and latitudes are associated with current ZIP Codes; thus, older ZIP Codes from the ZCBP that we are not able to account for using other methods may remain unmerged if not contained within the longitude/latitude database.

A3 PUMA Use

We use Public Use Microdata Areas (PUMAs) to control for residential location. PUMAs provide a more coarse geographic resolution than ideal, but do allow for some heterogeneity within major cities. In large CZs, residential PUMAs divide a larger area into smaller areas of roughly 100,000 people each, subject to data disclosure rules. This means that, at least within cities, there is some resolution into where people live in our data.

However, these are not constant over time. In the 1980 Census, residential PUMAs were based on county groups, and provide little additional resolution beyond CZs. After 1990, these became a bit more refined, however, 1990 residential PUMAs do not divide within census-designated places—this means that they do not distinguish areas within municipal boundaries. This is especially impactful in big cities where many of the survey respondents in our data live.

Differences over time are why we restrict analysis to 2000 and later for PUMA-enabled models. The table below gives the number of unique residential in each year bin.

Year	Unique Residential PUMAs	Unique POW PUMAs
1980	1,154	-
1990	1,726	-
2000	2,071	1,238
2005–11	2,072	1,260
2012–19	2,351	1,002

A4 Montgomery, AL commute mode statistics

Statistics regarding the mode choice of commuters in extremely segregated census tracts of 1960 Montgomery were compiled using Social Explorer. First, we identified census tracts where the racial composition of residents is at least 95% Black or 95% White. For these tracts, we tallied the number of total workers as well as the number listing their means of transportation to work as car, bus, or walking.[30] We then summed employment as a total and by mode across mostly-Black and mostly-White tracts, respectively, to produce the figures shown in the text.

Tract 53, in the northeast of Montgomery, appeared to be an outlier: it was 96% White, but only 14% of commuters used a car. The next lowest share in a mostly-White county was 86%. Upon further examination, the site is a military installation, likely explaining the different commuting patterns. We report totals with and without this tract.

Maps from which this data were derived are available at https://www.socialexplorer.com/6323c92504/view.

A5 Housing Prices and Stratification

Housing prices may provide a useful indicator of spatial stratification. This relation arises within a classic system-of-cities model with internally monocentric cities, like Henderson (1974). Cities with more productive industries (or region-wide consumer amenities) will grow spatially larger, producing longer average commutes as well as greater variation in commute times. Internal spatial equilibrium will in turn drive up house prices in relatively central portions of productive cities, raising average house prices relative to less-productive cities (which, in equilibrium, are smaller and feature shorter average commutes). Empirically, as shown in Figure A6, the patterns of persistence suggest a potential link. However, reverse causality could drive this relationship.

To rule out reverse causality, we adopt an instrumental variable (IV) approach. We employ the local sensitivity instrument of Guren et al. (2021), who develop a time-varying proxy for local housing supply elasticity to use as an instrument for housing price (as an alternative to, e.g., Saiz 2010; Mian, Rao, and Sufi 2013). The instrument is comprised of estimates from:

$$P_{cdt} = \delta_c \bar{P}_{(-c)dt} + \psi_0 \hat{\beta}_{ct} + \psi_1 m_{cdt} + \phi_c t + D_c + \epsilon_{cdt} \tag{A9}$$

where P_{cdt} is log mean housing price in CZ c in Census division d in year-bin t, $\bar{P}_{(-c)dt}$ is the leave-c-out log mean housing price in the Census division, $\psi_0 \hat{\beta}_{ct}$ controls for any effect of RRD and $\psi_1 m_{cdt}$ for share Black. CZ-specific time trends and fixed effects are included as $\phi_c t$ and D_c, respectively. ϵ_{cdt} is the error term. The estimates $\hat{\delta}_c \bar{P}_{(-c)dt}$ are

30. Technically, the category is "bus or streetcar", but Montgomery did not operate a streetcar at the time, see https://web.archive.org/web/20081204163028/http://www.montgomerytransit.com/history.html.

then used as a time-varying instrument for price in Equation 4.[31] The $\hat{\delta}_c$ are CZ-specific proxies for local housing supply elasticities, akin to Saiz (2010). Thus, the interacted term $\hat{\delta}_c \bar{P}_{(-c)dt}$ provides a measure of the local response to regional price shocks. This approach infers the effect of housing prices on the RRD from the differential response of cities to regional housing trends.

We are agnostic as to whether housing prices per se or some downstream channel that responds tightly to changes in housing prices are most at play, as we cannot delineate housing price changes from downstream channels. This suggests viewing housing price as a cluster of mechanisms in our setting, rather than the more direct consumption-wealth channel discussed in Guren et al. (2021). Identification requires that there is no unobserved factor correlated with changes in CZ-level housing prices that differentially affects CZs more sensitive to cross-sectional housing price variation (conditional on included controls)–that is, if housing prices respond to regional shocks differently according to factors separate from but correlated with housing supply elasticities. For example, if housing prices capitalize property tax expense, then identification is threatened if locations with inelastic housing supply systematically change property tax rates in response to regional housing demand shocks differently than elastic housing supply locations.

Table A9 shows estimates of the relationship between housing prices and the RRD. OLS estimates with year and CZ fixed effects indicate that a 10pp increase in housing prices is correlated with an increase in the RRD by about 0.7pp. Panel B shows first-stage estimates; the instruments are not weak and are highly correlated with CZ-level housing prices. The IV estimates are a bit smaller than the OLS results, but still find that a 10pp increase in housing prices leads to a 0.5pp increase in the RRD. These results are robust to the inclusion of controls for (log) commuting population and the share of workers in the CZ who are Black.[32]

High housing costs undo some of the partial convergence in the racialized difference in commute times, and these results are economically significant. As a counterfactual exercise, suppose that house prices were held to their 1980 (real) values. Using the IV estimate in Column 4, the average conditional racialized difference in 2012–19 would be 0.028 log points instead of the 0.049 log points we observe in Table A1. Said differently,

31. We differ in implementation from Guren et al. (2021) by using more granular geographies (CZs instead of core-based statistical areas and Census divisions instead of regions) and by estimating Equation A9 in levels rather than differences (though we retain CZ-specific time trends). First-stage point estimates are slightly smaller but roughly in line with Guren et al. (2021).

32. We prefer specifications without controls: city population is likely a bad control, as population and house price are jointly determined by common underlying demand and supply features.

aggregate RRD would be 43% lower today if real housing prices were flat over the last 40 years. High housing costs—indicative of spatial stratification—appear to be a key feature of observed patterns of persistence in the RRD.

Columns 5 and 10 provide an alternative test of stratification by comparing the relationship between neighborhood-level commute times and housing prices across CZs. We compute the simple correlation between tract-level average commute times and median home values within a given city. We expect that cities where neighborhood commute times and housing prices are negatively correlated (diverging) will have greater RRDs. This hypothesis holds true with marginal significance.[33]

These results are consistent with the causes and effects of housing price increases in the literature. Van Nieuwerburgh and Weill (2010) show increasing dispersion of house prices in the U.S. between 1975 and 2007, driven in part by the flow of workers to the most productive metropolitan areas. Guerrieri, Hartley, and Hurst (2013) in turn document substantial variation in housing price growth within cities and provide a model of neighborhood housing price dynamics in response to a citywide housing demand shock. Their model captures a channel of spatial gentrification, wherein lower-income neighborhoods near higher-income neighborhoods shift to being higher income. These neighborhoods are often those with a high degree of job access. Finally, Gyourko, Mayer, and Sinai (2013) show that high housing prices tend to crowd out lower income households even from municipalities within the same metropolitan area.

Evolving job access and time use preferences, as described by Su (2019) and Edlund, Machado, and Sviatschi (2021), provide a partial basis for such shifts. These papers relate rising wages and working hours (respectively) among high-paid workers to gentrification. These forces make commuting more costly, so these workers respond by moving to center-city neighborhoods and pushing up house prices there. Via the mechanisms in Guerrieri, Hartley, and Hurst (2013) and Gyourko, Mayer, and Sinai (2013), this then spills out in equilibrium, reducing affordability in high-access neighborhoods. We note that gentrification in these papers is one manifestation of spatial stratification. Our approach likely includes related processes, including racialized patterns of suburbanization.

33. Construction details for this measure are provided in the Appendix.

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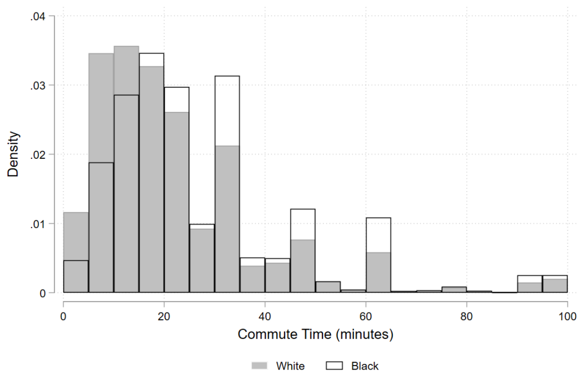
Additional Results

Figure A1: Distribution of Commute Times by Race in 1980 and 2012–19

(a) 1980



(b) 2012–19

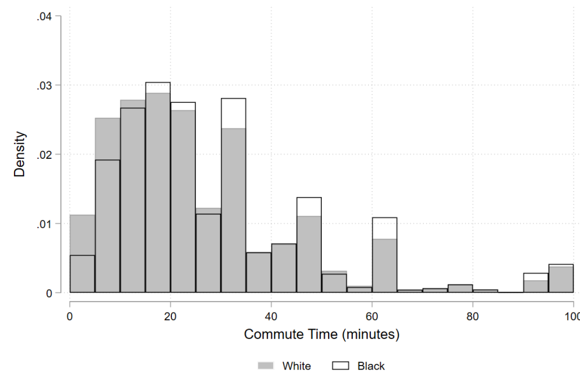
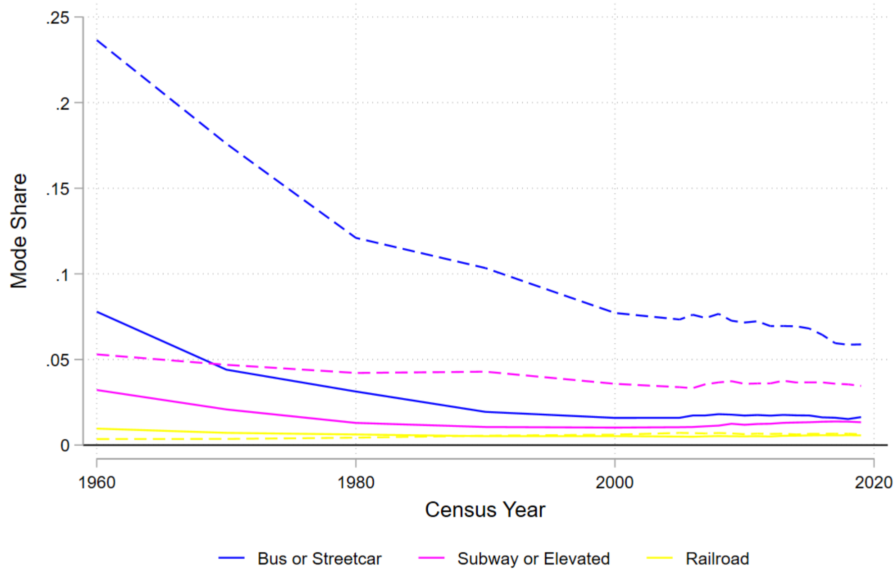


Figure A2: Commute Share by Mode (Nonauto)

(a) Unconditional Transit Share



(b) Unconditional Nontransit/Nonauto Share

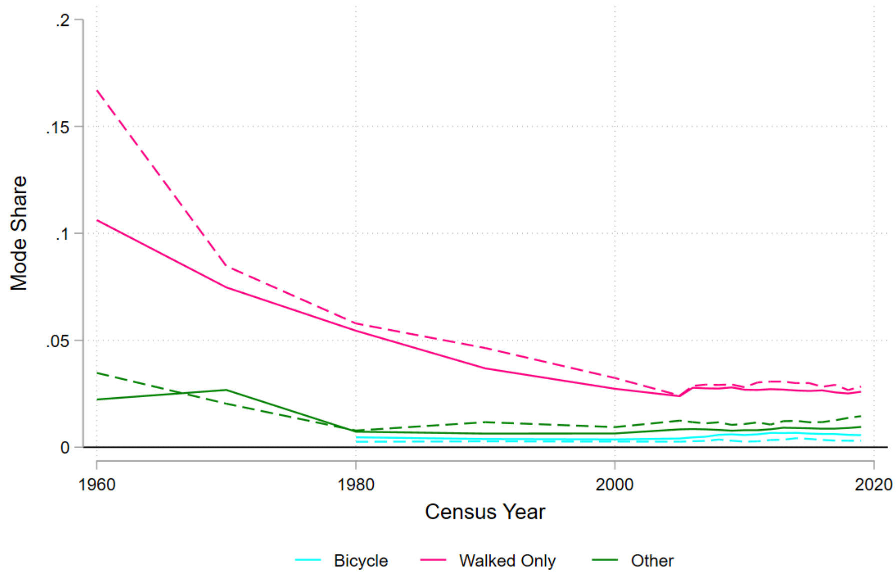


Figure A3: Access to Car in HH

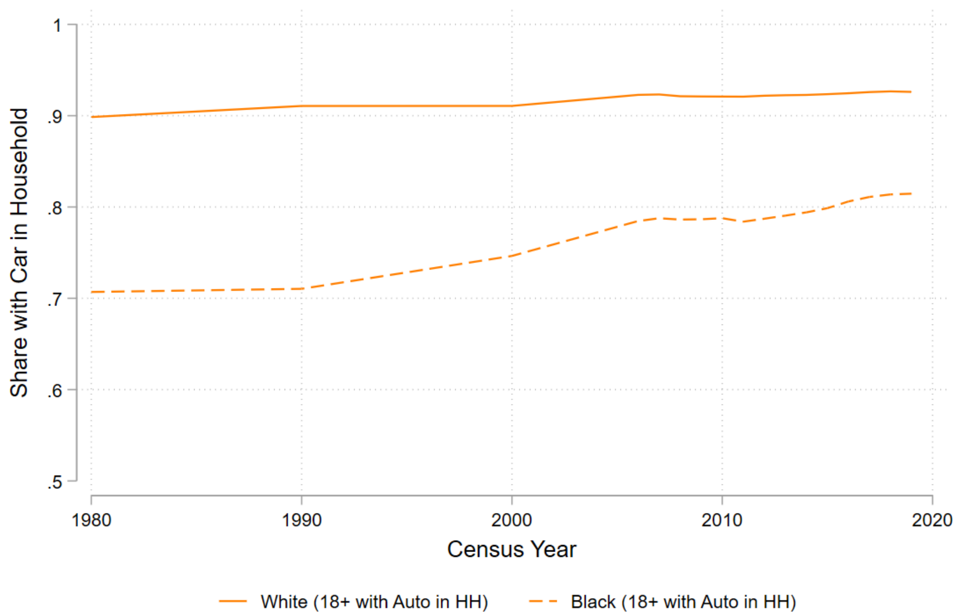
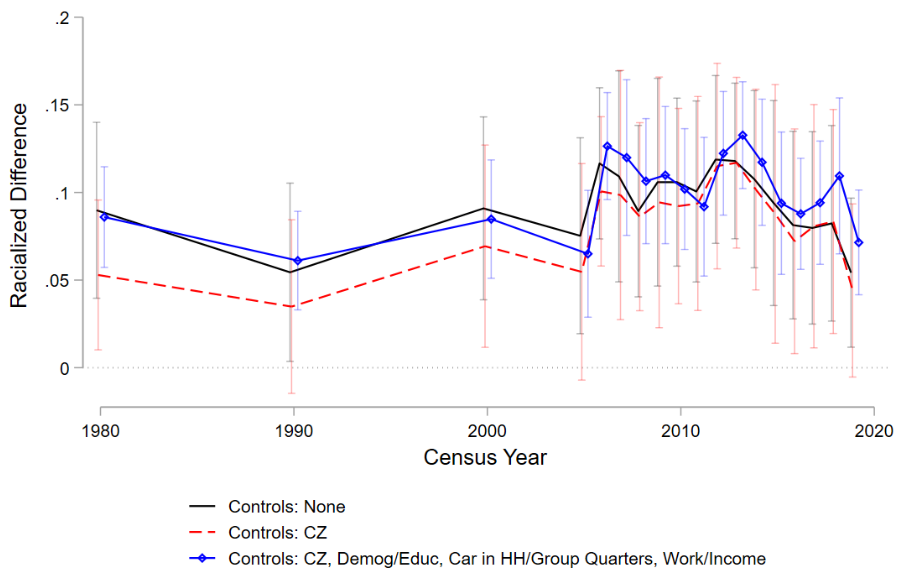


Figure A4: Racialized Difference in Commute Time by Transit Mode

(a) Racialized Difference Conditional on Mode = Bus & Streetcar



(b) Racialized Difference Conditional on Mode = Subway & Elevated

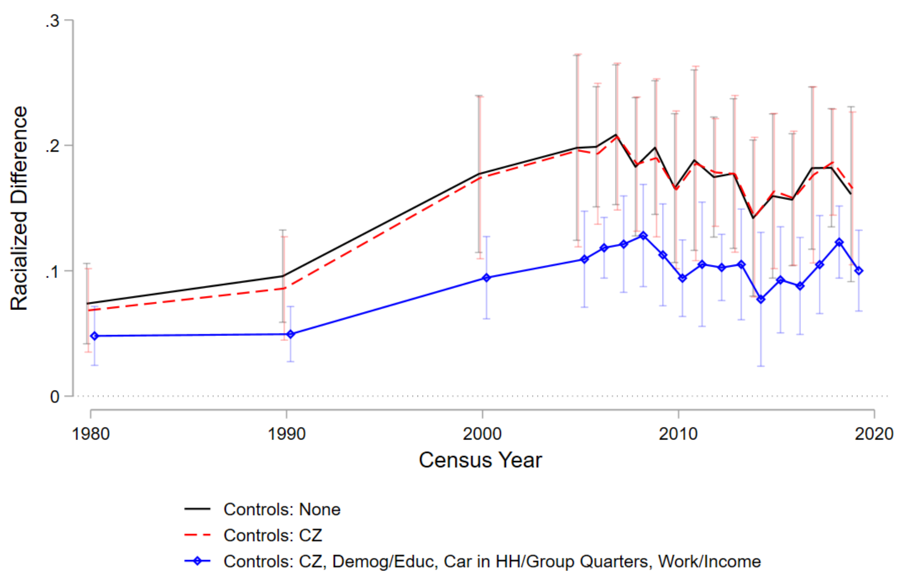


Figure A5: Racialized Difference in Commute Times are Present Conditional on Rental Prices

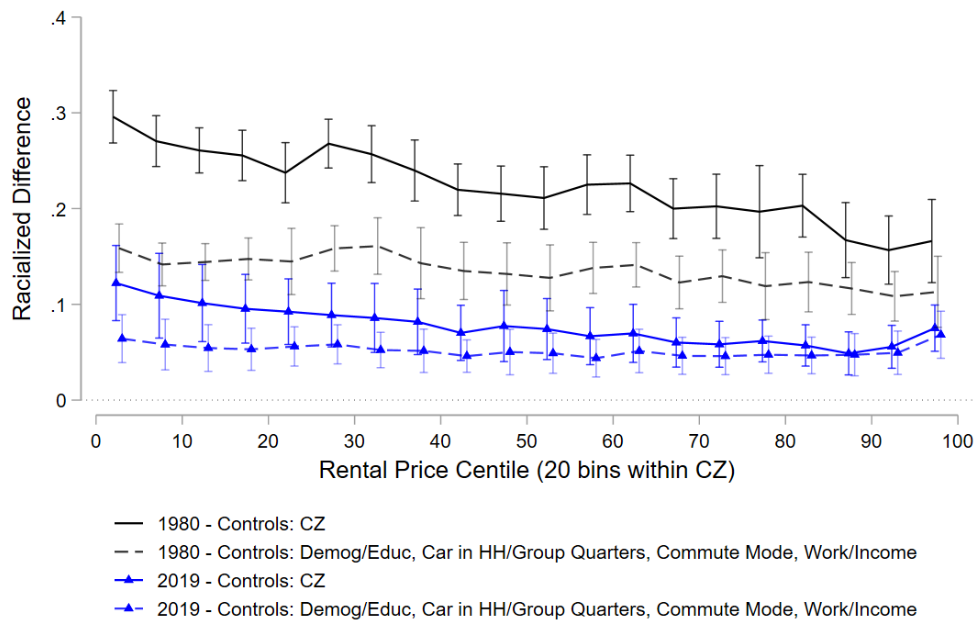
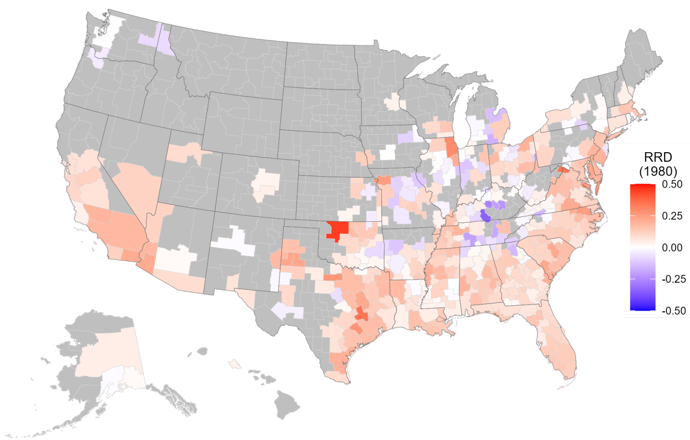
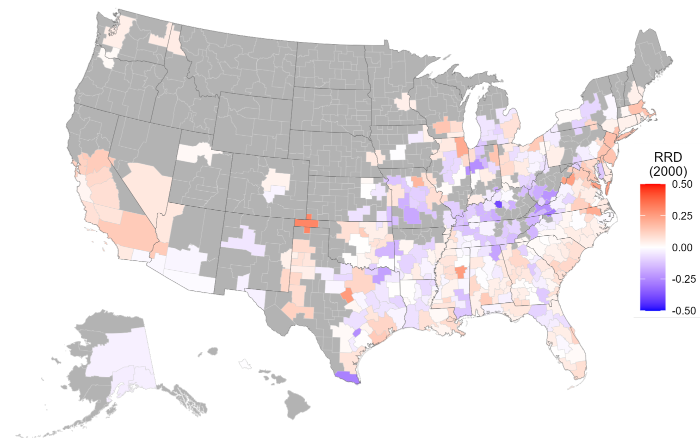


Figure A6: Maps of the Residual Racialized Difference (RRD) in Commute Time by CZ

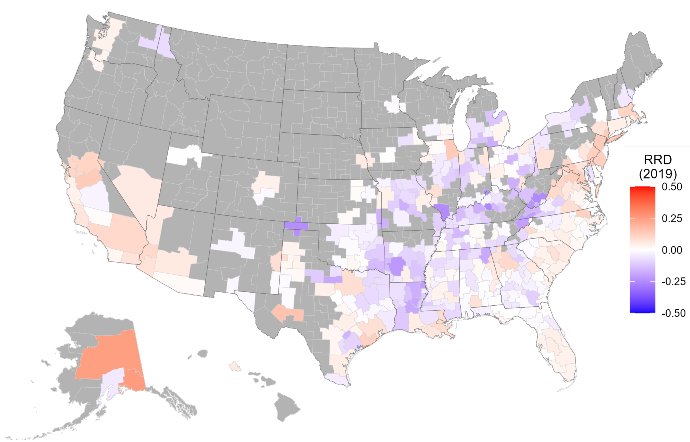
(a) RRD in 1980



(b) RRD in 2000



(c) RRD in 2012-19



(d) Change in RRD Over Time (2012–19 less 1980)

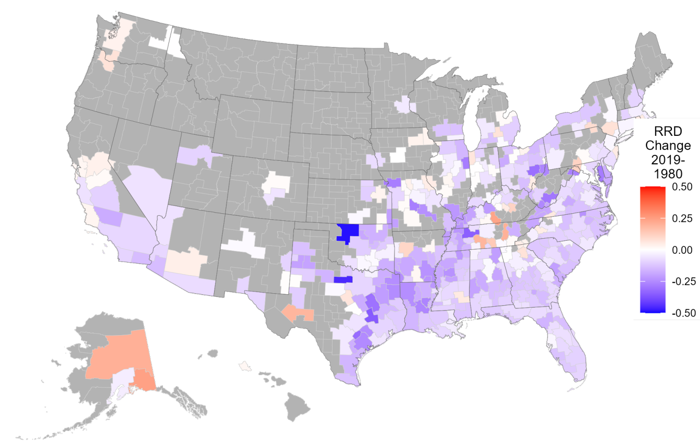


Figure A7: Evolution of Residual Racialized Difference (RRD) in 16 Big Cities

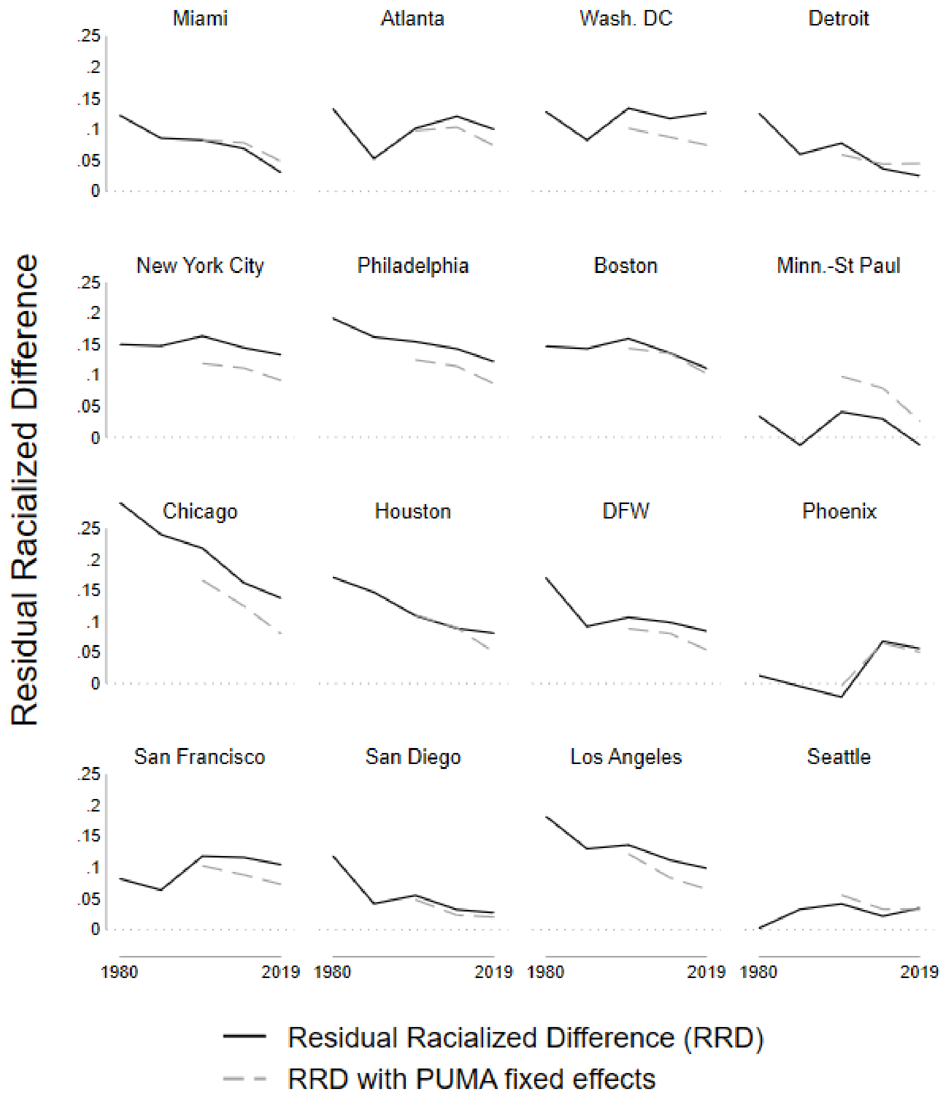


Figure A8: Persistence of Residual Racialized Difference (RRD) Across Cities. Note: Circle size indicates the size of the Black commuting population in 2012–19. Regression slope is estimated weighting each CZ by its Black commuting population in 2012–19, standard errors are robust to heteroskedasticity.

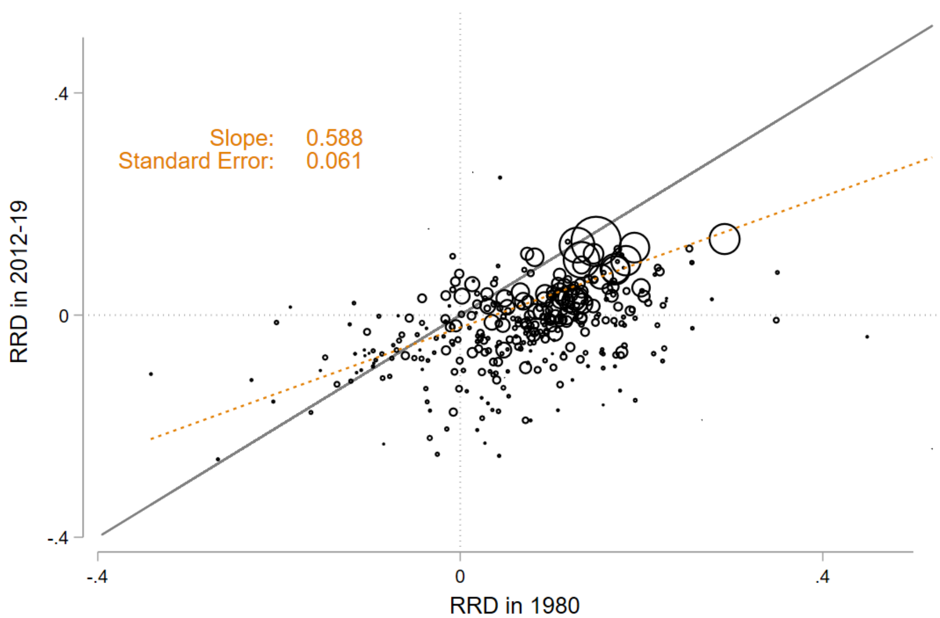


Table A1: Estimates of the Racialized Difference in Commute Time

	$\ln(\tau_{ict})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$1[\text{Black}] \times t_{1980}$	0.255***	0.172***	0.188***	0.179***	0.126***	0.125***
	(0.022)	(0.015)	(0.016)	(0.012)	(0.009)	(0.010)
$1[\text{Black}] \times t_{1990}$	0.187***	0.102***	0.120***	0.113***	0.068***	0.070***
	(0.029)	(0.020)	(0.021)	(0.018)	(0.010)	(0.011)
$1[\text{Black}] \times t_{2000}$	0.174***	0.087***	0.105***	0.101***	0.064***	0.071***
	(0.027)	(0.019)	(0.020)	(0.017)	(0.011)	(0.011)
$1[\text{Black}] \times t_{2005--11}$	0.147***	0.066***	0.087***	0.082***	0.047***	0.056***
	(0.027)	(0.018)	(0.019)	(0.017)	(0.010)	(0.010)
$1[\text{Black}] \times t_{2012--19}$	0.123***	0.045***	0.068***	0.064***	0.035***	0.046***
	(0.025)	(0.016)	(0.017)	(0.015)	(0.010)	(0.009)
Year Bin×CZ FEs	-	Y	Y	Y	Y	Y
Controls						
Demog. & Edu.	-	-	Y	Y	Y	Y
Car & GQ.	-	-	-	Y	Y	Y
Trans. Mode	-	-	-	-	Y	Y
Work & Income	-	-	-	-	-	Y

Data: Commuters 18 years of age and older in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone. Each column is a different specification with 47,952,072 observations. The dependent variable is log travel time top-coded at 99 minutes. Demographics include sex, educational attainment, age, marital and household status, and number of children in household. Car & GQ are indicators for car in the household and group quarters. Work and income controls are log income, an indicator for zero income, and indicators for industry and occupation. Controls are interacted with year bin. Observations weighted by adjusted person sample weights. Standard errors clustered by commuting zone. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table A2: Labor Force Participation Rates by Sex and Race, all people 18+

	White, all people 18+			Black, all people 18+		
	Male (1)	Female (2)	Total (3)	Male (4)	Female (5)	Total (6)
1980	0.713	0.451	0.575	0.601	0.471	0.530
1990	0.709	0.519	0.610	0.584	0.521	0.550
2000	0.684	0.532	0.605	0.543	0.524	0.533
2005–11	0.656	0.527	0.590	0.541	0.539	0.540
2012–19	0.642	0.526	0.582	0.551	0.553	0.552

Data: All people 18 years of age and older in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone.

Table A3: Effects Using Manski-style Bounds (Prime Age Workers)

	Table 1, Column 1		Table 1, Column 2		Table 1, Column 3		Table 1, Column 4	
	Baseline (1)	$\tau_{ct}^{\text{NILF}} = Q_{0.95}(\tau_{i \in ct})$ (2)	Baseline (3)	$\tau_{ct}^{\text{NILF}} = Q_{0.95}(\tau_{i \in ct})$ (4)	Baseline (5)	$\tau_{ct}^{\text{NILF}} = Q_{0.95}(\tau_{i \in ct})$ (6)	Baseline (7)	$\tau_{ct}^{\text{NILF}} = Q_{0.95}(\tau_{i \in ct})$ (8)
$1[\text{Black}] \times t_{1980}$	0.253***	0.258***	0.163***	0.182***	0.178***	0.144***	0.169***	0.098***
	(0.022)	(0.022)	(0.014)	(0.011)	(0.016)	(0.013)	(0.012)	(0.011)
$1[\text{Black}] \times t_{1990}$	0.177***	0.258***	0.091***	0.192***	0.108***	0.150***	0.103***	0.098***
	(0.028)	(0.024)	(0.019)	(0.013)	(0.020)	(0.014)	(0.018)	(0.012)
$1[\text{Black}] \times t_{2000}$	0.163***	0.276***	0.077***	0.205***	0.094***	0.174***	0.090***	0.122***
	(0.026)	(0.023)	(0.018)	(0.012)	(0.019)	(0.012)	(0.017)	(0.011)
$1[\text{Black}] \times t_{2005--11}$	0.134***	0.205***	0.054***	0.147***	0.075***	0.122***	0.072***	0.081***
	(0.026)	(0.019)	(0.016)	(0.010)	(0.017)	(0.010)	(0.016)	(0.010)
$1[\text{Black}] \times t_{2012--19}$	0.111***	0.175***	0.034**	0.119***	0.057***	0.098***	0.055***	0.061***
	(0.024)	(0.020)	(0.015)	(0.011)	(0.015)	(0.010)	(0.014)	(0.011)
Year Bin×CZ FEs	-	-	Y	Y	Y	Y	Y	Y
Demog. & Edu. Controls	-	-	-	-	Y	Y	Y	Y
Car & GQ Controls	-	-	-	-	-	-	Y	Y
Observations	31,772,111	42,782,454	31,772,111	42,782,454	31,772,111	42,782,454	31,772,111	42,782,454

Data: Commuters (odd Columns) or all people (even Columns) between the ages of 25 and 54, inclusive, in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone. Demographics include sex, educational attainment, age, marital and household status, and number of children in household. Car & GQ are indicators for car in the household and group quarters. Standard errors clustered by commuting zone. See text for description of bounding exercise. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table A4: Racialized Difference in Commute Time by Mode and CZ Type and with Residential PUMA Controls

	Big Transit CZs					Big Non-Transit CZs				Other CZs			
	All	Car	Bus	Subway	Walk	All	Car	Bus	Walk	All	Car	Bus	Walk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
A. Year-Specific Estimates													
1[Black] × t_{1980}	0.177***	0.201***	0.110***	0.049***	0.177***	0.133***	0.134***	0.098**	0.236***	0.094***	0.091***	0.043***	0.288***
	(0.023)	(0.026)	(0.024)	(0.012)	(0.018)	(0.014)	(0.014)	(0.031)	(0.042)	(0.005)	(0.006)	(0.010)	(0.015)
1[Black] × t_{1990}	0.139***	0.145***	0.083**	0.053***	0.175***	0.081***	0.077***	0.036	0.203***	0.033***	0.025***	0.029***	0.256***
	(0.019)	(0.023)	(0.026)	(0.011)	(0.025)	(0.016)	(0.018)	(0.024)	(0.023)	(0.005)	(0.006)	(0.011)	(0.013)
1[Black] × t_{2000}	0.155***	0.155***	0.100**	0.097***	0.168***	0.084***	0.077***	0.081	0.240***	0.028***	0.019***	0.060***	0.303***
	(0.012)	(0.014)	(0.033)	(0.017)	(0.020)	(0.010)	(0.011)	(0.045)	(0.034)	(0.005)	(0.005)	(0.015)	(0.013)
1[Black] × $t_{2005-11}$	0.136***	0.129***	0.113***	0.116***	0.116***	0.066***	0.063***	0.089**	0.138***	0.016***	0.008*	0.086***	0.212***
	(0.007)	(0.006)	(0.027)	(0.018)	(0.027)	(0.012)	(0.013)	(0.031)	(0.036)	(0.004)	(0.005)	(0.012)	(0.011)
1[Black] × $t_{2012-19}$	0.122***	0.115***	0.110***	0.107***	0.070***	0.050***	0.044**	0.095**	0.151***	0.009**	0.0005	0.098***	0.176***
	(0.007)	(0.007)	(0.027)	(0.017)	(0.016)	(0.013)	(0.016)	(0.033)	(0.028)	(0.004)	(0.004)	(0.011)	(0.011)
Observations	6,408,425	5,250,340	311,886	376,453	247,151	3,381,131	3,160,925	89,535	77,753	38,162,516	35,944,455	352,559	1,359,836
B. Year-Specific Estimates, with year-bin×PUMA FEs (2000 and later only)													
1[Black] × t_{2000}	0.121***	0.125***	0.072**	0.022**	0.155***	0.081***	0.079***	0.058	0.186***	0.048***	0.042***	0.058***	0.268***
	(0.007)	(0.008)	(0.025)	(0.007)	(0.021)	(0.010)	(0.010)	(0.035)	(0.027)	(0.005)	(0.005)	(0.015)	(0.013)
1[Black] × $t_{2005-11}$	0.105***	0.104***	0.080***	0.037**	0.135***	0.070***	0.069***	0.059**	0.158***	0.034***	0.029***	0.076***	0.187***
	(0.006)	(0.006)	(0.013)	(0.011)	(0.015)	(0.009)	(0.008)	(0.018)	(0.036)	(0.005)	(0.005)	(0.010)	(0.012)
1[Black] × $t_{2012-19}$	0.080***	0.076***	0.069***	0.034**	0.085***	0.045***	0.041***	0.053**	0.136***	0.023***	0.017***	0.075***	0.147***
	(0.004)	(0.004)	(0.015)	(0.010)	(0.017)	(0.004)	(0.005)	(0.022)	(0.030)	(0.004)	(0.004)	(0.010)	(0.011)
Observations	4,679,100	3,844,123	209,789	286,316	168,743	2,605,071	2,443,058	65,138	53,409	29,513,107	27,969,466	244,834	907,781
C. With year-bin×PUMA×POW-PUMA FEs (2000 and later only)													
1[Black] × t_{2000}	0.084***	0.084***	0.068***	0.015*	0.143***	0.069***	0.065***	0.053	0.190***	0.046***	0.039***	0.057***	0.269***
	(0.008)	(0.009)	(0.019)	(0.007)	(0.021)	(0.011)	(0.011)	(0.034)	(0.032)	(0.004)	(0.004)	(0.014)	(0.014)
1[Black] × $t_{2005-11}$	0.063***	0.058***	0.068***	0.024*	0.132***	0.051***	0.050***	0.055**	0.158***	0.025***	0.019***	0.064***	0.190***
	(0.006)	(0.006)	(0.009)	(0.010)	(0.017)	(0.012)	(0.012)	(0.020)	(0.042)	(0.003)	(0.004)	(0.010)	(0.011)
1[Black] × $t_{2012-19}$	0.058***	0.052***	0.062***	0.029**	0.082***	0.035***	0.030***	0.046*	0.141***	0.017***	0.010***	0.068***	0.147***
	(0.007)	(0.007)	(0.010)	(0.009)	(0.018)	(0.005)	(0.006)	(0.021)	(0.031)	(0.003)	(0.003)	(0.009)	(0.011)
Observations	4,675,736	3,842,451	209,601	286,151	168,261	2,602,007	2,441,245	65,046	53,080	29,494,524	27,959,105	244,308	905,279

Data: All commuters in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone. Columns 1–5 consider "Big Transit Cities", CZs with sizable heavy-rail transit: New York City, Boston, Chicago, Philadelphia, Washington, D.C., San Francisco, Atlanta, and Los Angeles. Columns 6–9 consider "Big Non-Transit Cities": Dallas-Fort Worth, Houston, Miami, Phoenix, Seattle, Detroit, San Diego, and Minneapolis-St. Paul. Columns 10–13 consider all other CZs. Columns 2–5, 7–9, and 11–13 further restrict the sample based on commute mode. Each column in each panel is for a different specification. The dependent variable is log travel time top-coded at 99 minutes. Each column includes demographic controls and work and income controls interacted with year bin, as well as commuting-zone-by-year-bin fixed effects. Columns 1, 6, and 10 include transit mode controls. Panel B includes residential-PUMA-by-year-bin fixed effects and so only uses data from 2000; Panel C further adds interactions with POWPUMA-by-year-bin fixed effects. Observations weighted by adjusted person sample weights. Standard errors clustered by commuting zone. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table A5: Summary Statistics of the Residual Racialized Difference (RRD)

Year Bin	N	Mean	SD	Min	Max
A. All CZs					
1980	338	0.126	0.070	-0.342	0.521
1990	338	0.076	0.073	-0.318	0.240
2000	338	0.075	0.075	-0.395	0.308
2005–11	338	0.060	0.069	-0.390	0.223
2012–19	338	0.048	0.065	-0.259	0.257
B. CZs with More Than 200k Workers in All Years					
1980	87	0.135	0.063	-0.057	0.291
1990	87	0.091	0.066	-0.102	0.240
2000	87	0.093	0.066	-0.117	0.218
2005–11	87	0.078	0.058	-0.115	0.162
2012–19	87	0.065	0.054	-0.094	0.137
C. CZs with Less Than 200k Workers in All Years					
1980	251	0.097	0.082	-0.342	0.521
1990	251	0.024	0.071	-0.318	0.221
2000	251	0.014	0.073	-0.395	0.308
2005–11	251	-0.003	0.070	-0.390	0.223
2012–19	251	-0.015	0.063	-0.259	0.257

Estimates of the Residual Racialized Difference (RRD) in commute time and CZ-level summary statistics. RRD values are estimated for each CZ in each year bin as explained in section 3. RRDs are only reported for CZs with at least 1,000 total employed persons and with greater than 50 unique Black commuter Census respondents in all five year bins. Observations weighted by the number of Black commuters in each CZ-by-year-bin cell.

Table A6: RRD by CZ, for the 87 CZs with More Than 200k Workers

Largest City in CZ	CZ Code	RRD in 2019	2019 Rank	RRD in 1980	1980 Rank	Change in RRD (2019-1980)	Rank of Change
Chicago, IL	24300	0.137	87	0.291	87	–0.154	4
New York City, NY—Newark, NJ	19400/19600	0.133	86	0.150	79	–0.017	69
Washington, DC—Arlington, VA	11304	0.126	85	0.129	70	–0.002	74
Philadelphia, PA—Wilmington, DE	19700/19800	0.122	84	0.192	85	–0.070	45
Boston, MA	20500	0.111	83	0.147	78	–0.036	63
Sacramento, CA	37400	0.111	82	0.074	33	0.037	81
San Francisco, CA	37800	0.105	81	0.082	39	0.023	79
Atlanta, GA	9100	0.100	80	0.134	72	–0.034	64
Los Angeles, CA	38300	0.098	79	0.183	84	–0.084	37
New Orleans, LA	3300	0.091	78	0.134	73	–0.043	59
Dallas, TX—Forth Worth, TX	33100/33000	0.084	77	0.170	82	–0.086	34
Houston, TX	32000	0.081	76	0.171	83	–0.090	32
Poughkeepsie, NY	19300	0.075	75	–0.001	10	0.076	87
Pittsburgh, PA	16300	0.073	74	0.109	54	–0.036	62
Baltimore, MD	11302	0.070	73	0.155	80	–0.085	35
Reading, PA	19100	0.065	72	0.119	62	–0.054	54
Gary, IN	14900	0.061	71	–0.006	7	0.066	85
Honolulu, HI	34701	0.057	70	0.037	21	0.020	78
Phoenix, AZ	35001	0.056	69	0.013	14	0.043	82
Las Vegas, NV	37901	0.054	68	0.115	60	–0.061	51
Omaha, NE	28202	0.053	67	0.126	67	–0.072	43
Allentown, PA	19000	0.051	66	0.123	66	–0.072	44
Cleveland, OH	15200	0.050	65	0.199	86	–0.150	5
Fayetteville, NC	1400	0.043	64	0.134	74	–0.091	31
Austin, TX	31201	0.043	63	0.102	50	–0.059	52
Orlando, FL	7400	0.042	62	0.109	53	–0.067	46
Bridgeport, CT	20901	0.042	61	0.066	29	–0.024	66
Denver, CO	28900	0.038	60	0.029	16	0.009	76
St. Louis, MO	24701	0.038	59	0.093	45	–0.055	53
Kansas City, MO	29502	0.038	58	0.122	64	–0.084	36
San Jose, CA	37500	0.037	57	0.101	49	–0.064	50
Providence, RI	20401	0.036	56	–0.016	4	0.052	84
Columbia, SC	8100	0.036	55	0.111	57	–0.075	41
Dayton, OH	12501	0.035	54	0.101	48	–0.065	47
West Palm Beach, FL	7100	0.035	53	0.131	71	–0.096	24
Seattle, WA	39400	0.035	52	0.002	12	0.033	80
Portland, OR	38801	0.031	51	–0.042	2	0.073	86
Tampa, FL	6700	0.031	50	0.049	26	–0.018	67
Miami, FL	7000	0.030	49	0.123	65	–0.092	28
Raleigh, NC	1701	0.029	48	0.111	56	–0.081	39
Charlotte, NC–Gastonia, NC	900/800	0.029	47	0.127	69	–0.098	23
Indianapolis, IN	14200	0.029	46	0.092	44	–0.064	49
San Diego, CA	38000	0.027	45	0.119	63	–0.092	30
Richmond, VA	2400	0.025	44	0.069	30	–0.044	58
San Antonio, TX	31301	0.025	43	0.074	35	–0.049	55
Detroit, MI	11600	0.025	42	0.126	68	–0.102	20
Memphis, TN	5202	0.021	41	0.135	75	–0.113	16

Milwaukee, WI	24100	0.017	40	0.147	77	–0.130	8
Birmingham, AL	10700	0.017	39	0.030	18	–0.014	71
Nashville, TN	5600	0.015	38	0.052	27	–0.037	61
Tucson, AZ	35100	0.013	37	0.087	41	–0.074	42
Racine, WI	24000	0.013	36	0.044	23	–0.031	65
Wichita, KS	29301	0.013	35	0.030	17	–0.017	68
Jacksonville, FL	7600	0.007	34	0.083	40	–0.076	40
Rockford, IL	24400	0.007	33	0.114	59	–0.108	18
Columbus, OH	15900	0.006	32	0.089	42	–0.082	38
Des Moines, IA	27501	0.002	31	0.001	11	0.001	75
Albany, NY	18600	–0.001	30	0.012	13	–0.013	72
Virginia Beach, VA	2000	–0.001	29	0.117	61	–0.118	14
Salt Lake City, UT	36100	–0.002	28	0.091	43	–0.093	27
Atlantic City, NJ	19500	–0.005	27	–0.057	1	0.052	83
Harrisburg, PA	19200	–0.007	26	–0.017	3	0.010	77
Oklahoma City, OK	33803	–0.008	25	0.099	47	–0.107	19
Toledo, OH	13501	–0.008	24	0.113	58	–0.121	11
Knoxville, TN	302	–0.009	23	0.160	81	–0.169	1
Greenville, SC	8300	–0.009	22	0.110	55	–0.119	13
Minneapolis, MN	21501	–0.013	21	0.035	19	–0.047	56
El Paso, TX	30601	–0.017	20	0.071	31	–0.088	33
Cincinnati, OH	12701	–0.018	19	0.047	24	–0.065	48
Louisville, KY	13101	–0.019	18	–0.005	8	–0.014	70
Springfield, MA	20800	–0.019	17	0.077	37	–0.096	25
Albuquerque, NM	34901	–0.021	16	–0.009	6	–0.012	73
Fresno, CA	37200	–0.025	15	0.074	34	–0.099	21
Canton, OH	15000	–0.026	14	0.107	52	–0.133	7
Madison, WI	23100	–0.028	13	0.095	46	–0.124	10
Tulsa, OK	30402	–0.030	12	0.138	76	–0.168	2
Greensboro, NC	500	–0.033	11	0.105	51	–0.137	6
Buffalo, NY	18000	–0.035	10	0.081	38	–0.116	15
Youngstown, OH	16400	–0.044	9	0.054	28	–0.098	22
Peoria, IL	23900	–0.044	8	–0.003	9	–0.041	60
Manchester, NH	20600	–0.050	7	0.043	22	–0.092	29
Erie, PA	16500	–0.050	6	0.077	36	–0.127	9
Baton Rouge, LA	3500	–0.063	5	0.048	25	–0.110	17
Grand Rapids, MI	12200	–0.063	4	–0.016	5	–0.047	57
South Bend, IN	13600	–0.067	3	0.027	15	–0.094	26
Syracuse, NY	17700	–0.084	2	0.036	20	–0.120	12
Little Rock, AR	4200	–0.094	1	0.072	32	–0.166	3

Table A7: Correlations between CZ-Level Population and Share Black and RRD

	1980			2012–19			Panel		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(Pop)	0.0204***	0.0268***	0.0369**	0.0355***	0.0379***	0.0473***	0.0435+	0.0436*	0.0281
	(0.0055)	(0.0064)	(0.0124)	(0.0025)	(0.0022)	(0.0037)	(0.0237)	(0.0220)	(0.0273)
% Black		0.2989***	0.2203**		0.1254***	0.1165**		0.2436+	0.3046
		(0.0519)	(0.0715)		(0.0274)	(0.0376)		(0.1343)	(0.2170)
Cities	All	All	>200k	All	All	>200k	All	All	>200k
CZ & Year FEs	-	-	-	-	-	-	Y	Y	Y
N	338	338	87	338	338	87	1690	1690	435
R^2	0.196	0.331	0.390	0.587	0.626	0.686	0.861	0.864	0.885

Data: Estimated RRDs and CZ-level characteristics for CZs with at least 1,000 total employed persons and greater than 50 unique Black commuter Census respondents. Columns 1–3 only consider 1980, Columns 4–6 only consider 2012–19, and Columns 7–9 use all years. Columns 3, 6, and 9 only consider CZs with at least 200,000 total commuters in all five year bins. Each column is for a different specification. The dependent variable in each specification is the estimated RRD for each CZ-by-year-bin cell. Columns 7–9 include two-way fixed effects by CZ and year bin. Models are weighted by the Black commuting population in the CZ-by-year-bin cell. Standard errors in Columns 1–6 are robust to heteroskedasticity, and in Columns 7–9 are clustered by commuting zone. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table A8: Two-Way Fixed Effects Estimates of CZ-Level Correlates of the RRD, CZs Greater than 200k Employed Population in All Years

	Φ_{ct}^{Black}/ Φ_{ct}^{White} (1)	Dissim-ilarity (2)	Centr-ality (3)	Ln Hwy Miles (4)	Transit Mode Share (5)	Ave. Car Time (6)	Ln House Value (7)	$\rho_{ct}(P,\tau)$ (8)
Panel A. No Controls								
Measure	-0.0597**	0.0176	-0.0290	-0.0523**	0.3393*	0.0069**	0.0621***	-0.0478*
	(0.0211)	(0.0691)	(0.0464)	(0.0189)	(0.1615)	(0.0025)	(0.0139)	(0.0216)
Panel B. Controlling for Log Population								
Measure	-0.0601**	0.0558	-0.0028	-0.0491**	0.3407*	0.0053*	0.0575**	-0.0401*
	(0.0184)	(0.0647)	(0.0422)	(0.0180)	(0.1601)	(0.0024)	(0.0175)	(0.0195)
Mean of Measure (earliest)	1.1820	0.6882	-0.0389	5.26	0.0806	22.6	11.9	-0.0798
Mean of Measure (most recent)	1.1176	0.5866	-0.0341	5.37	0.0647	26.3	12.4	-0.0878
Sample Years	’90-’19	’80-’19	’80-’19	’80-’00	’80-’19	’80-’19	’80-’19	’80-’19
N	1352	1670	1671	773	1690	1690	1690	1670

Data: Estimated RRDs and CZ-level characteristics for CZs with at least 1,000 total employed persons and greater than 50 unique Black commuter Census respondents. Each column in each panel is for a different specification. The dependent variable in each specification is the estimated RRD for each CZ-by-year-bin cell. The column title indicates the which CZ-level characteristics (“Measure”) is being used as the independent (right-hand-side) variable. All models include two-way fixed effects by CZ and year bin. Panel B further includes log commuting population as a control. Models are weighted by the Black commuting population in the CZ-by-year-bin cell. Standard errors clustered by commuting zone. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table A9: Two-Way-Fixed-Effect and IV Estimates of Housing Price Effect on RRD

	All Cities					Cities with >200k				
	OLS (1)	OLS (2)	IV (3)	IV (4)	Sort. (5)	OLS (6)	OLS (7)	IV (8)	IV (9)	Sort. (10)
A. Estimates										
P_{cdt}	0.0621***	0.0611***	0.0497+	0.0500*		0.0592***	0.0591***	0.0475	0.0518+	
	(0.0139)	(0.0156)	(0.0256)	(0.0240)		(0.0150)	(0.0148)	(0.0308)	(0.0266)	
Ln(Pop)		0.0292		0.0318			0.0199		0.0209	
		(0.0189)		(0.0195)			(0.0204)		(0.0205)	
% Black		0.2908*		0.2822*			0.3360		0.3321	
		(0.1333)		(0.1386)			(0.2075)		(0.2138)	
$\rho_{ct}(P, \tau)$					-0.0478*					-0.0774
					(0.0216)					(0.0534)
B. First Stage										
$\hat{\delta}_c \bar{P}_{(-c)dt}$			0.6298***	0.6150***				0.6118***	0.6111***	
			(0.1104)	(0.1233)				(0.1174)	(0.1223)	
F-stat, CD			1307.2	1271.7				350.1	351.0	
F-stat, KP			32.5	24.9				27.1	25.0	
N	1690	1690	1690	1690	1670	435	435	435	435	435

Data: Estimated RRDs and CZ-level characteristics for CZs with at least 1,000 total employed persons and greater than 50 unique Black commuter Census respondents in all five year bins. Each column is for a different specification, Panel B presents the first-stage results corresponding to Panel A. The dependent variable in each specification is the estimated RRD for each CZ-by-year-bin cell. All models include two-way fixed effects by CZ and year bin. Columns 1–5 use all CZs that are not too noisy; Columns 6–10 use only CZs with at least 200,000 commuters in all five year bins. Columns 1, 2, 6, and 7 provide OLS estimates of the correlation between CZ-level housing prices and RRD, whereas Columns 3, 4, 8, and 9 use the local sensitivity instrument, $\hat{\delta}_c \bar{P}_{(-c)dt}$. Columns 5 and 10 show the effect of CZ-by-year-bin specific correlation between tract-level average housing prices and commute times on RRD. CD and KP refer to Cragg-Donald and Kleibergen-Paap tests, respectively. Models are weighted by the Black commuting population in the CZ-by-year-bin cell. Standard errors clustered by commuting zone. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.