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 50.3 more minutes commuting per week in 1980 than White commuters; this difference declined to 22.4 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, persistent differences in commute times today arise in large, segregated, congested, and—especially—expensive cities, revealing the limits of cars in overcoming entrenched racialization of other factors of commuting.

*Dr. Martin Luther King, Jr., in a 1955 speech given during the Montgomery bus boycott, said Black commuters "have been inflicted with the paralysis of crippling fears on buses" and that "[this] problem has existed over endless years." We thank Nassir Holden and Nathan Schor for excellent research assistance, and Anil Kumar, Jeffrey Lin, and comments received at the 2021 Meetings of the Urban Economics Association for scholarly advice.

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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 was arrested, but her arrest ignited the local Black community, brought local leaders together to form the Montgomery Improvement Association (MIA), and motivated them to lead a boycott of the buses until a more just solution was achieved.[1] The year-long boycott involved many Black bus commuters: in the 1960 Census, only 36% of commuters in the most segregated Black census tracts of central Montgomery commuted by car.[2] In addition to coordinating carpooling services for the many Black bus commuters, the MIA organizers faced a myriad of other challenges. 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).

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. These three factors have changed significantly since the 1960s. Residential segregation, as measured by the Black-White dissimilarity index, has declined somewhat 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; Black workers have greater opportunities in a wider array of occupations and industries (see, e.g., Bahn and Cumming 2020). Lastly, 85% of Black workers now commute by car, a far cry from the transit and walking dependence of Black commuters in 1950s Montgomery. With more Black workers having access to homes in a wider array of neighborhoods, jobs in a wider variety of occupations and industries, and cars, are commuting outcomes in American cities today equitable by race?

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, with the Los Angeles Bus Riders Union filing suit over heavy investment in White suburbs relative to the communities of color in Los Angeles proper and adjacent neighborhoods (*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).

The short answer is no. While the *racialized difference* in commute times has declined from 50.3 minutes per week in 1980, Black commuters today still spend 22.4 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, on neighborhoods, and on cities that collectively obligate Black commuters into spending more time commuting between home and work.

We develop a decomposition framework to quantify the racialized difference in commute times and determine what portion of its evolution worked through channels observable in our data.[4] Two factors explain more than half of the 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 the racialized difference either. Income is positively correlated with commute time, and 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 24% to changes in travel mode and 13% to changes in industry, occupation, and income. Much of the aggregate convergence from travel mode is attributable to an increase in car usage among Black commuters. In 1980, 88% of White commuters and 76% of Black commuters used an automobile. These shares increased to 92% of White commuters and 85% of Black commuters by 2019. Intriguingly, demographics and commuting zone (CZ) of residence play almost no role in the decline. The remainder of the overall decline (63%) flows through other channels besides observable commuter-level characteristics.

To go further, we compare patterns of persistence in the racialized difference across cities by investigating segregation and related spatial factors (like job-residence mismatch

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; Neumark 2018).

and low travel speed) that heighten its effect on commute times (Kain 1968). The extent and commuting implications of segregation vary across CZs. High segregation in cities like Chicago might create long commutes for Black workers who live far from major job centers. Even car ownership may not ensure an easy commute for Black residents of segregated neighborhoods. By contrast, Birmingham, AL, is nearly as segregated, but its small extent (and many freeways) may offer drivers easy access even to jobs across town. We describe this confluence of factors as *spatial stratification*: the organization of a city whereby segregated Black neighborhoods feature higher travel costs to jobs than do segregated White neighborhoods.

We estimate 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. The remaining portion is strongly correlated with city population, suggesting that a large population is now necessary (but insufficient) for a city to generate a racialized difference in commute times. We investigate city-level ingredients for spatial stratification that may contribute to these patterns. We find that segregation and differential access to employment centers both play a role in the persistently high RRD in large cities today. Similarly, infrastructural ingredients of spatial stratification—less freeway construction and expanding transit, indicators of slower travel speeds—are associated with a larger RRD. Lastly, high housing price growth is a significant driver of persistent positive RRD, a result consistent with spatial stratification. Indeed, had housing prices remained at their 1980 levels, the racialized difference would today be 40% smaller.

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 heterogeneous experiences 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 large cities with the ingredients of spatially stratified job access, and among transit commuters everywhere. The evolution of the racialized difference in commuting reflects both meaningful gains for many Black workers and durable barriers to continued 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. This updates prior work that focused on the 1970s and 1980s in a subset of cities (Gabriel and Rosenthal 1996; Petitte and Ross 1999; Taylor and Ong 1995). Johnston-Anumonwo (1997), McLafferty (1997), and Johnston-Anumonwo (2001) also study specific cities using 1980 and 1990 commuting data. An often integrated literature shows that mode influences differences in labor market outcomes between Black and White workers. Poor labor market outcomes for Black workers are associated with lack of automobile access (Ong 2002; Raphael and Stoll 2001; Ong and Miller 2005; Gobillon, Selod, and Zenou 2007; Gautier and Zenou 2010), and automobile use plays an outsized role in the reduction of commute times for Black commuters (Johnston-Anumonwo 1997; 2001; Taylor and Ong 1995).[5] A related and growing literature also examines gendered differences in commuting (see, e.g., Black, Kolesnikova, and Taylor 2014; Gutierrez 2018; Liu and Su 2020; Hu 2021).

We extend decomposition methods used in the literature on gender and race wage differences to study individual and city-level explanations of the difference in commuting times (Altonji and Blank 1999; Blau and Kahn 2017; DiNardo, Fortin, and Lemieux 1995; Chamberlain 2016). Like this 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 (Blau and Kahn 2017). Importantly, discrimination may influence observable individual characteristics as well (education, travel mode, residential location, occupation, etc.).

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). Lee and Lin (2018) explore how the persistence of neighborhood-level income sorting relates to natural amenities. 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 neighbor-

5. 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 5 miles over the speed limit (King 2010).

hoods. In large cities with large Black populations and high-income Black neighborhoods, this result does not hold. They find that race alone—through possible channels of psychological costs and benefits, White flight, and racial discrimination—and not financial constraints (wealth, housing prices) is driving income and racial neighborhood sorting.

Lastly, 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 (Wiese 2005; Card, Mas, and Rothstein 2008; Blair 2017) 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). 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.

The rest of the paper proceeds as follows. Section 2 describes our data. Section 3 showcases the main descriptive statistics that motivate our empirical analyses. Section 4 discusses the methodology used to construct the decomposition, and develops several explanatory variables used to investigate the residual racialized difference by city. Section 5 presents the main regressions and decomposition results. Section 6 investigates spatial stratification using the residual racialized difference by CZ.

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, i.e., those in the labor force actively working outside the home. For a limited set of descriptive variables on mode share, we also draw from 1960 and 1970 Census microdata.

We use slightly modified 1990 commuting zones as our base geography, following 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.[6] 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 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 Census/ACS data; we introduce these as needed below and provide details in the Appendix.

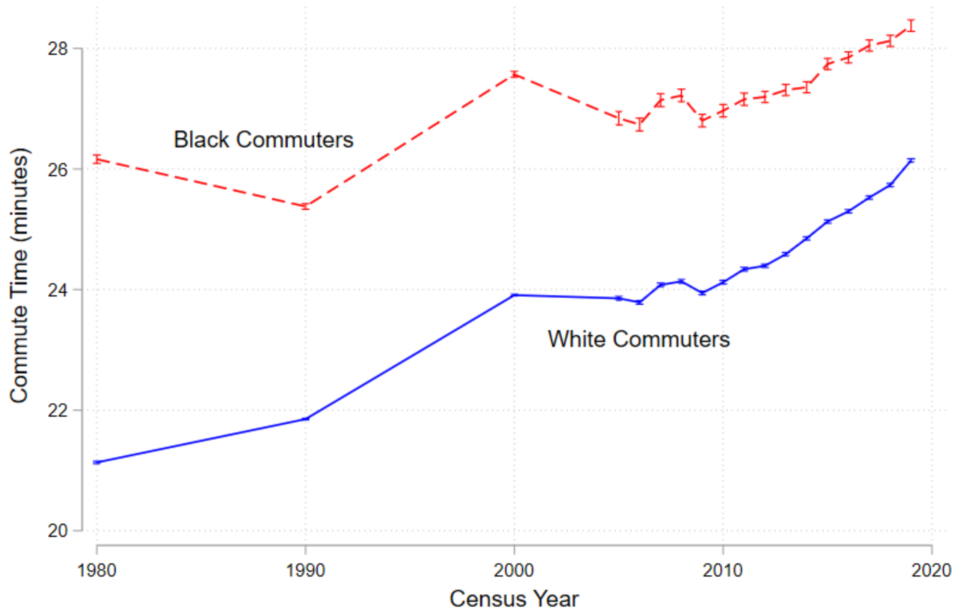
We rely on the definitions of race used in the data. These have evolved over time, though our results are not overly sensitive to these details. For our primary analyses, we denote as "Black" those observations that are recorded as "Black alone or in combination." However, prior to 2000, the Census did 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.[7]

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).

6. 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.

7. 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.

Figure 1: Average (Unconditional) Commute Times by Race



3 Descriptive Statistics

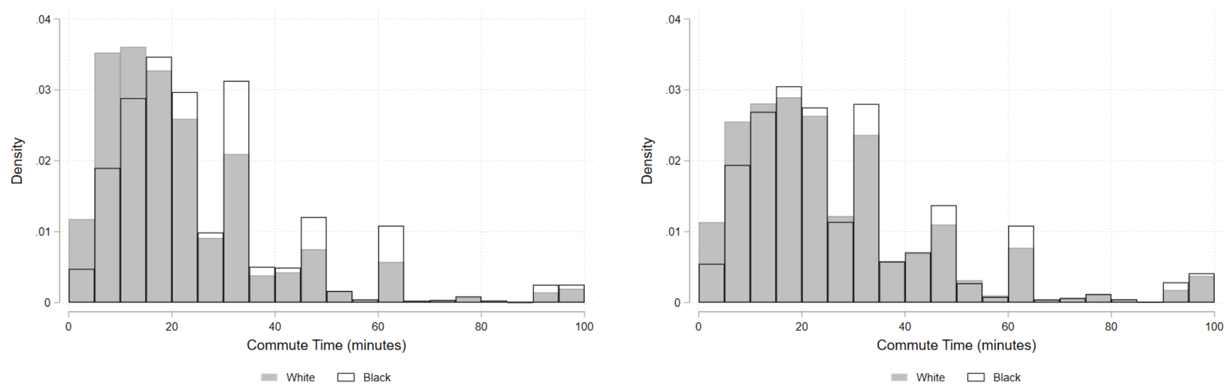
Figure 1 graphs the unconditional average one-way commute times in each sample year since the Census began asking questions about travel time. In 1980, the average commute among Black workers was just over 26 minutes, while the average commute among White workers was just over 21 minutes. There was some convergence over the next decade, as average commutes rose to 22 minutes among White workers while commutes fell to about 25.5 minutes among Black workers. After 1990, average commutes trended upward together. By 2019, the average commute among White workers was almost 26 minutes while the average commute among Black workers was just over 28 minutes.

We also show the full distribution of commute times for White and Black commuters in 1980 and 2012–19 in Figure 2, broken into 5-minute wide bins. In 1980, there were substantially more Black commuters in the 30, 45, and 60 minute commute time bins than White commuters, and substantially fewer between 0 and 15 minutes. This pattern of difference is still visible in the 2012–19 histogram, though the distributions are somewhat closer together. Also of note, there are substantially more Black than White commuters with commutes of 90 minutes or longer in both time periods.

Mode is a key determinant of travel time. To provide context, we establish a few

Figure 2: Distribution of Commute Times by Race in 1980 and 2012–19

(a) 1980 (b) 2012–19

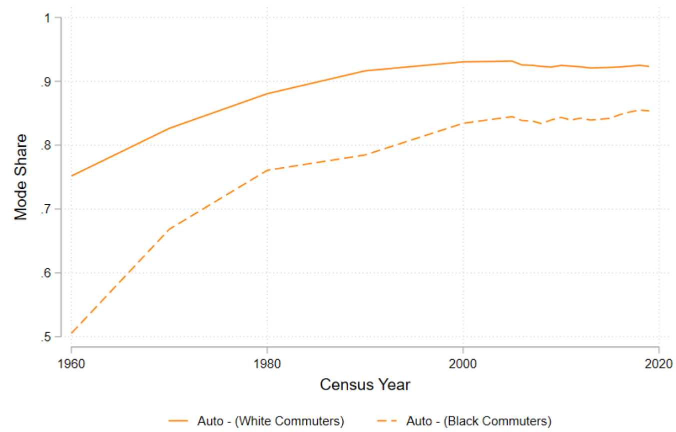


facts about commutes on different modes. Figure 3 reports the share of commuters that use each mode in each sample year. For this variable, we can extend our window of study to 1960. The solid lines denote the share for White commuters and dashed lines the corresponding share for Black commuters. Figure 3a shows the rise of automobile commuting. About 76% of White commuters used private vehicles in 1960, rising to 88% in 1980 and 92% in 2019. 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. 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.

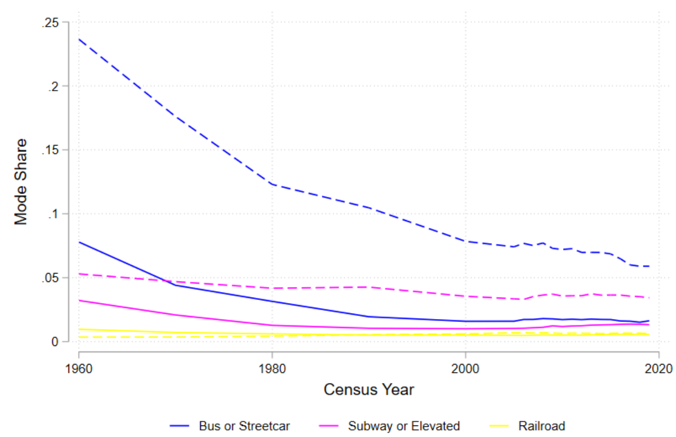
The increase in automobile share came at the expense of transit share, in particular for buses and streetcars. Figure 3b shows the decline in the share of commuters using buses and streetcars, falling from about 8% of White commuters in 1960 to 3.5% in 1980 and just 2% in 2019. For Black commuters, there was an even greater decline, from 24% in 1960 down to just over 12% in 1980 and about 6% in 2019. 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.

Figure 3: Commute Share by Mode

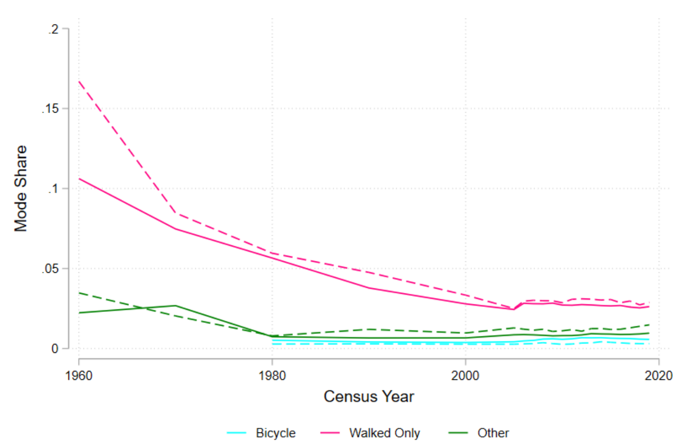
(a) Unconditional Auto Share



(b) Unconditional Transit Share



(c) Unconditional Nontransit Share



There was also a large decline in the share of commuters that walk to work, as shown in Figure 3c. In 1960, nearly 17% of Black commuters and 11% of White commuters walked to work. By 1980, 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).

Differences in commute times for Black and White commuters persist when examining specific modes and are not decreasing uniformly. Figure 4 reports the evolution of average commute times by mode from 1980 to 2019, with 2005–2011 and 2012–2019 binned together. Solid blue lines denote average travel time for White commuters and dashed red lines show the corresponding time for Black commuters. All three transit modes have longer average commutes than driving, while bicycling and walking show shorter average commutes (other is a bit longer on average than driving). Travel times are generally trending upward for most modes, with the possible exception of subway.

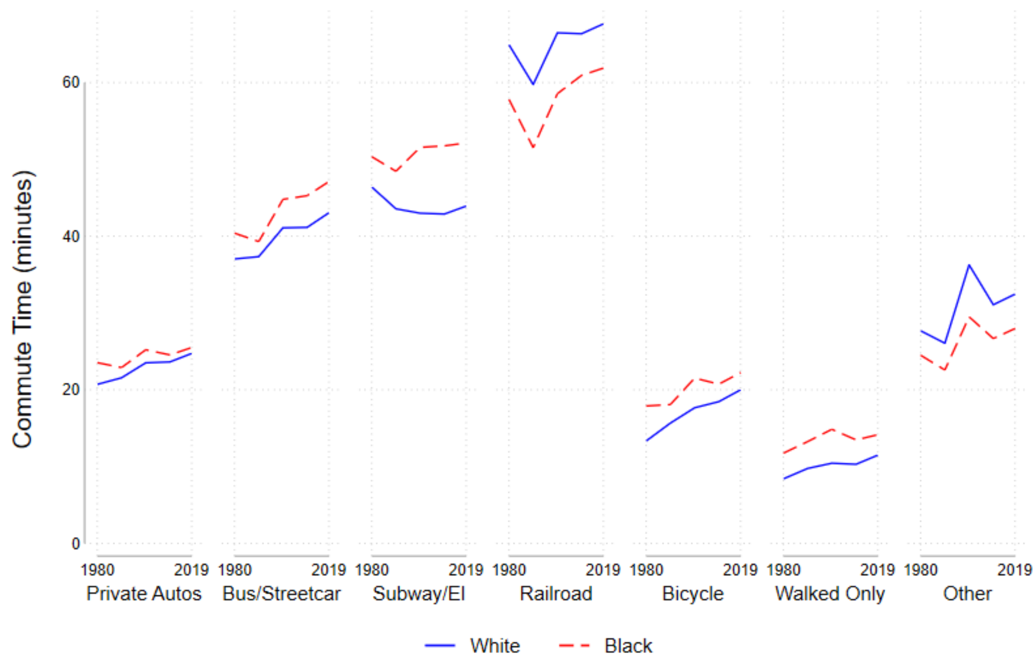
For most modes, Black commuters face longer travel times than White commuters (the only exceptions are railroad and other, which together contain about 3% of the employed population). Times for private automobiles evolved similarly to overall times, showing some degree of convergence between 1980 and 2019. For transit modes, however, differences in average commute times have been static or increasing. This 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.

4 Methodology

Our baseline measure of the racialized difference in commute times between Black and White workers is a simple regression of log commute time in minutes on race. For commuter i in commuting zone c in year bin t, we specify:

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

Figure 4: Unconditional Commute Times by Travel Mode



where τ is the log 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 by commuting zone throughout the paper. The β coefficient corresponds to the overall racialized difference, $\Delta_t = \beta_t$.

We extend the baseline model to account for selection into different commuting zones, variation across time, and a variety of individual characteristics. The purpose of this exercise is to observe how the coefficient on $\mathbb{1}[\text{Black}]$ changes when these various controls are included in the following specification:

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

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 group variables into four sets based on the information they contain:

- *Demographics and Education*: sex; indicators for education (less than high school, high school, college graduate, and masters or higher); a quadratic in age; marital status; head of household; and indicators for numbers of children (zero, one or two, and three or more).

- *Transportation Mode*: indicators for each mode, including 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*: an indicator for zero income; log income (set to 0 if zero income); indicators for industry and for occupation (1990 IPUMS basis).
- *Commuting Zone*: fixed effects for each commuting zone of residence.

When specifications report year-bin-specific estimates of β^*, controls are also interacted with year bins 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, it is important to note that there are two significant caveats in their interpretation. The first challenge is conceptual: which estimate (β, β^*, or one in between) should we take as being the "truest" measure of the racialized difference? The values of these covariates may themselves be determined in part by other manifestations of structural racism, in which case these covariates may lead to collider bias in the estimation of the racialized difference. Alternatively, we interpret the response of the estimates to these covariates as a way to understand the varied channels through which the racialized difference manifests.

The measure may also reflect selection into the workforce and into employment, as we do not observe commute times for those who do not commute for work. There is conflicting evidence about how adjusting for labor force participation might impact β and β^*. 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. On the other hand, 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. We acknowledge this may be an important margin for adjustment, and control for a wide variety of individual and city characteristics to limit such concerns. The likely consequence is that our results underestimate the true difference. That is, accounting for the entry would likely produce larger estimates of the racialized difference.

4.1 Decomposition

We now describe how to interpret the coefficients β_t and β_t^* in a decomposition framework (Kitagawa 1955). Consider a model with heterogeneous coefficients by race:

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

where B indexes the sample and coefficients if $\mathbb{1}[\text{Black}_{ict}] = 1$, and W indexes the sample and coefficients if $1[\text{Black}_{ict}] = 0$. The overall racialized difference can be decomposed as follows, per Fortin, Lemieux, and Firpo 2011:

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

where $\bar{x}^k$ is the group-k average of x and p_c^k is the share of the overall population of k that lives in c; the time-varying coefficient notation is suppressed for brevity. $\Delta^{\text{Explained}}$ is the portion of the racialized difference that operates through channels associated with observed characteristics, and $\Delta^{\text{Unexplained}}$ is the portion that operates through unobserved channels.

Fortin (2008) describes a "regression-compatible" variant of this decomposition framework that we adopt to simplify estimation and exposition. It assumes that the coefficients estimated from a single-regression model like Equation (2) provide a valid counterfactual for conditional commuting times. Equivalently, this requires that μ capture the relevant conditional effect regardless of race (i.e., $\mu^B = \mu^W = \mu$). 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 the racialized difference unexplained by observables. The decomposition identifies the role of each channel in determining $\Delta_t^{\text{Explained}}$:

$$\Delta_t^{\text{Explained}} = \Delta_t^{\text{Demographics \& Education}} + \Delta_t^{\text{Transit Mode}} + \Delta_t^{\text{Work \& Income}} + \Delta_t^{\text{Commuting Zone}}$$

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

4.2 City-Level Heterogeneity

We use a two-step approach to explore CZ-level factors associated with heterogeneity in the racialized difference in commute times. The first step is to estimate CZ-by-year-bin-specific models to produce a panel of CZ-specific racialized difference. As these are conditional 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 in that we estimate a separate β^* 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.[8] In some specifications, we include CZ and year-bin fixed effects in the second stage to further limit the role of unobserved factors.

Our selection of CZ-level measures to include in the second stage is motivated by the desire to describe how city-level characteristics contribute to the spatial stratification of people into longer commutes. Our hypothesis is that more sorting (larger racialized difference) is more likely to occur in cities that have longer commutes in general but still retain some variation in commute length so observable sorting can take place. Thus, some measures listed in Section 6 attempt to describe the general commuting environment while others are mechanisms that may contribute to longer commutes in general. These variables consider spatial and aspatial aspects of city-level population, employment, and urban form. While many of these variables may be endogenous with respect to the RRD, our intent is generally to document and describe.

5 Racialized Difference in Commuting

We now estimate the racialized difference in commute times, describe its relation to observable characteristics, and explore its evolution over the last forty years. We refer to observable features like commute mode, residential location, and demographic and job

8. This two-step approach is equivalent to adding CZ-level controls to Equation 2, and so the portion of $\Delta_{\{t\}}$ explained by this second step is conceptually a subset of $\Delta^{\text{Unexplained}}_{\{t\}}$. See Appendix A1 for discussion.

characteristics as *channels*. They are not 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)—but schooling itself remains heavily segregated (Erickson 2016; Logan and Burdick-Will 2016). No factor is necessarily upstream of racialization.

5.1 The Role of Observable Individual Characteristics

Table 1 reports estimates of β_t and β_t^* that correspond to Equations (1) and (2), respectively. Column 1 includes only year-bin dummies and provides baseline measures of the racialized difference in commute times, Δ_t. The 1980 difference of 26.3 log points implies a 30.1% longer unconditional average commute for Black commuters than White commuters. The difference declines consistently over the observed time period, falling to 12.4 log points (13.2%) in 2012–19. The majority of this partial convergence occurs before 1990.

Column 2 introduces CZ-by-year-bin fixed effects to assess the role of the differential distribution of the Black and White commuting population across commuting zones with longer (e.g., New York) and shorter (e.g., Salt Lake City) average commutes. In this specification, the estimate of β_t^* compares only people living in the same commuting zone at the same time. Accounting for this first-order channel reduces the estimates to 18.0 log points (19.7%) in 1980 and 4.6 log points in 2012–19 (4.7%). Again, the majority of the partial convergence occurs between 1980 and 1990.

The next columns introduce individual, commute, and job-related characteristics. These columns estimate β_t^* in Equation (2), and the estimated coefficients capture the unexplained racialized difference arising through channels *other than* those that are observed. Column 3 adds in demographic and education characteristics, Column 4 instead adds transportation mode, and Column 5 adds in both demographic and education characteristics and transportation mode. Column 6 further adds work and income characteristics. Accounting for travel mode substantially reduces the estimate of β_t^*, suggesting that mode is a central factor in the production of the racialized difference in commuting. All other controls have relatively little effect, or even increase the estimate of β_t^*.

Figure 5 graphically depicts estimates of β_t and β_t^* before (black line) and after (red,

Table 1: Estimates of the Racialized Difference in Commute Time

	$\ln(\tau_{ict})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$1[\text{Black}] \times t_{1980}$	0.263***	0.180***	0.198***	0.129***	0.139***	0.136***
	(0.022)	(0.015)	(0.016)	(0.008)	(0.008)	(0.010)
$1[\text{Black}] \times t_{1990}$	0.191***	0.106***	0.126***	0.062***	0.076***	0.079***
	(0.029)	(0.020)	(0.022)	(0.009)	(0.010)	(0.011)
$1[\text{Black}] \times t_{2000}$	0.178***	0.091***	0.110***	0.056***	0.071***	0.078***
	(0.027)	(0.019)	(0.020)	(0.010)	(0.011)	(0.011)
$1[\text{Black}] \times t_{2005-11}$	0.150***	0.069***	0.090***	0.034***	0.051***	0.061***
	(0.027)	(0.018)	(0.019)	(0.010)	(0.010)	(0.010)
$1[\text{Black}] \times t_{2012-19}$	0.124***	0.046***	0.070***	0.018*	0.037***	0.049***
	(0.025)	(0.017)	(0.017)	(0.009)	(0.009)	(0.009)
Year Bin×CZ FEs	-	Y	Y	Y	Y	Y
Controls						
Demog. & Edu.	-	-	Y	-	Y	Y
Trans. Mode	-	-	-	Y	Y	Y
Work & Income	-	-	-	-	-	Y

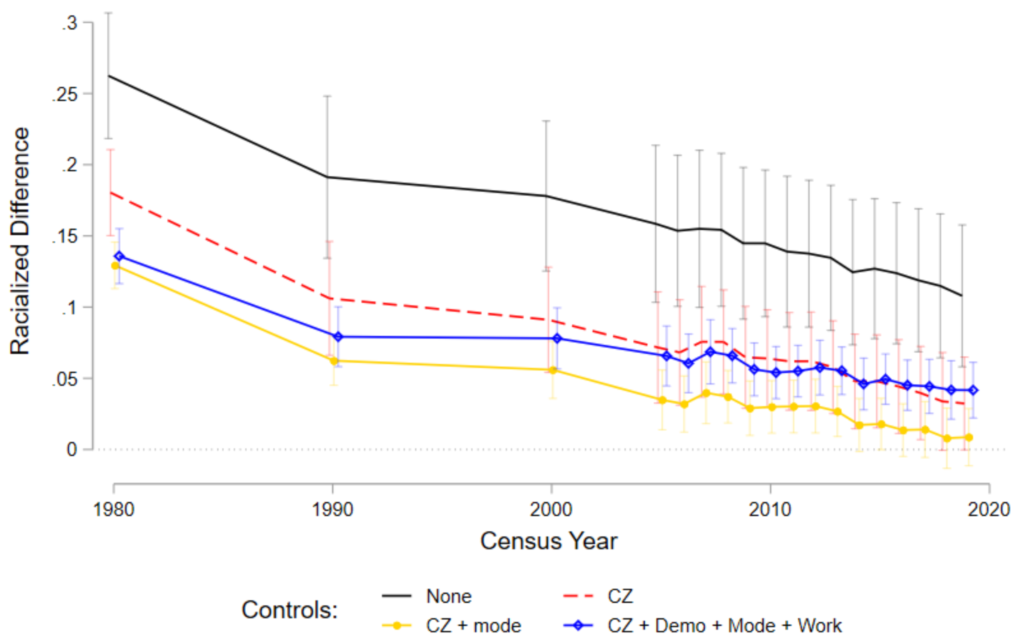
Data: All commuters in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone. Each column is for a different specification; in each, the number of observations is 48,767,398. The dependent variable is log travel time top-coded at 99 minutes. Demographics include sex, educational attainment, age, marital and household status, and number of children in household. Work and income controls are log income, and 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.

blue, and yellow lines) conditioning on the same observable characteristics.[9] Figure 5 highlights that the relative ordering of the specifications shown in Table 1 is relatively stable over time, with a notable exception: conditioning on demographic and job characteristics does not alter the estimate of β_t^* much in 1980, whereas the same exercise increases β_t^* substantially in later years.

Next, we use the decomposition described in Section 4 to precisely discuss the relative contribution of the different channels. We first replicate Columns 1 and 6 of Table 1 as Columns 1 and 2 of Table 2, respectively. These correspond to Δ and $\Delta^{\text{Unexplained}}$. The

9. These results are similar but not identical to Table 1: each year beginning in 2005 is estimated with single-year coefficients instead of multi-year bins.

Figure 5: Estimates of the Racialized Difference in Commuting Time



remaining columns of Table 2 characterize the contribution of the various groups of characteristics to the explained portion of Δ. Because we follow the partial decomposition method proposed by Gelbach (2016) to avoid sequential bias, the estimates in Columns 2–6 of each row of Table 2 conveniently sum to the estimate in Column 1. Table 2 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.

Transportation mode plays an important role in accounting for the racialized difference in each year, and is the largest observed factor in its decline over time. It accounts for about 28% of the racialized difference in 1980 and about 33% in 2018, though in levels $\Delta_{\{t\}}^{\text{Tr. Mode}}$ falls by nearly half. Figure 3 indicates substantial but incomplete convergence in the modes used by Black and White commuters. Despite its central role among the observable characteristics, the partial convergence in mode explains only about one quarter (24%) of the overall decline in the racialized difference in commute time.

A disproportionate share of Black workers continue to live in commuting zones with relatively long commutes, and this factor explains a substantial share of the overall difference in commuting times. But there is essentially no convergence on this front: CZ of residence does not explain any of the decline in racialized difference in commuting since

Table 2: Decomposing the Racialized Difference in Commute Time Due to Observable Individual Characteristics

	Δ_t	$\Delta_t^{\text{Unexplained}}$	$\Delta_t^{\text{Explained}}$			
			$\Delta_t^{\text{Demog.}}$	$\Delta_t^{\text{Tr. Mode}}$	$\Delta_t^{\text{Work/Inc.}}$	Δ_t^{CZ}
	(1)	(2)	(3)	(4)	(5)	(6)
Decomposition						
$1[\text{Black}] \times t_{1980}$	0.263***	0.136***	-0.008***	0.073***	-0.001	0.062***
	(0.022)	(0.010)	(0.000)	(0.016)	(0.002)	(0.008)
		51.7%	-3.0%	27.8%	-0.2%	23.7%
$1[\text{Black}] \times t_{1990}$	0.191***	0.079***	-0.009***	0.063***	-0.007***	0.065***
	(0.029)	(0.011)	(0.000)	(0.018)	(0.002)	(0.009)
		41.4%	-5.0%	32.9%	-3.4%	34.0%
$1[\text{Black}] \times t_{2000}$	0.178***	0.078***	-0.008***	0.050***	-0.011***	0.069***
	(0.027)	(0.011)	(0.000)	(0.013)	(0.002)	(0.009)
		43.9%	-4.6%	28.1%	-6.3%	39.0%
$1[\text{Black}] \times t_{2005-11}$	0.150***	0.061***	-0.009***	0.049***	-0.014***	0.063***
	(0.027)	(0.010)	(0.000)	(0.014)	(0.002)	(0.009)
		40.5%	-6.1%	33.0%	-9.5%	42.1%
$1[\text{Black}] \times t_{2012-19}$	0.124***	0.049***	-0.008***	0.040***	-0.019***	0.063***
	(0.025)	(0.009)	(0.000)	(0.012)	(0.001)	(0.010)
		39.2%	-6.6%	32.5%	-15.4%	50.4%
Components of Change						
$\frac{\Delta^k_{1980}-\Delta^k_{2012-19}}{\Delta_{1980}-\Delta_{2012-19}}$	-	62.6%	0.0%	23.7%	12.9%	-0.7%

Data: All commuters 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 48,767,398. Column 1 is the unconditional racialized difference in commute time. Columns 2–6 report the contribution of a group of variables to the level and the share of Δ_t. The specification corresponds to Column 6 of Table 1. Demographics include sex, educational attainment, age, marital and household status, and number of children in household. Work and income controls are log income, and indicator for zero income, and indicators for industry and occupation. Standard errors clustered by commuting zone. Components of change are calculated as $(\Delta^k_{1980} - \Delta^k_{2012-19})/(\Delta_{1980} - \Delta_{2012-19})$ for each group of variables k. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

1980. As the unconditional racialized difference fell, the measured contribution of CZ of residence increased from 24% in 1980 to 50% in 2012–19.

Job-related factors (including income) do not matter very much in 1980 but are an increasingly important factor over time, accounting for -15% of the difference in unconditional commute times by 2012–19. As shown in Figure 5, the negative sign means that differences in income and work characteristics increase the estimate of β_t^* differences in commute time. 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 0.012 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 has supported the partial convergence in commute times: changes in work and income covariates explain about 13% of the decline in Δ since 1980. Lastly, other observable demographic characteristics like age and education account for very little of the difference in each year-bin, and none of the decline over time.

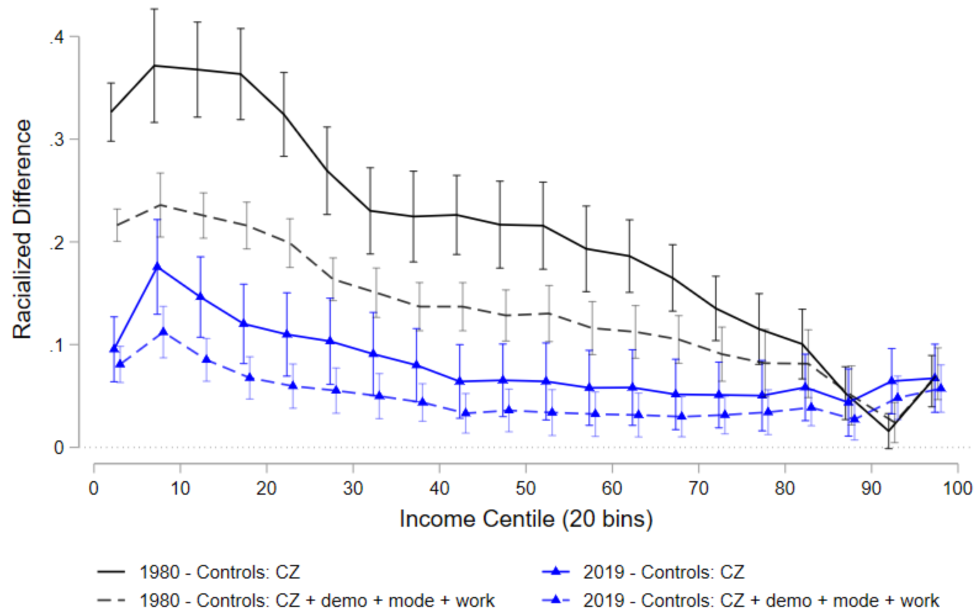
Unobserved factors account for 39%–52% of the racialized difference in each year, and changes to these factors account for the majority (nearly 63%) of its decline since 1980. While we later investigate the role of urban spatial processes like residential segregation in accounting for the decline of $\Delta_{\{t\}}^{\text{Unexplained}}$, we first examine aggregate patterns of heterogeneity in the racialized difference by income and mode. These ensure that our results are not clouded by assumptions of linearity or averaging across heterogeneous experiences, and are also of interest in their own right.

5.2 Heterogeneity in Racialized Difference by Income

While we included income as a control in the preceding results, the production of the racialized difference may vary across income levels. To study this heterogeneity, Figure 6 plots estimates of $\mathbb{1}[\text{Black}]$ interacted with twenty equally sized bins along the 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 just commuting zone fixed effects (like Column 2 of Table 1). Dotted lines also include individual, transportation mode, and job-related characteristics (like Column 6 of Table 1).

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 23 log points (26%) at the 10th income percentile in 1980. Workers in this income range likely face greater challenges in covering the expense 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 distribu-

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



tion. 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 in 2012–2019, although overall levels are lower. The difference is unconditionally about 17 log points (19%) 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.[10] 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 attractive amenities that

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

the rich value more than a short commute. In line with this latter possibility, we find a positive correlation between income and commute time in our data. In our estimates of Equation 2, the coefficient on income varies between 0.051–0.058.[11] 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*.

5.3 Differences by Mode

Mode is a central determinant of commute times. As shown in Table 2, mode explains 28%–33% of the unconditional racialized difference in commute times, 24% of its decline from 1980–2019, and as much 66% of the difference conditional on CZ. In this section, we estimate mode-specific models of the racialized difference in commute times 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.

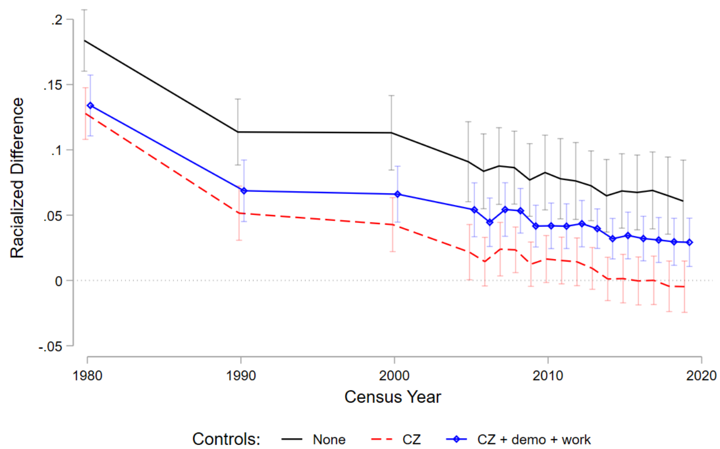
Figure 7a shows the racialized difference for commuters using private automobiles (inclusive of carpooling), motorcycles, or taxis. Given the high share of commuters that use automobiles, this figure is broadly similar to Figure 5. Controlling for just CZ and year bin, the difference declines from 13 log points in 1980 to zero by 2019. However, once demographics and job characteristics are included, a positive and significant difference is once 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 bus commuters, however, barely declines between 1980 and 2019. Figure 7b shows that the racialized difference in bus commute times falls somewhat between 1980 and 1990, but then increases substantially from 1990 to 2013 before decreasing again through 2019. In addition to differential patterns in residential and workplace location, this may reflect a decline in quality of bus service for Black commuters relative to White commuters (McKenzie 2013). Given the large declines in bus share among Black commuters (and smaller declines among White commuters) shown in Figure 3b, the difference may also indicate poorer service to increasingly marginalized commuters.

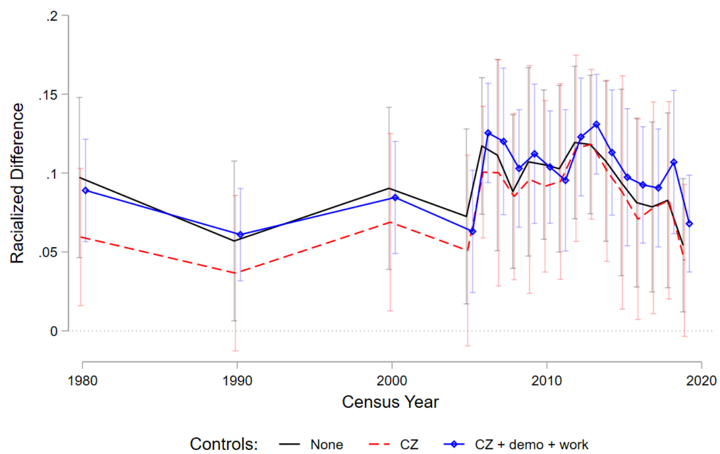
11. In specifications with CZ of residence but no other controls, the coefficient is even larger: 0.105–0.128.

Figure 7: Racialized Difference in Commute Time by Mode

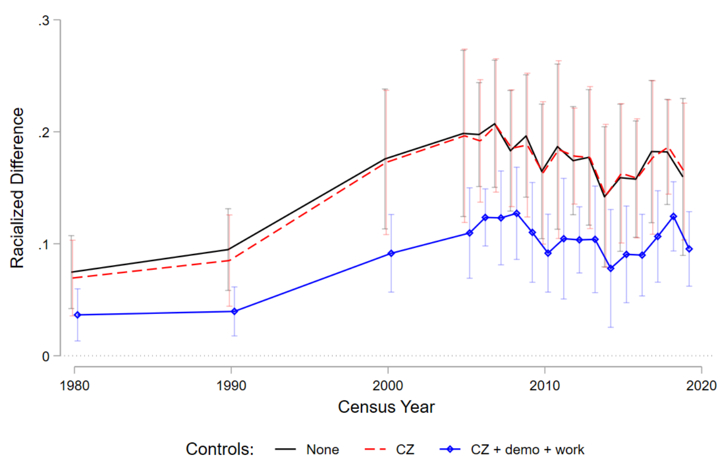
(a) Racialized Difference Conditional on Mode = Car



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



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



Among subway commuters, the racialized difference in commute times increases substantially during earlier decades. Figure 7c reveals a clear divergence in subway commute times through 2006, with less patterned movements since then. As very few cities have subways, the role of CZ of residence is greatly diminished in these regressions: all CZs with subways have long average commutes. Unlike for the other modes or the aggregate results, controlling for demographic and job characteristics actually decreases the difference in commute time for subway riders.

Conditioning on subway ridership restricts the sample to CZs with subway systems, and to residence/workplace pairs with subway stations. These CZs are largely expensive coastal cities, and the neighborhoods and workplaces served are largely central; about 44% of subway commuters today live in the five boroughs of New York City and commute to Manhattan.[12] Neighborhoods with subway access have a distinct racial and class geography that has been heavily shaped by gentrification. In New York, the Black communities of Bed-Stuy and Harlem have experienced gentrification, pushing many Black residents to more-distant neighborhoods. Gentrification may account for both distinctive features of subway commuters: first, the Black commuters displaced are those with lower incomes, while the White residents of the most central areas have high incomes and short commutes. Second, gentrification during our sample period may help account for the *growth* of the racialized difference among subway commuters. Conditioning on subway commuters brings these within-CZ spatial factors to the fore, and we explore them more directly in the next two sections.

5.4 Finer Controls for Residential Geography

We now turn to the role of within-CZ urban spatial processes. Census microdata limit the residential geographic resolution available. Nevertheless, we provide two additional exercises to determine whether residential location explains differences in commute times by race. First, we build on the above individual-level models but use somewhat finer geographic areas than CZs, and second, we use tract-level regressions to investigate even finer spatial variation (at the cost of individual-level data). These geographic controls capture part of the unexplained variation under some conditions, but data limitations prevent us from drawing strong conclusions about the role of urban spatial processes.

Starting in 2000, the Census provides PUMAs that are of a fine enough spatial scale

12. https://www1.nyc.gov/assets/planning/download/pdf/planning-level/housing-economy/nyc-ins-and-out-of-commuting.pdf

to approximate subregions of urban commuting zones. Incorporating PUMA fixed effects controls for meso-scale regional differences and sorting within larger CZs.[13] Because PUMA vintages prior to 2000 contain much less geographic resolution, we do not report results that include them. By construction, PUMAs contain at least 100,000 residents. The ability of PUMAs to differentiate sub-CZ spatial patterns thus depends on CZ size. In smaller CZs, PUMAs may be able to broadly distinguish central cities from surrounding areas, or distinguish between polycentric towns. By contrast, PUMAs in the largest CZs contain dozens of PUMAs that can capture relatively nuanced distinctions within cities, as well as across suburbs.

Table 3 reports aggregate and mode-specific measures of β_t^* from Equation 2. Panel A excludes the PUMA fixed effects, while Panel B includes them. All the specifications condition on observable demographic and job characteristics (and transportation mode in Column 1), and so are similar to Column 6 in Table 1. Column 1 of Table 3 shows a clear downward trend in β_t^* over time, both with and without PUMA fixed effects. The similarity between the estimates of β_t^* across the panels indicates that accounting for residential geography at the PUMA level does not explain the racialized difference in commute times over the period 2000–2019 among commuters as a whole. To the extent that PUMAs 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 are not a primary driver of the decline in β_t^*.

Columns 2–5 of Table 3 repeat this exercise but condition the sample by mode (as in Section 5.3). The results for car commuters in Column 2 are qualitatively and quantitatively similar to the overall results: the estimate of β_t^* trends down over time, and controlling for PUMA of residence does not make a notable difference.

Column 3 in Panel A again shows a slight increase in the racialized difference for bus commuters, as seen in Figure 7b; it is at 10.4 log points (10.9%) as of 2012–19. Controlling for PUMA of residence leads to a moderate decrease in the estimate of β_t^* in Panel B; it is at 7.1 log points (7.4%). This suggests that geography plays more of a role in determining differential commute times by race for bus commuters than for automobile commuters.

Subway (and elevated rail) commuters are in Column 4. Here we see a sizeable increase in the estimate of β_t^* over time, from 3.6 log points in 1980 to 10.2 log points in 2012–19 (in Panel A). Among subway commuters, Panel B reveals that residential geog-

13. 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.

Table 3: Racialized Difference in Commute Time by Mode and with Residential PUMA Controls

	All Modes (1)	Car (2)	Bus (3)	Subway (4)	Walk (5)
A. Year-Specific Estimates					
$1[\text{Black}] \times t_{1980}$	0.136***	0.134***	0.089***	0.036***	0.299***
	(0.010)	(0.012)	(0.016)	(0.011)	(0.015)
$1[\text{Black}] \times t_{1990}$	0.079***	0.069***	0.061***	0.040***	0.279***
	(0.011)	(0.012)	(0.015)	(0.011)	(0.018)
$1[\text{Black}] \times t_{2000}$	0.078***	0.066***	0.085***	0.091***	0.291***
	(0.011)	(0.011)	(0.018)	(0.018)	(0.022)
$1[\text{Black}] \times t_{2005-11}$	0.061***	0.047***	0.102***	0.114***	0.208***
	(0.010)	(0.009)	(0.016)	(0.019)	(0.023)
$1[\text{Black}] \times t_{2012-19}$	0.049***	0.035***	0.104***	0.102***	0.172***
	(0.009)	(0.008)	(0.016)	(0.019)	(0.018)
N	48,767,398	45,071,097	770,058	397,298	1,743,047
B. Year-Specific Estimates, with year-bin×PUMA FEs (2000 and later only)					
$1[\text{Black}] \times t_{2000}$	0.076***	0.069***	0.069***	0.022***	0.255***
	(0.006)	(0.006)	(0.012)	(0.007)	(0.016)
$1[\text{Black}] \times t_{2005-11}$	0.060***	0.053***	0.079***	0.036***	0.196***
	(0.005)	(0.006)	(0.007)	(0.010)	(0.013)
$1[\text{Black}] \times t_{2012-19}$	0.043***	0.034***	0.071***	0.033***	0.153***
	(0.004)	(0.004)	(0.008)	(0.009)	(0.012)
N	37,362,675	34,765,319	528,659	302,729	1,161,492

Data: All commuters in the Census (1980, 1990, 2000) and ACS (2005–2019) with race Black alone or in combination or White alone. Columns 2–5 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. Column 1 of both panels includes transit mode controls (Panel A Column 1 replicates Column 6 of Table 1). Panel B includes residential-PUMA-by-year-bin fixed effects and so only uses data from 2000 and later because pre-2000 PUMAs are too geographically coarse. Observations weighted by adjusted person sample weights. Standard errors clustered by commuting zone. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

raphy 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. For subway (and elevated) commuters, residential geography is central to the racialized difference in commute times. As described above, restricting our sample to subway commuters also restricts our sample to very large cities where PUMAs are small enough (relative to the city) to capture meaningful spatial variation.

Finally, Column 5 examines the subset of commuters who use the second most popular mode: walking. This mode shows a large estimate of β_t^* that declines somewhat over the last forty years, but remains sizeable relative to other modes. The difference of 29.9 log points (34.8%) in 1980 fell to a still large 17.2 log points (18.8%) by 2012–19. Controlling for PUMA of residence lowers the point estimate of β_t^* by a sizeable (1.2–3.6 log points) amount. Nevertheless, the racialized difference remains substantial: 15.3 log points (16.5%) in 2012–19.

As noted above, PUMAs are a more meaningful geographic control in large cities: Manhattan alone has more than 10 PUMAs, while small CZs may have a single PUMA for the entire center city and inner suburbs. The large role played by PUMAs among subway commuters might not be due to subways *per se*; instead it might follow from restricting the sample to large cities. To investigate this possibility, we also estimate the models shown in Table 3 on three major subsets of cities: big transit CZs, big non-transit CZs, and all other CZs.[14] Results, shown in Table A1, suggest an important (but not determinative) role for spatial processes within CZs.

Across all years, baseline estimates of β_t^* are largest in big transit CZs, followed by big non-transit CZs; this also holds among car commuters.[15] For other CZs and in recent years, the estimates of β_t^* are very small, and nearly zero in some specifications: the racialized difference in commute times within these CZs is mediated nearly entirely through observable channels. Indeed, PUMA of residence tends to raise the estimates of β_t^*—although, as noted, PUMAs in smaller CZs may be less spatially informative.

Within large cities, PUMAs capture meaningful variation in the racialized difference in commute times. Furthermore, conditioning on PUMA of residence appears to matter particularly in large transit CZs, relative to other large CZs. Among car commuters, PUMAs lower the estimates of β_t^* by 2.7–4.0 log points in big transit CZs, but negligibly (or not at all) in non-transit large CZs and other CZs. Among bus commuters in large transit and non-transit CZs, our estimates of β_t^* are relatively similar and relatively stable, while the corresponding estimates in other CZs trended upward to converge with the estimates for large CZs. PUMAs lower the estimates of β_t^* by a similar amount (2–4 log points) among large CZs as well as for other CZs in recent years. For walkers, the residual difference is smaller in big transit CZs and biggest in non-transit and especially other CZs, perhaps reflecting selection into walking due to limited or unreliable transit options for non-car

14. Big transit CZs are those with sizeable 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.

15. We do not condition on subway and elevated ridership in big non-transit and other CZs.

commuters in these cities.

Lastly, we analyze census tract-level average commute times and Black residential population shares to investigate whether finer-scale residential location explains differences in commute times. This analysis, which we detail in Appendix A4, is not directly comparable to the other results presented in this section. However, it allows for tract-level fixed effects, which flexibly control for time-invariant tract-level factors that might drive commuting differences. Results are shown in Table A5. Unconditional results accord closely with coefficients in Column 1 of Table 1, providing assurance that tract-level Black population share is a reasonable proxy for individual race in this setting. Models that include tract fixed effects and control for transit share show a significant racialized difference between 4.3–8.7 log points; these results do not exhibit a clear trend over time. While a bit smaller than $\Delta^{\text{Explained}}$ in Table 2, this measure's significance suggests that residential location, at least as measured by census tracts, cannot entirely explain differences in commuting time.

We take several insights from these results, in particular relating to the persistence of the racialized difference in commute times. First, the relatively slow rate of conditional convergence in big transit CZs suggests that factors distinct to large, transit-dependent cities may play a role in the overall persistence. This insight is reinforced by the near-complete conditional convergence among car commuters in our other-CZ subsample of smaller cities. Second, the relatively large effect of PUMA of residence on conditional convergence in big transit CZs suggests a potential role for internal spatial processes in this persistence. For example, the conditional divergence among subway riders since 1980 is nearly entirely accounted for by PUMA of residence. PUMA of residence remains a relatively coarse measure of residential location, and does not speak to changing geographies of employment (see, e.g., Miller 2018, for how the suburbanization of jobs disproportionately impacts Black employment). Nor do these approaches account for investments in transportation infrastructure that would mediate any relationship between segregation and racialized difference in commuting outcomes. We tackle these questions next.

6 City-Level Heterogeneity and Spatial Stratification

Convergence in the share of Black and White commuters driving to work accounts for the majority of the *explained* convergence in commute times. But in some cities—large, segregated, and congested or transit-dependent—a car may be insufficient to ensure a fast commute. Further, high land costs may price a car (and parking) beyond the reach of many households; these attributes may be a barrier to a car-based convergence. In this section, we explore CZ-level variation in the constellation of attributes that we term *spatial stratification*, and evaluate whether this process may help account for patterns of persistence and decline in the racialized difference in commute times.

We understand spatial stratification as the organization of a city whereby segregated Black neighborhoods feature higher travel costs to major job sites than do segregated White neighborhoods. This equilibrium outcome reflects the confluence of several ingredients, including residential segregation, employment sites that are closer to segregated White neighborhoods, and long commutes or slow travel speeds. Residential segregation is a facet of essentially all U.S. cities to varying degrees, although levels of segregation have declined in some places since 1980. The co-location of employers and White neighborhoods has been a concern of urban economists at least since Kain (1968), and Miller (2018) documents its continued persistence. However, in small cities—or "fast cities," whereby long distances can be traversed quickly, e.g., due to freeway investment—patterns of segregation and unequal job access may be overcome.

We relate measures of the ingredients of spatial stratification to the racialized difference in commute times by CZ. Using CZ-by-year-bin models that condition on the same observable controls used in Column 6 in Table 1, we estimate CZ-specific measures of the *residual racialized difference*; this is β^*_{ct} in Equation 3. For brevity, 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.[16] We weight all statistics and models by the number of Black commuters in that CZ and year bin to account for heteroskedasticity.

We next examine patterns of persistence [carto]graphically. Cross-city persistence in the RRD is especially visible in large, coastal cities—precisely those where the ingredients for spatial stratification are likely to be prominent. We identify and construct several panel measures of these factors to test the hypothesis. Lastly, several of the ingredients to spatial stratification—for example, a large city suffering from congestion, with unequal access to jobs—are also features that may reflect (or induce) high average house prices. Using house prices as a potential indicator of spatial stratification, we test the hypothesis that within-city stratification plays a key role in the evolution and persistence of the RRD.

16. 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.

Table 4: Summary Statistics of the Residual Racialized Difference (RRD) and CZ Characteristics

	Years	N	Mean	SD	Min	Max
	1980	341	0.131	0.072	-0.339	0.485
	1990	341	0.070	0.072	-0.326	0.246
Residual Racialized Difference (RRD)	2000	341	0.068	0.077	-0.412	0.247
	2005-11	341	0.053	0.073	-0.384	0.220
	2012-19	341	0.032	0.070	-0.257	0.230
Employed Population	All	1705	1,581,252	2,258,153	3,420	8,511,690
Black Share of Employed Population	All	1705	0.204	0.110	0.004	0.598
Dissimilarity Index	All	1684	0.568	0.148	0.000	0.908
Employment Concentration (Black)	1990–2019	1363	0.572	0.178	0.041	0.996
Employment Concentration (White)	1990–2019	1363	0.452	0.085	0.071	0.658
Centrality	All	1685	-0.022	0.075	-0.255	0.862
Miles of Highway	1980–2000	786	241	208	0	999
Transit Mode Share	All	1705	0.051	0.083	0.000	0.342
Average Travel Time (Auto)	All	1705	24.466	3.325	10.653	35.944
Average House Price	All	1705	223,698	122,847	74,165	842,038
Corr(Commute Time, House Price)	All	1684	-0.118	0.217	-1.000	1.000

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 4. 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. Summary statistics pool data from all available years. Observations weighted by the number of Black commuters in each CZ-by-year-bin cell.

6.1 Patterns of Persistence

Table 4 reports summary statistics by year bin of the RRD across CZs. The weighted mean difference in 1980 is 13.1 log points, which falls to 3.6 log points by 2012–19. Minimum and especially maximum values both narrow. Despite this, however, the dispersion of the RRD does not decrease notably.[17]

Figure 8 shows the spatial distribution of the RRD in 1980, 2000, and 2012–19. Red indicates a positive RRD, white corresponds to zero, and blue indicates a negative RRD. The bottom right panel presents the change in RRD from 1980 to 2012–19 using the same scale. The RRD is positive and pervasive across most of the nation in 1980. Throughout much of the Northeast and the South, as well as in the West, most places show large and positive RRDs. Within the South, the Black Belt of counties with larger Black populations appears to have elevated RRDs, and rural counties elsewhere—as well as Chicago—are

17. Mean RRD values in Table 4 are similar to $\Delta^{\text{Unexplained}}$ estimated with heterogeneous effects of characteristics by CZ (see Appendix for details), but differ because they refer to a restricted set of CZs and weight by Black commuting population instead of total commuting population. $\Delta^{\text{Unexplained}}$ estimated with heterogeneous effects of characteristics by CZ is 0.105 in 1980 and 0.038 in 2012–19.

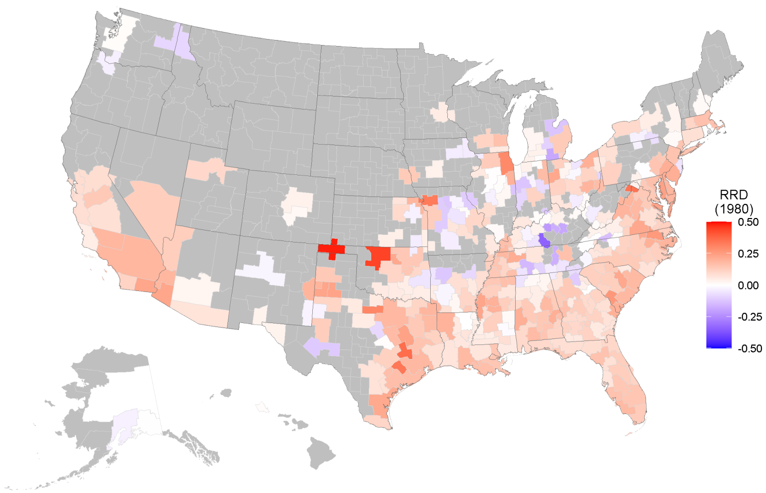
positive outliers. Only a few predominately rural areas concentrated in the Midwest and non-coastal Upper South experience a negative difference. In 2000, the previously positive RRD in parts of the South and Midwest begins to fade, a trend that continues through 2012–19. Large cities generally see smaller changes. Positive RRD remains visible in major cities across regions, with the Northeast Corridor and West Coast showing particularly elevated levels.

The cities with notable persistence are suggestive of the same factors identified above as inputs to spatial stratification: large cities with many neighborhoods far from job centers. The largest U.S. cities are all notable for their visible persistence. The autocorrelation in CZ-level RRD between 1980 and 2012–19 is relatively high, at 0.57 (see Figure A2). However, this is driven primarily by CZs with larger populations. The magnitude of correlation between the RRD and population nearly doubles over the same period, and the variation in the RRD explained by population alone more than triples from 17% to 59% (see Table A2). In contrast, the correlation of CZ-level Black share of the commuting population drops substantially over the same period. However, panel models that rely only on within-CZ changes see smaller and insignificant coefficients on population and Black population share. These findings together suggest an increasing role for features that vary strongly with city size in determining the RRD. However, because the within-city effect of population growth over time is only weakly associated with larger RRD, the mechanism is likely related to large cities but is not necessarily driven by changes in city population *per se*.

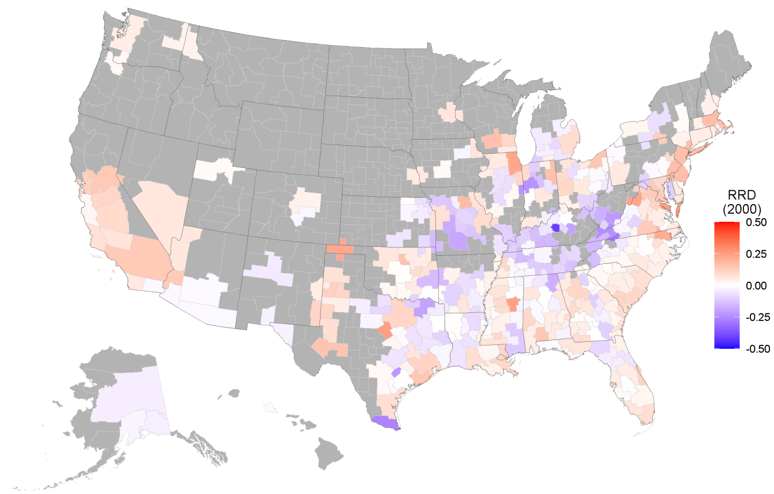
We relate these patterns of persistence to several potential ingredients of spatial stratification in Appendix Figure A3, which plots CZ-level RRD for two year-bins (usually 1980 and 2012–2019, depending on data availability) against measures of these ingredients. Among other findings, Panel C shows that in 1980, residential segregation across cities was relatively uncorrelated with the RRD. By contrast, a clear positive relationship developed in more recent years among larger CZs. Panel E shows a similar evolution between the RRD and our measure of job access for Black households: CZs with a larger Gini index—signifying little overlap between employment centers and the neighborhoods that Black workers reside—have larger values of the RRD. In the next section, we further explore the links between spatial stratification and the generation of persistent racialized difference in commuting.

Figure 8: Maps of the Residual Racialized Difference (RRD) in Commute Time by CZ

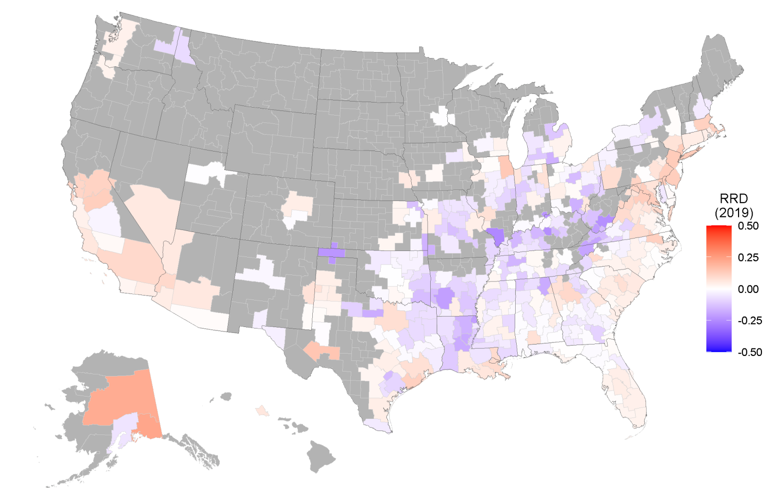
(a) RRD in 1980



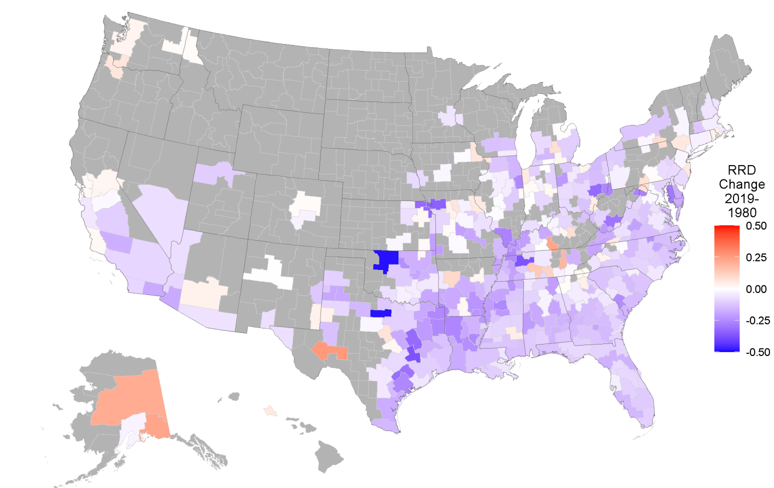
(b) RRD in 2000



(c) RRD in 2012-19



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



6.2 Ingredients of Spatial Stratification

We develop measures of the ingredients of spatial stratification, including population characteristics and urban form, and investigate how these relate to the RRD across large CZs and over time. Our measures are guided by the following intuition: the racialized difference in commute time must reflect a difference in residential location, in workplace location, or in the mode and speed of travel between them. The spatial extent of larger cities implies the potential for longer-distance (and more-variable-distance) commutes, a feature amplified by the slower speeds of bigger cities (Couture, Duranton, and Turner 2018). But even in big cities, some locations are close to workplaces. Our measures of spatial stratification aim to test whether more-stratified places, or places with slower speeds, can account for the correlation between city size and persistent RRD.

While there are many candidate measures of urban form, we focus on a few observable (and constructable) time-varying measures that reflect combinations of residential location, workplace, or travel speed by race. We present this generally as suggestive (and not causal) evidence of mechanisms that point towards future avenues of research.[18]

Table 5 presents panel estimates of regression correlates of the city-level residual difference. We consider CZs with populations over 200,000 (results using all CZs are shown in Appendix Table A3). Because many measures are highly dependent on city size, we provide unconditional estimates (Panel A) and estimates in which we control for log population (Panel B); results are largely consistent 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 average changes in the measure. These estimates therefore reflect the correlation between the *changes of the measure and changes in the RRD*. Column labels indicate explanatory variables; in all cases the dependent variable is the RRD.

Columns 1–3 suggest that the spatial patterning of Black and White commuters plays a role in persistent RRDs, and perhaps in its decline. First, we investigate segregation using a dissimilarity index; higher values indicate higher levels of segregation. Cities with declining levels of segregation tend to also see faster declines in the RRD (Column 1), hence the persistence of segregation can help account for the persistence in the RRD.[19] Next,

18. Our approach is not exhaustive: There may be other factors that play a role in the large (but incomplete) decline of the RRD, such as transit provision, that we do not investigate.

19. Similar results using the Hutchens' Square Root Index are shown in the Appendix. The Appendix also includes details on variable construction as well as a discussion of the shortcomings of aspatial measures of segregation.

Table 5: Two-Way Fixed Effects Estimates of CZ-Level Correlates of the RRD

	Dis-simi-larity (1)	Black Empl. Conc. (2)	White Empl. Conc. (3)	Cen-tral-ity (4)	Log Hwy Miles (5)	Transit Mode Share (6)	Ave. Car Time (7)
Panel A. No Controls							
Measure	0.2448*	0.2379**	-0.2927+	0.0098	-0.0791**	0.4587**	0.0056+
	(0.1160)	(0.0707)	(0.1692)	(0.0801)	(0.0285)	(0.1716)	(0.0032)
Panel B. Controlling for Log Population							
Measure	0.2863*	0.2282**	-0.2392	0.0404	-0.0710**	0.4604**	0.0047
	(0.1147)	(0.0731)	(0.1559)	(0.0696)	(0.0245)	(0.1570)	(0.0033)
N	450	360	360	450	264	450	450
Sample Years	'80-'19	'90-'19	'90-'19	'80-'19	'80-'00	'80-'19	'80-'19

Data: Estimated RRDs and CZ-level characteristics for CZs with at least 1,000 total employed persons, 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. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

we use an aspatial measure of job access for Black and White commuters to investigate whether differential changes to job access across cities can account for the persistence in the RRD. We calculate a jobs-to-people *balance* measure using Lorenz Curves that is akin to the measure proposed by Bento et al. (2005), but we calculate it separately for Black and White workers. A larger value implies that jobs and residences are more unequally distributed across ZIP Codes.[20] Column 2 shows that cities where Black workers increasingly tend to reside in ZIP Codes with relatively few jobs also exhibit increases in the RRD, while Column 3 shows the reverse for White workers.

Together, these results suggest that segregation and job access play a role in the persistently high RRDs in large cities today. Increasingly limited access to centers of employment for Black workers may represent city-level patterns of job suburbanization over time. While our data are not suited to directly measure job suburbanization, Miller (2018) finds that Black workers are less likely than White workers to work in suburbs and that job suburbanization led to declines in Black employment rates between 1970 and 2000.

20. For more details, see the Appendix. We omit 1980 from the analysis as ZIP Code unemployment data are not available for 1980.

For those workers that remain in the labor market, efforts to relocate to job-proximate suburban locations may be met by significant barriers associated with discrimination in housing and mortgage markets (Yinger 1995; Christensen, Sarmiento-Barbieri, and Timmins 2021).

Column 4 presents a spatial phenomenon that *could have* mattered, but seems not to: the centrality of the residential population within the CZ.[21] Cities that become more decentralized over time—more sprawling—may be locations of increasing commuting times in general. Conversely, increasing centralization may indicate increasing levels of congestion and slower travel speeds. Coefficients in Column 4 are positive, indicating increasing centrality is associated with increases in the RRD; however, they are highly insignificant.[22] Centralized cities (like Chicago) and decentralized cities (like Dallas) are both capable of producing large RRDs.

Columns 5–7 suggest that slower cities have larger RRDs. All else equal, cities with features consistent with slower travel speeds (i.e., those with fewer freeway miles or more transit commuters) will have more variable job access across residential locations. This variation creates the possibility of a spatial origin to the RRD.[23] To assess the relationship between highway investment and the RRD, we use city-level highway mileage data from Baum-Snow (2007). In line with this hypothesis, cities that add more freeway miles see larger declines in the RRD (Column 5). Similarly, CZs with faster declines in transit commuting see larger declines in the RRD (Column 6). Lastly, cities that see larger increases in the average travel time of all car commuters also see larger increases in the RRD (Column 7). All of these results are consistent with the idea that large cities may have large RRDs because travel in those cities became slower over time.

Lastly, Figure A1 in the Appendix shows time trends of the RRDs for 16 large cities. These panels display three aspects of heterogeneity worth noting: the level of the RRD, its change over time, and the role of PUMA of residence. The RRD estimates for Chicago, Philadelphia, and Los Angeles are all over 0.2, while the fast-growing cities of Phoenix and Seattle are under 0.1 for most of the sample period. Chicago, Houston, and Detroit saw steep declines while New York City, San Francisco, and Boston saw relatively flat

21. The measure of centrality is adapted from Galster et al. (2001) and can be interpreted as to what degree a population is more centrally located than would be expected on average—larger values indicate greater population centrality with respect to the city's central business district (CBD). For details on construction, see Appendix.

22. We also investigated relative centrality of Black and White commuters; these results are insignificant.

23. See Couture, Duranton, and Turner (2018) for a discussion of the determinants of travel speed; freeway miles are correlated with faster travel throughout their specifications.

levels of RRD; Phoenix and Seattle saw growth from low levels. The RRD estimates for several cities—notably, including many with subway systems—are meaningfully smaller after accounting for PUMA of residence: New York, Chicago, Washington, San Francisco, Philadelphia, and Los Angeles. The contribution of PUMA of residence to the RRD is smaller but growing in Dallas, Houston, and Atlanta.

6.3 Housing Prices and Stratification

As we conceptualize it, spatial stratification arises from the confluence of residential segregation, easier access to job sites from segregated White neighborhoods, and factors like congestion or transit dependence that cause slower travel speeds. Several of these ingredients are also associated with high house prices: inelastic housing supply, whether due to land availability or regulation, pushes new construction to an urban fringe that is relatively far from jobs, inducing higher house prices in more job-accessible regions.[24] Expensive cities thus feature greater internal variation in job access than cheap cities. This underlying variation contributes to an economic landscape around which socioeconomic forces may orient the racial geographies of the city.[25]

We argue, therefore, that high house prices are a useful indicator of spatial stratification.[26] Empirically, as shown in Figure 8, the patterns of persistence suggest a potential link. However, reverse causality could drive this relationship. Cities with high estimated RRDs due to stratification may be more desirable if there is a preference for segregation, driving up housing prices.

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

24. Lens and Monkkonen (2016) test the link directly, showing that restrictive land-use regulations are associated with income segregation for high- and middle-income households. Relatedly, Hanson, Schnier, and Turnbull (2012) report "drive-'til-you-qualify" behavior, wherein credit constrained households sort further from central cities.

25. This idea is similar to the relationship identified by Lee and Lin (2018), who show that cities with high internal variation in the presence of natural amenities (rivers, hillsides, coastlines, etc.) feature relatively stable internal distributions of income, with the rich clustering in high-amenity locations. Here, we highlight the variation in job access, which might be thought of as a "second-nature" amenity (Cronon 1991), and the spatial distribution of racialized groups.

26. 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).

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:

$$P_{cdt} = \delta_c \bar{P}_{(-c)dt} + \psi_0 \hat{\beta}_{ct} + \psi_1 m_{cdt} + \phi_c t + D_c + \epsilon_{cdt} \tag{5}$$

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 then used as a time-varying instrument for price in Equation 4.[27] 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 6 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

27. 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 5 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).

Table 6: 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}	0.0676*** (0.0137)	0.0655*** (0.0162)	0.0502* (0.0253)	0.0494* (0.0246)		0.0622*** (0.0150)	0.0620*** (0.0150)	0.0478 (0.0304)	0.0524* (0.0262)	
Ln(Pop)		0.0249 (0.0204)		0.0286 (0.0215)			0.0123 (0.0210)		0.0137 (0.0213)	
% Black		0.1626 (0.1357)		0.1536 (0.1377)			0.2729 (0.1964)		0.2691 (0.2003)	
$\rho_{ct}(P,\tau)$					-0.0500* (0.0220)					-0.0754 (0.0541)
B. First Stage										
$\hat{\delta}_c\bar{P}_{(-c)dt}$			0.6274*** (0.1218)	0.6140*** (0.1315)				0.6048*** (0.1319)	0.6056*** (0.1331)	
F-stat, CD			1285.9	1244.6				345.1	346.8	
F-stat, KP			26.6	21.8				21.0	20.7	
N	1705	1705	1705	1705	1673	450	450	450	450	450

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. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

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.[28]

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 1. Said differently, 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 rela-

28. 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.

tionship 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.[29]

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.

7 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 the racialized difference in commute times was transformed: whereas Black

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

workers spent 50.4 minutes per week longer commuting than White workers in 1980, the difference was 22.4 minutes by 2019. The 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.

About 37% of the decline in the racialized difference in commute times arises from a partial convergence in observable characteristics, especially car use. Notably, the difference in automobile use between Black and White commuters declines from 12pp to 7pp over the last four decades. Job characteristics increasingly interact with race to determine commute time: controlling for occupation, industry, and income together increases the conditional racialized difference, especially in recent years. However, 63% of the decline is not accounted for by changes to the individual characteristics that we observe. Some observable characteristics that contribute to the level of the racialized difference play no role in its decline: throughout our study period, Black workers are disproportionately likely to live in commuting zones with long commutes. Likewise, our measure of residential location is not a central channel of decline, although the measure is fairly coarse.

We turn to CZ-level heterogeneity to investigate the determinants of persistence, especially the different roles that spatial stratification plays across cities. Large and congested cities may be relatively impervious to car-based convergence. High land prices make cars expensive and slow travel speeds transform extant racial and employment segregation into a racialized commute differential.[30] As many of the ingredients for spatial stratification also reflect high housing costs, we use high housing prices to indicate spatially stratified cities. Increasing house prices at the CZ level are associated with a larger residual racialized difference in commute times. This effect is quantitatively important: were all cities held at their 1980 housing price levels, the average racialized difference in 2012-19 would be 0.028 log points instead of the 0.049 log points we observe.

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),

30. Car-based convergence has other problems too: while cars can ease travel, they do nothing to address underlying segregation or the racism at its root (see, e.g., Steil and Charles 2020). Car commuters are subject to anti-Black policing strategies (Jefferson-Jones 2020), and car-based commuting plays a non-negligible role in carbon emissions (e.g., Brand et al. 2021).

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 born by Black commuters and their families.

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Appendix

A1 Additional Derivations for Two-Step Decomposition

Footnote 8 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 $\Delta^{\text{Unexplained}}_{\{t\}}$. 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:

$$\begin{aligned} \ln(\tau_{ict}) &= \alpha^W_{ct} + x'_{ict}\mu^W_{ct} + \tilde{\lambda}_{ct} + \epsilon^{W*}_{ict} && \text{if } \mathbb{1}[\text{Black}_{ict}] = 0 \\ \ln(\tau_{ict}) &= \alpha^B_{ct} + x'_{ict}\mu^B_{ct} + \tilde{\lambda}_{ct} + \epsilon^{B*}_{ict} && \text{if } \mathbb{1}[\text{Black}_{ict}] = 1. \end{aligned}$$

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

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

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

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

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):

$$\Delta = \sum p_c \tilde{\Delta}_c + \sum (p^B_c - p^W_c)\tilde{\lambda}_c$$

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

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

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

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

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

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 4, 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.[31]

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).

A2 City-Level Heterogeneity Measures

Below we describe the full set of measures considered. Note that not all appear in the main text. We include all measures and variations on measures here for clarity and transparency. Regression results based on measures not included in the main text are found in Tables A3 and A4.

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

31. 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.

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 consider two measures of segregation: Dissimilarity Index (Duncan and Duncan 1955; Massey and Denton 1988) and the Square Root Index (Hutchens 2001). 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 and the Square Root Index for a given commuting zone are constructed as follows:

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

$$SquareRoot = 1 - \sum_{i=1}^{N}\left(\frac{w_i}{W} * \frac{b_i}{B}\right)^{1/2} \tag{A3}$$

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 for both indexes indicate more White and Black separation. Population counts from the Decennial Census and ACS are used to construct both indexes.

Balance of jobs versus housing

Following Bento et al. (2005), we construct a measure that indicates how evenly distributed jobs are relative to population. This measure is akin to Massey and Denton's

Gini coefficient. We consider the relationship between jobs and the total population of employed people as well as employed White and Black people separately. The Gini coefficient is the area between the Lorenz curve and the 45 degree line. To produce the curve, ZIP Codes in each commuting zone are ordered from smallest number of jobs to largest number of jobs and plotted against the cumulative percent of employed population for those ZIP Codes.

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 constructed by the Census Bureau.[32]

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

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

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 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.

Commute time and housing value

We consider two measures to account for the spatial relationship between housing values and commute time. The first is 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 second measure is based on the absolute difference in percentile rank of commute time and housing value. Specifically, we rank tracts within a commuting zone by longest commute time to shortest commute time (worst commute to best commute) and rank tracts from lowest median housing value to highest median housing value. We then average the tract absolute difference between the two rankings for each commuting zone.

Both measures are computed for the following 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.

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
1980	1,154
1990	1,726
2000	2,071
2005–11	2,071
2012–19	2,035

A4 Tract-level Analysis

We provide additional analysis of (geonormalized) census-tract level average commuting times. This has the advantage of allowing us to include census-tract fixed effects to control for time-invariant factors that determine commute times, like distance to the CBD. However, a disadvantage is that relatively few controls are available, and we can only include tract-level shares and averages.

Specifically, we index census tracts by a and estimates variants of:

$$\ln(\bar{\tau}_{act}) = \beta_t^* s_{act}^{\text{Black}} + \bar{x}'_{act}\mu + \xi_a + \lambda_{ct} + u_{act}, \tag{A4}$$

where $\bar{\tau}_{act}$ is the average commute time in a, s_{act}^{Black} is the Black residential population share in a, $\bar{x}_{act}$ are tract-level averages functioning as controls (we use 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}. Results are shown in Table A5 on both observed tract-level travel times, and tract-level travel times augmented with imputed values for missing tracts as discussed in Appendix A2.

A5 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.[33] 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.

Appendix References

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33. 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.

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Additional Results

Figure A1: Evolution of Residual Racialized Difference (RRD) in 16 Big Cities

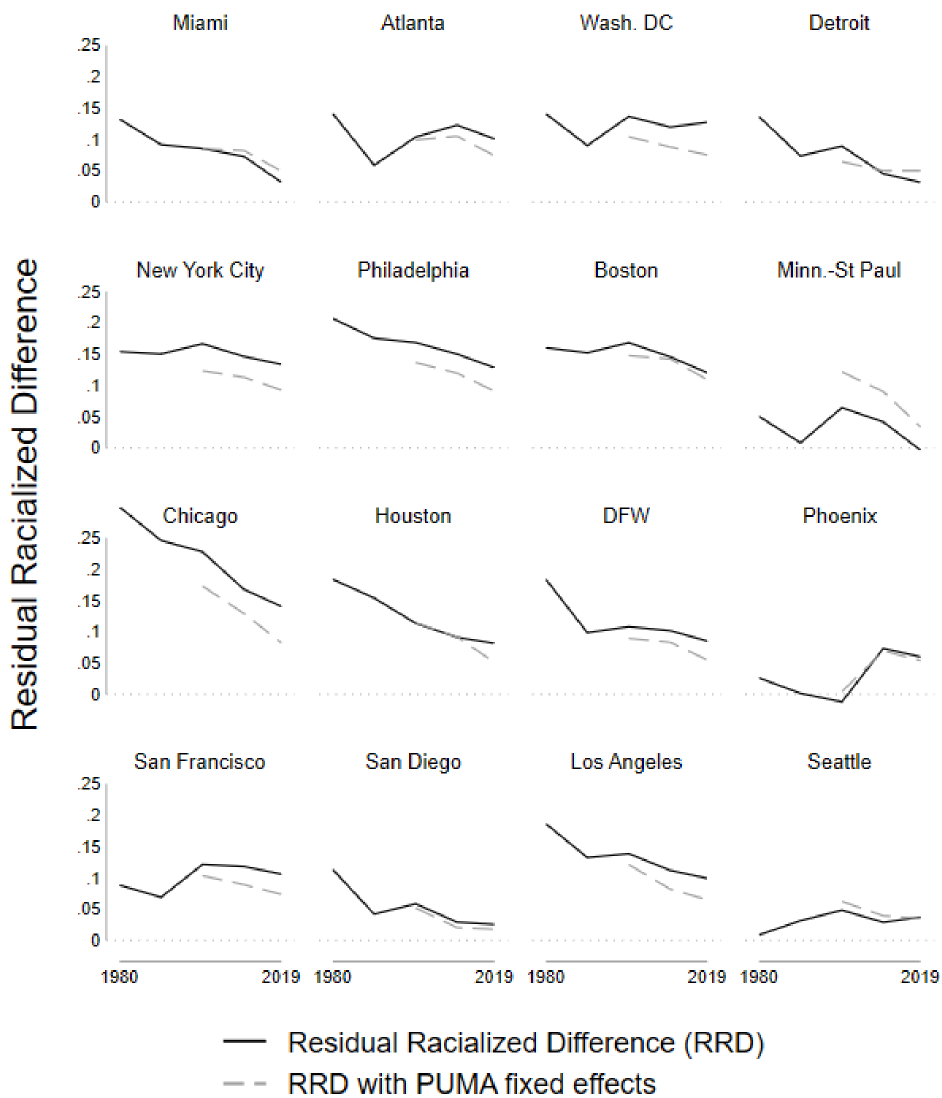


Figure A2: Persistence of Residual Racialized Difference (RRD) Across Cities. Note: Circle size indicates the size of the Black commuting population in 2012–19. Regression slope is estimated weighting each CZ by its Black commuting population in 2012–19, standard errors are robust to heteroskedasticity.

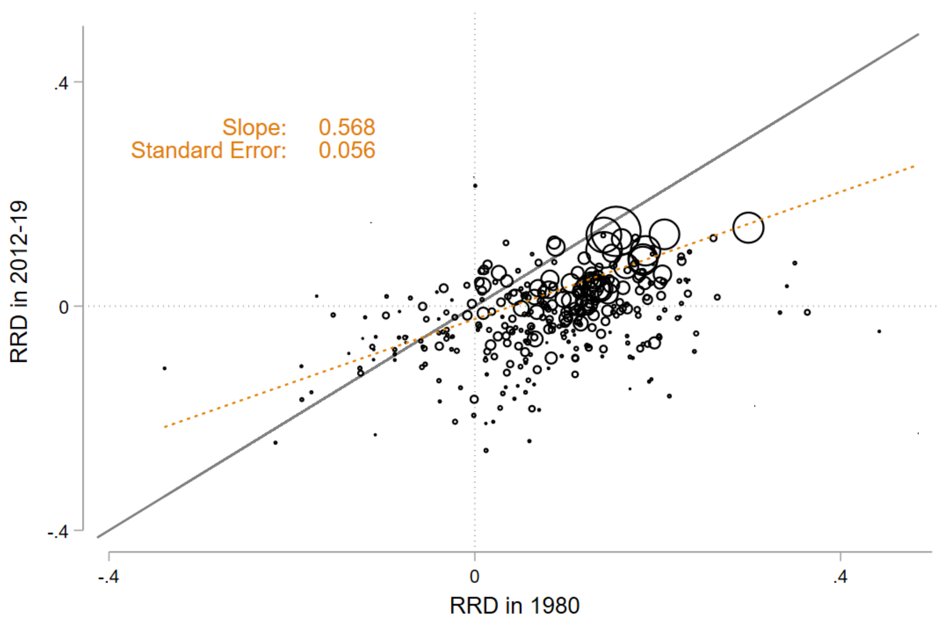
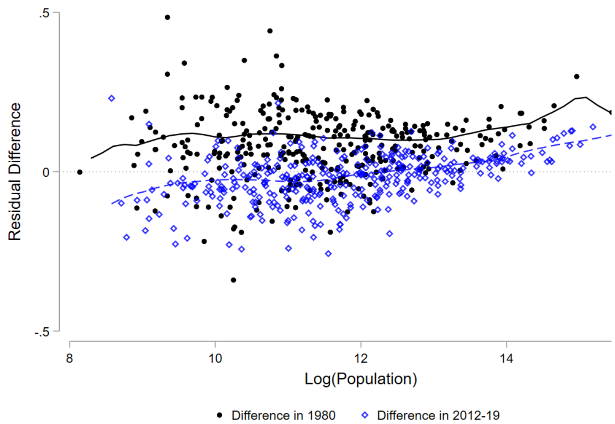
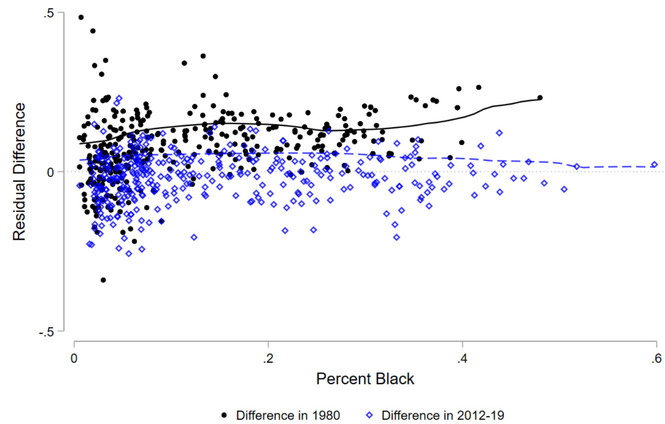


Figure A3: Racialized difference in commute by CZ and urban characteristics from 1980 to 2012-19

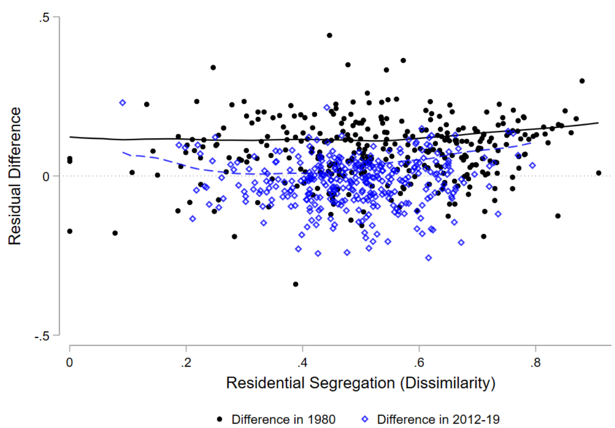
(a) Population



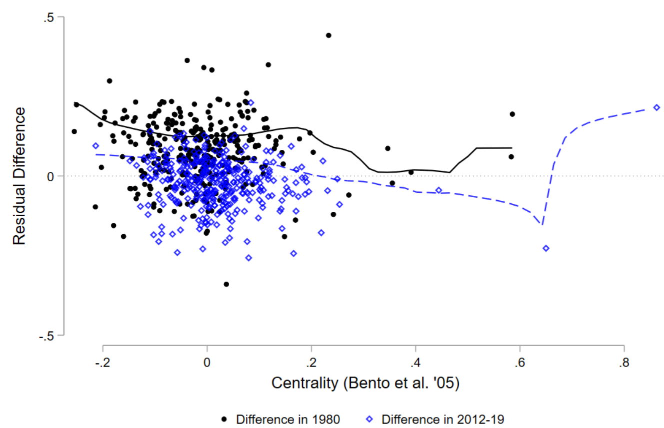
(b) Black share of commuters



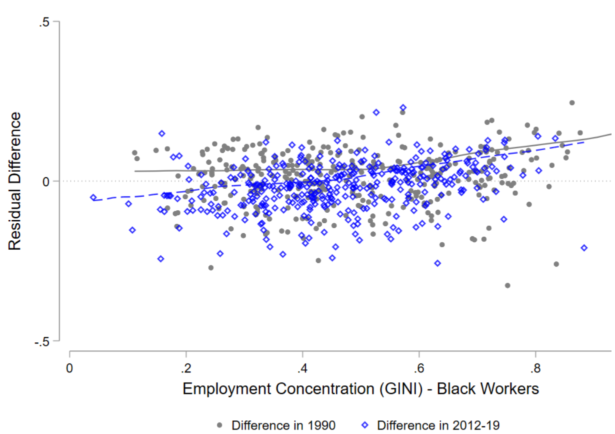
(c) Dissimilarity



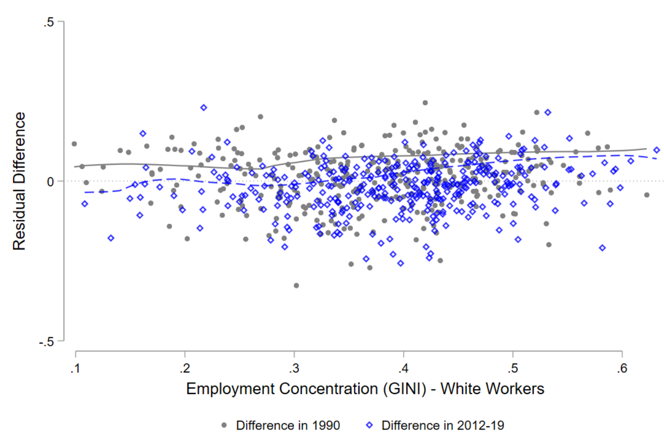
(d) Centrality



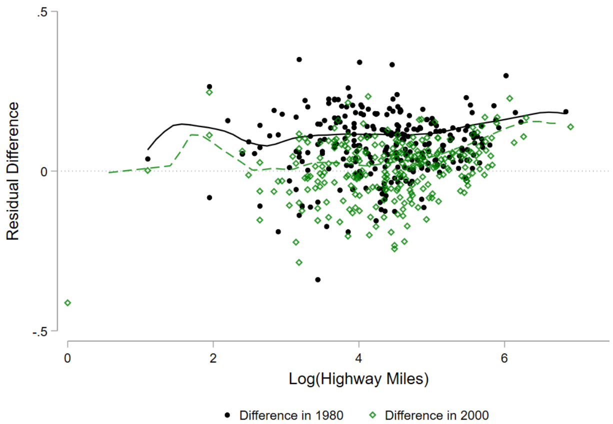
(e) Black employment concentration (Gini)



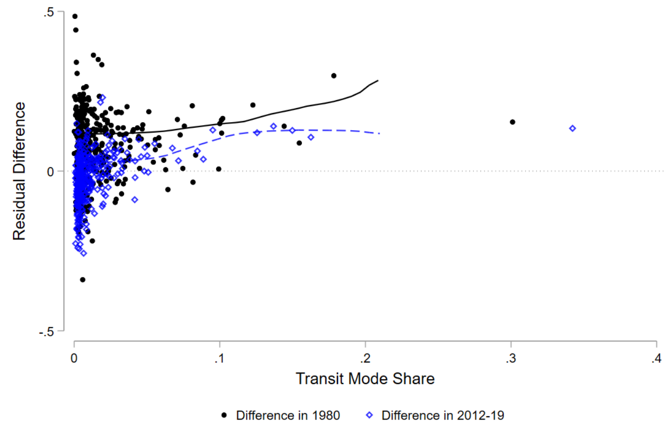
(f) White employment concentration (Gini)



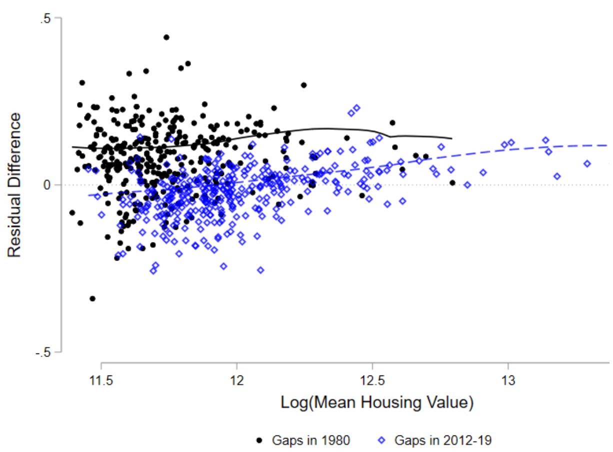
(g) Log miles of 2- and 3-digit highways



(h) Transit mode share



(i) Log average house value



(j) Corr(neighborhood commute, house value)

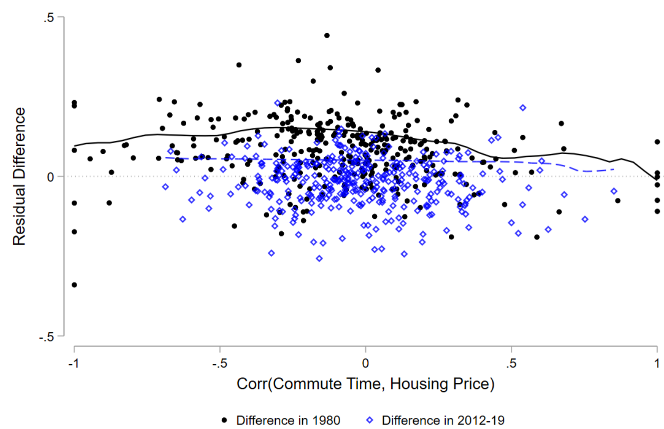


Table A1: Racialized Difference in Commute Time by Mode and CZ Type and with Residential PUMA Controls

	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}	0.184***	0.210***	0.108***	0.038**	0.229***	0.145***	0.141***	0.107**	0.276***	0.108***	0.097***	0.055***	0.340***
	(0.023)	(0.026)	(0.029)	(0.012)	(0.022)	(0.014)	(0.013)	(0.034)	(0.049)	(0.005)	(0.006)	(0.011)	(0.016)
1[Black] × t_{1990}	0.145***	0.151***	0.080**	0.043***	0.219***	0.089***	0.081***	0.042*	0.248***	0.043***	0.028***	0.035***	0.326***
	(0.019)	(0.024)	(0.027)	(0.011)	(0.025)	(0.015)	(0.017)	(0.022)	(0.025)	(0.005)	(0.006)	(0.011)	(0.013)
1[Black] × t_{2000}	0.161***	0.161***	0.095**	0.094***	0.194***	0.090***	0.082***	0.086*	0.275***	0.035***	0.023***	0.067***	0.362***
	(0.013)	(0.015)	(0.035)	(0.018)	(0.025)	(0.008)	(0.009)	(0.044)	(0.041)	(0.005)	(0.005)	(0.015)	(0.013)
1[Black] × $t_{2005-11}$	0.138***	0.131***	0.109***	0.116***	0.143***	0.071***	0.065***	0.089**	0.166***	0.022***	0.010**	0.093***	0.268***
	(0.007)	(0.007)	(0.030)	(0.019)	(0.033)	(0.011)	(0.012)	(0.032)	(0.034)	(0.005)	(0.005)	(0.012)	(0.012)
1[Black] × $t_{2012-19}$	0.124***	0.117***	0.107***	0.107***	0.094***	0.052***	0.044**	0.096**	0.179***	0.014***	0.002	0.101***	0.223***
	(0.007)	(0.007)	(0.029)	(0.018)	(0.019)	(0.012)	(0.016)	(0.035)	(0.028)	(0.004)	(0.004)	(0.012)	(0.011)
Observations	6,491,943	5,314,304	317,202	377,870	256,602	3,432,918	3,205,900	91,234	81,198	38,842,537	36,550,893	361,622	1,405,247
B. Year-Specific Estimates, with year-bin×PUMA FEs (2000 and later only)													
1[Black] × t_{2000}	0.125***	0.128***	0.072**	0.022**	0.154***	0.086***	0.081***	0.065	0.188***	0.054***	0.045***	0.062***	0.317***
	(0.007)	(0.009)	(0.024)	(0.007)	(0.022)	(0.010)	(0.010)	(0.035)	(0.026)	(0.005)	(0.005)	(0.015)	(0.013)
1[Black] × $t_{2005-11}$	0.106***	0.104***	0.079***	0.036**	0.134***	0.073***	0.071***	0.061**	0.136***	0.039***	0.030***	0.081***	0.237***
	(0.006)	(0.007)	(0.015)	(0.011)	(0.015)	(0.008)	(0.008)	(0.018)	(0.034)	(0.005)	(0.005)	(0.010)	(0.012)
1[Black] × $t_{2012-19}$	0.082***	0.077***	0.068***	0.034***	0.088***	0.047***	0.041***	0.055*	0.138***	0.027***	0.018***	0.077***	0.187***
	(0.005)	(0.004)	(0.016)	(0.010)	(0.016)	(0.004)	(0.005)	(0.024)	(0.032)	(0.004)	(0.004)	(0.010)	(0.011)
Observations	4,730,009	3,884,881	212,557	287,120	173,408	2,639,666	2,473,849	66,125	55,198	29,993,000	28,406,589	249,977	932,886

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. Technically, Miami has a heavy-rail transit system; its scale, ridership, and/or ridership per mile are relatively small compared to the other cities. 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 of both panels include transit mode controls. Panel B includes residential-PUMA-by-year-bin fixed effects and so only uses data from 2000 and later because pre-2000 PUMAs are too geographically coarse. 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: 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)	0.0188***	0.0251***	0.0334**	0.0352***	0.0373***	0.0455***	0.0404+	0.0402+	0.0215
	(0.0056)	(0.0066)	(0.0126)	(0.0024)	(0.0022)	(0.0037)	(0.0243)	(0.0232)	(0.0279)
% Black		0.3325***	0.2358**		0.1146***	0.1047**		0.1260	0.2485
		(0.0552)	(0.0736)		(0.0280)	(0.0386)		(0.1359)	(0.2032)
Cities	All	All	>200k	All	All	>200k	All	All	>200k
CZ & Year FEs	-	-	-	-	-	-	Y	Y	Y
N	341	341	90	341	341	90	1705	1705	450
R^2	0.171	0.304	0.336	0.590	0.621	0.657	0.860	0.861	0.883

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 A3: Effects of Various CZ-level Characteristics on Residual Racialized Difference, All Qualifying CZs

	Aggregates		Transportation Chars.			Highways		Segregation		Centrality				Employment Concentration				Sorting on Time	
	% Black	Ln(Hous. Val.)	% Transit	Ave. Transit Time	Ave. Car Time	Log 2dig Miles	Log 2+3dig Miles	Dis- simi- larity	Hut- chens	Total	Black	White	Black – White	Total	Black	White	Black – White	Corr(Time, Hous.)	|%Hous. -%Time|
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Cross-Sectional Estimates																			
Panel A. Unconditional																			
Measure 1980	0.141*	0.064*	0.262+	0.002**	0.009**	0.023*	0.024**	0.127**	0.151**	-0.168	-0.005	-0.142	0.007					-0.037+	-0.197*
	(0.057)	(0.027)	(0.139)	(0.001)	(0.003)	(0.009)	(0.008)	(0.047)	(0.052)	(0.140)	(0.011)	(0.089)	(0.013)					(0.019)	(0.085)
Measure 2000	0.043	0.116***	0.600***	0.005***	0.015***	0.035***	0.043***	0.243***	0.284***	-0.318**	0.005	-0.294***	0.028*	0.383***	0.258***	0.300***	0.320***	-0.064*	-0.332
	(0.054)	(0.015)	(0.150)	(0.001)	(0.002)	(0.010)	(0.007)	(0.053)	(0.051)	(0.101)	(0.009)	(0.062)	(0.012)	(0.071)	(0.033)	(0.080)	(0.047)	(0.030)	(0.234)
Measure 2012–19	-0.075	0.110***	0.485***	0.005***	0.015***			0.266***	0.316***	-0.374***	-0.021+	-0.228***	0.014	0.495***	0.280***	0.394***	0.298***	0.010	0.252
	(0.048)	(0.008)	(0.111)	(0.001)	(0.001)			(0.051)	(0.048)	(0.069)	(0.011)	(0.051)	(0.012)	(0.060)	(0.024)	(0.077)	(0.041)	(0.031)	(0.181)
Panel B. Controlling for Log Population																			
Measure 1980	0.313***	-0.019	0.081	0.001+	0.005+	0.004	0.001	-0.012	0.073	-0.086	-0.035**	-0.023	-0.029**					-0.073***	-0.361***
	(0.049)	(0.026)	(0.131)	(0.001)	(0.003)	(0.009)	(0.009)	(0.055)	(0.090)	(0.114)	(0.011)	(0.089)	(0.010)					(0.021)	(0.095)
Measure 2000	0.251***	0.047*	0.331**	0.003***	0.009***	-0.014*	-0.005	-0.020	0.058	-0.051	-0.016*	-0.056	-0.012	-0.048	0.151***	-0.126	0.172***	-0.091***	-0.458***
	(0.038)	(0.020)	(0.116)	(0.000)	(0.002)	(0.006)	(0.008)	(0.056)	(0.067)	(0.069)	(0.008)	(0.048)	(0.008)	(0.094)	(0.045)	(0.077)	(0.044)	(0.020)	(0.117)
Measure 2012–19	0.117***	0.051***	0.187**	0.002***	0.008***			-0.128**	-0.091	-0.031	-0.028***	0.029	-0.026***	0.086	0.090**	0.016	0.064*	-0.007	0.011
	(0.025)	(0.012)	(0.064)	(0.000)	(0.001)			(0.048)	(0.057)	(0.055)	(0.008)	(0.028)	(0.007)	(0.054)	(0.034)	(0.044)	(0.029)	(0.014)	(0.071)
Panel Estimates																			
Panel C. Unconditional																			
Measure	0.128	0.068***	0.339*	0.001**	0.007**	-0.043*	-0.055**	0.032	0.081	-0.018	-0.018	-0.012	-0.019+	-0.066	0.076+	-0.101	0.111*	-0.030	-0.123
	(0.159)	(0.014)	(0.157)	(0.000)	(0.002)	(0.017)	(0.020)	(0.070)	(0.084)	(0.047)	(0.011)	(0.042)	(0.012)	(0.078)	(0.042)	(0.064)	(0.045)	(0.019)	(0.097)
Panel D. Controlling for Log Population																			
Measure	0.126	0.064***	0.341*	0.001*	0.005*	-0.039*	-0.051**	0.067	0.111	0.006	-0.014	0.010	-0.017	-0.052	0.076+	-0.071	0.095*	-0.027	-0.110
	(0.136)	(0.017)	(0.162)	(0.000)	(0.002)	(0.016)	(0.019)	(0.065)	(0.077)	(0.042)	(0.010)	(0.040)	(0.011)	(0.071)	(0.040)	(0.060)	(0.043)	(0.018)	(0.095)
Sample	’80-’19	’80-’19	’80-’19	’80-’19	’80-’19	’80-’00	’80-’00	’80-’19	’80-’19	’80-’19	’80-’19	’80-’19	’80-’19	’90-’19	’90-’19	’90-’19	’90-’19	’80-’19	’80-’19

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 row in each column in each panel is for a different specification (for 140 total models). 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. “Black - White” indicates the difference in Black and White variants of a measure. Panel A provides unconditional cross-sectional estimates the relationship between a measure and RRD in 1980, 2000, and 2012–19. Panel B is similar, but includes log-CZ commuting population as a control. Panels C and D use all years of data and include two-way fixed effects by CZ and year bin; Panel D further include log-CZ commuting population as a control. Models are weighted by the Black commuting population in the CZ-by-year-bin cell. Standard errors in Panels A and B are robust to heteroskedasticity, and in Panels C and D are clustered by commuting zone. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table A4: Effects of Various CZ-level Characteristics on Residual Racialized Difference, Only CZs with 200k or More Commuters

	Aggregates		Transportation Chars.			Highways		Segregation		Centrality				Employment Concentration				Sorting on Time	
	% Black (1)	Ln(Hous. Val.) (2)	% Transit (3)	Ave. Transit Time (4)	Ave. Car Time (5)	Log 2dig Miles (6)	Log 2+3dig Miles (7)	Dis- simi- larity (8)	Hut- chens (9)	Total (10)	Black (11)	White (12)	Black – White (13)	Total (14)	Black (15)	White (16)	Black – White (17)	Corr(Time, Hous.) (18)	∣%Hous. -%Time∣ (19)
Cross-Sectional Estimates																			
Panel A. Unconditional																			
Measure 1980	0.147	0.062+	0.226	0.003+	0.011**	0.042**	0.038**	0.281*	0.273**	-0.266	-0.005	-0.274+	0.014					-0.155*	-0.816**
	(0.090)	(0.037)	(0.143)	(0.002)	(0.004)	(0.014)	(0.012)	(0.119)	(0.103)	(0.246)	(0.015)	(0.150)	(0.015)					(0.061)	(0.308)
Measure 2000	0.045	0.122***	0.483***	0.006***	0.016***	0.044**	0.065***	0.353***	0.348***	-0.352+	-0.003	-0.463***	0.020	0.462***	0.407***	0.303	0.404***	-0.067+	-0.375
	(0.083)	(0.022)	(0.122)	(0.002)	(0.003)	(0.014)	(0.013)	(0.070)	(0.067)	(0.181)	(0.015)	(0.094)	(0.015)	(0.098)	(0.054)	(0.191)	(0.070)	(0.039)	(0.351)
Measure 2012–19	0.027	0.085***	0.344***	0.005***	0.014***			0.285***	0.279***	-0.270*	-0.032+	-0.267***	-0.006	0.605***	0.341***	0.459**	0.327***	-0.006	0.111
	(0.072)	(0.012)	(0.074)	(0.001)	(0.001)			(0.063)	(0.061)	(0.107)	(0.017)	(0.077)	(0.017)	(0.070)	(0.036)	(0.152)	(0.066)	(0.051)	(0.317)
Panel B. Controlling for Log Population																			
Measure 1980	0.250**	-0.030	-0.116	-0.000	0.004	0.018	-0.000	0.122	0.171	-0.172	-0.010	-0.142	-0.002					-0.144**	-0.757**
	(0.075)	(0.032)	(0.135)	(0.001)	(0.003)	(0.014)	(0.011)	(0.128)	(0.126)	(0.209)	(0.015)	(0.156)	(0.012)					(0.045)	(0.243)
Measure 2000	0.145**	-0.002	0.100	0.001	0.005*	-0.008	-0.004	0.120+	0.136+	-0.344**	0.010	-0.203**	0.016	-0.154	0.175*	-0.137	0.180*	-0.053*	-0.334*
	(0.045)	(0.017)	(0.106)	(0.001)	(0.002)	(0.010)	(0.011)	(0.068)	(0.071)	(0.109)	(0.011)	(0.076)	(0.010)	(0.142)	(0.068)	(0.126)	(0.070)	(0.021)	(0.130)
Measure 2012–19	0.113**	0.020	0.105	0.001+	0.008***			0.021	0.022	-0.207*	-0.003	-0.057	0.001	0.096	0.104*	0.063	0.070	-0.017	-0.159
	(0.037)	(0.015)	(0.070)	(0.001)	(0.002)			(0.052)	(0.054)	(0.080)	(0.014)	(0.059)	(0.011)	(0.098)	(0.049)	(0.090)	(0.054)	(0.024)	(0.112)
Panel Estimates																			
Panel C. Unconditional																			
Measure	0.272	0.062***	0.459**	0.001	0.006+	-0.080**	-0.079**	0.245*	0.295*	0.010	-0.008	0.001	-0.011	-0.284	0.238**	-0.293+	0.268**	-0.076+	-0.267
	(0.216)	(0.015)	(0.172)	(0.001)	(0.003)	(0.029)	(0.029)	(0.116)	(0.119)	(0.080)	(0.012)	(0.082)	(0.014)	(0.216)	(0.071)	(0.169)	(0.081)	(0.045)	(0.216)
Panel D. Controlling for Log Population																			
Measure	0.248	0.061***	0.460**	0.001	0.005	-0.067**	-0.071**	0.286*	0.316**	0.040	-0.006	0.034	-0.009	-0.234	0.228**	-0.239	0.242***	-0.072+	-0.247
	(0.203)	(0.017)	(0.157)	(0.001)	(0.003)	(0.024)	(0.024)	(0.115)	(0.114)	(0.070)	(0.010)	(0.080)	(0.013)	(0.196)	(0.073)	(0.156)	(0.071)	(0.042)	(0.204)
Sample	’80-’19	’80-’19	’80-’19	’80-’19	’80-’19	’80-’00	’80-’00	’80-’19	’80-’19	’80-’19	’80-’19	’80-’19	’80-’19	’90-’19	’90-’19	’90-’19	’90-’19	’80-’19	’80-’19

Data: Estimated RRDs and CZ-level characteristics for CZs with at least 1,000 total employed persons, greater than 50 unique Black commuter Census respondents, and at least 200,000 total commuters in all five year bins. Each row in each column in each panel is for a different specification (for 140 total models). 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. “Black - White” indicates the difference in Black and White variants of a measure. Panel A provides unconditional cross-sectional estimates the relationship between a measure and RRD in 1980, 2000, and 2012–19. Panel B is similar, but includes log-CZ commuting population as a control. Panels C and D use all years of data and include two-way fixed effects by CZ and year bin; Panel D further include log-CZ commuting population as a control. Models are weighted by the Black commuting population in the CZ-by-year-bin cell. Standard errors in Panels A and B are robust to heteroskedasticity, and in Panels C and D are clustered by commuting zone. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table A5: Tract-Level Estimates of Racialized Difference in Commute Time

	(1)	(2)	(3)	(4)	(5)
A. Observed Tract-level Travel Times					
Share Black in Tract $\times t_{1980}$	0.245***	0.129***	0.032	0.032	0.064***
	(0.042)	(0.024)	(0.030)	(0.029)	(0.016)
Share Black in Tract $\times t_{1990}$	0.179***	0.040	-0.046*	-0.042*	0.021
	(0.046)	(0.031)	(0.021)	(0.019)	(0.014)
Share Black in Tract $\times t_{2000}$	0.197***	0.073*	0.005	0.018	0.087***
	(0.047)	(0.035)	(0.024)	(0.023)	(0.013)
Share Black in Tract $\times t_{2006-10}$	0.116***	-0.023	-0.047	-0.026	0.059***
	(0.034)	(0.027)	(0.027)	(0.025)	(0.011)
Share Black in Tract $\times t_{2014-18}$	0.100**	-0.026	-0.047	-0.025	0.065***
	(0.037)	(0.025)	(0.024)	(0.022)	(0.013)
N	294,906	294,741	294,741	294,741	294,686
B. Observed and Imputed Tract-level Travel Times					
Share Black in Tract $\times t_{1980}$	0.245***	0.129***	0.032	0.032	0.063***
	(0.042)	(0.024)	(0.030)	(0.029)	(0.016)
Share Black in Tract $\times t_{1990}$	0.179***	0.040	-0.046*	-0.042*	0.021
	(0.046)	(0.031)	(0.021)	(0.019)	(0.014)
Share Black in Tract $\times t_{2000}$	0.197***	0.073*	0.005	0.018	0.086***
	(0.047)	(0.035)	(0.024)	(0.023)	(0.012)
Share Black in Tract $\times t_{2006-10}$	0.132**	0.014	-0.038	-0.019	0.043***
	(0.047)	(0.035)	(0.025)	(0.024)	(0.011)
Share Black in Tract $\times t_{2014-18}$	0.112*	-0.004	-0.048	-0.029	0.044***
	(0.049)	(0.038)	(0.029)	(0.028)	(0.012)
N	346,631	346,522	346,522	346,522	346,478
Year Bin×CZ FEs	-	Y	Y	Y	Y
Controls					
Share Transit in Tract	-	-	Y	Y	Y
Distance to CBD	-	-	-	Y	-
Tract FEs	-	-	-	-	Y

Data: Average observed and imputed 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, and the model is described in Appendix A4. Each column in each panel is for a different specification. The dependent variable is log average travel time in a census tract. Central Business District (CBD) locations is derived from Google Maps as in (Manduca 2021). Controls are interacted with year bin. Standard errors clustered by commuting zone. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.