Explaining Recent Trends in US School Segregation

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Abstract

Public school segregation in the United States has changed substantially over the past quarter century. The fraction of minority-segregated schools has roughly doubled, but the fraction of white-segregated schools has decreased at an even faster rate. As a result, the prevalence of segregated schools has decreased in most parts of the country. Using data on the universe of US public school enrollments, we develop an empirical approach that allows us to decompose observed changes in segregation into discriminatory, demographic and residual (non-discriminatory, non-demographic) channels. Although segregation and discrimination have often been treated as synonymous, we find that the discriminatory channel has been the least important of the three in explaining recent trends. Instead, demographic change, largely due to Hispanic immigration, is the most important channel. These findings are particularly pronounced in the largest urban areas in the country, which not only experience the largest changes in segregation during this period but are also the areas in which policymakers are most concerned about the pernicious effects of segregation.

JEL Codes: R13, J15, I20

1 Introduction

School segregation has occupied a prominent role in the public sphere since the landmark *Brown v. Board of Education* (1954) ruling and the Elementary and Secondary Education Act (1966), which identified the reduction of segregation as a primary goal of federal education policy. Indeed, policymakers seeking to reduce inequality in student achievement, graduation rates, and long-run outcomes in the labor market have good reason to target school segregation: exposure to a higher concentration of minority students has been repeatedly found to reduce minority achievement,[1]

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[1] Cutler and Glaeser (1997); Guryan (2004); Card and Rothstein (2007); Hanushek et al. (2009); Fryer Jr (2010); Billings et al. (2013).

and segregated schools have been linked to long-run adverse effects on the occupational aspirations, expectations, and attainment of minority students.[2] In this paper, we analyze the universe of public school enrollments in the United States over a quarter century to document how school segregation has evolved and what have been the key determinants of this trend.

Segregation has been inexorably linked to racial discrimination by academics, policymakers, courts and the general public alike. The seminal paper in economics on the topic opens with the statement "This paper is about the segregation that can result from discriminatory individual choices" (Schelling (1969)).[3] The most recent and widely-publicized government report on the state of school segregation highlights the role of discrimination in its title.[4] Since the *Brown* ruling, the US Supreme Court has heard no fewer than 27 cases on school segregation that hinged on whether minority students faced discrimination.[5] And the association between segregation and discrimination is extremely strong within the general public, as evidenced by internet searches for the terms (Figure 1).

Recent well-publicized reports have noted that minority-segregated schools (over 75% minority)[6] are becoming more prevalent in the country (e.g., Orfield et al. (2014)), which has prompted many people to blame it on racial discrimination.[7] However, this should be viewed in the context of a broader trend: In 1988, 9% of schools were minority-segregated; by 2014, 23% of schools were. At the same time, in 1988, 68% of schools were white-segregated (over 75% white), but by 2014, only 47% were. Hence, white-segregated schools have been disappearing faster than minority-segregated schools have been appearing. Discrimination is unlikely to generate this pattern by itself, as theory predicts that discrimination would lead to an increase in both white- and minority- segregated

[2] Granovetter (1986); Julius (1987); Wells and Crain (1994).

[3] Similarly, consider the introductions to the most cited works on this topic in sociology ("As long as blacks continue to be segregated in American cities, the United States cannot be called a race-blind society" (Massey and Denton (1992), p.3)) and history ("It will be the theme of following chapters to show in some detail how Negro preachers, teachers, professionals, and businessmen have had to build their whole economic and social existence on the basis of the segregation of their people, in response to the dictates of the white society. To state the situation bluntly: these upper class Negroes are left free to earn their living and their reputation in the backwater of discrimination... they are kept fully aware of the wider range of opportunities from which they are excluded by segregation and discrimination. (Myrdal (1944), p.29)).

[4] See the April 2016 Government Accounting Office (GAO) report: "Better Use of Information Could Help Agencies Identify Disparities and Address Racial Discrimination".

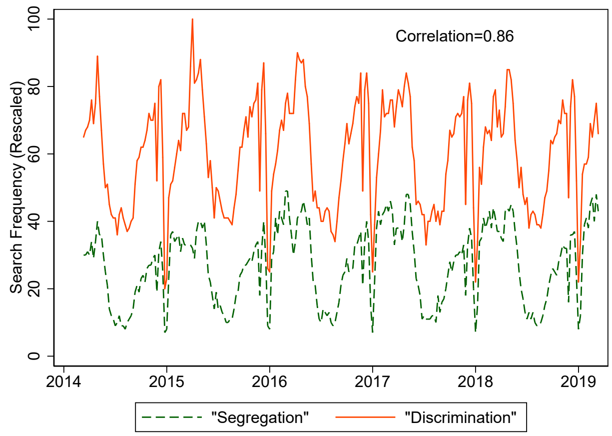
[5] See American Bar Association annual meeting notes from 2013, "Timeline of Supreme Court School Desegregation Cases from Brown to Fisher".

[6] Throughout this paper, we follow GAO nomenclature and use the term "minority" to refer only to black and Hispanic students (including white Hispanics). This classification does not affect any of our conclusions.

[7] See, e.g., Bouie, Jamelle, "Still Separate and Unequal," *Slate,* 5/15/14.

schools.

Figure 1: Internet Searches for “Segregation” and “Discrimination”, March 2014-March 2019



Notes: Data obtained from Google Trends on March 8, 2019. Each line shows the total number of weekly google searches from the United States for the terms “Segregation” and “Discrimination” rescaled between 0 and 100. The correlation of search activity for these terms is 0.86.

Indeed, discrimination is not the only cause of segregation. There are three exhaustive mechanisms by which the racial compositions of schools – and in turn the overall level of school segregation – can change. First, they may change if parents intentionally segregate by sorting to specific schools explicitly because of their favorable racial compositions. This *discriminatory* mechanism generates the dynamic social multiplier effects described in the seminal Schelling (1969) model of segregation. If parents prefer that their children attend schools with more peers of the same race, then inflows of minorities may lead to a positive feedback loop in which successively more (fewer) minority (white) students enroll in some schools, while the opposite occurs in other schools. This ultimately leads to a highly segregated school system (Becker and Murphy (2000)). Second, the racial compositions of schools may change if there is an aggregate *demographic* change in the local school market. For instance, an influx of minorities to a city may mechanically impact the racial compositions of schools as these minority students must enroll somewhere in the city. Third, the racial compositions of schools may change if parents of different races seek different schools for reasons other than their racial compositions (this can include other school and neighborhood characteristics). This *residual* mechanism is non-discriminatory in the sense that parents may find their children to be enrolled in segregated schools even though that was not their intention.

Empirical researchers have explored aspects of each of these mechanisms in isolation. For example, Boustan (2010) has analyzed white flight, or the decision of whites to leave areas that have experienced an increase in minority share, which falls under the discriminatory mechanism. Cascio and Lewis (2012) demonstrate that Hispanic immigration has affected the racial compositions of schools in California, which falls under the demographic mechanism. And Lutz (2011) analyze the effects of court ordered desegregation policies and various other local policies, respectively, on school segregation, which falls under the residual mechanism. However, no single study has assessed the relative importance of these mechanisms against one another. Indeed, the interplay between these mechanisms raises three practical obstacles to identify their roles in school segregation. First, identifying changes in segregation due to discrimination requires us to identify how parents' choices are influenced by the racial compositions of schools versus other school and neighborhood features (including unobserved ones). Second, the discriminatory mechanism implies that treatment effects are dynamic. For instance, a shock to a school may affect enrollments of white and minority students differently, and ensuing responses to the change in racial composition will then amplify its effect in the future. Third, it is necessary to account for the general equilibrium consequences of all schools reacting to shocks at the same time. For example, aggregated demographic shocks simultaneously affect many schools, and the responses to these shocks in one school may in turn later affect other schools to varying degrees depending on their substitutability.

In this paper, we build on previous work (e.g., Bayer et al. (2004, 2007); Wong (2013); Caetano and Maheshri (2017)) to develop a novel empirical approach to decompose observed changes in segregation into the discriminatory, demographic and residual channels for all public schools in the United States. Our approach makes three innovations over existing approaches, each of which is found to be highly empirically relevant. First we analyze the dynamic process of segregation in a non-stationary environment. This allows us to explicitly account for aggregate demographic changes in the student body, which are found to be critical determinants of segregation. Second, we model how segregation evolves in a general equilibrium framework in which changes in enrollment at one school directly affect enrollments at close substitute schools. We find that neglecting these general equilibrium concerns leads to a dramatic overstatement of the the role of the discriminatory mechanism in explaining segregation. Third, we conduct our analysis at a much larger scale than has ever been undertaken. The breadth of our analysis – the entire country over a long period of time – is critical to our aims as it reveals rich geographic heterogeneity in school segregation, discrimination, and changing demographics and explores their dynamic interactions.

To briefly preview our results, the discriminatory mechanism has been the least important and the demographic mechanism has been the most important. However, the relative roles of each mechanism varies dramatically across the country. The demographic mechanism explains most of the trends in the larger, more urban commuting zones, which have incidentally experienced the largest changes in segregation levels in recent decades. However, in more sparsely populated commuting zones that have been less exposed to demographic change, the discriminatory and residual mechanisms play larger roles.

In choosing to conduct our analysis at scale, we must necessarily abstract away from other features specific to local schooling markets which are difficult to catalog and compare across every school in the country over decades (e.g., school choice policies, court-ordered desegregation policies). Although these local differences have been shown to have shaped segregation patterns (e.g., Clotfelter et al. (2006); Bifulco and Ladd (2007); Cascio et al. (2008, 2010); Lutz (2011)), our analysis complements this literature by assigning these effects entirely to a residual channel. This allows us to explore the importance of discrimination and demographics in explaining school segregation while fostering a comparison of the magnitudes of their effects against the effects of all other local characteristics of schooling markets, many of which are unobservable to researchers.

The results of our decomposition follow from several empirical fundamentals. We find that white parents respond negatively to minority peers throughout the country, but these responses are moderate in size and more negative in densely populated areas. In contrast, we find that black and Hispanic parents strongly seek similar peers for their children. This is particularly pronounced in areas where same-race peers are scarce, which tend to be smaller and more rural. In areas where same-race peers are plentiful, minority parents seek similar peers for their children less intensely. As a result, the discriminatory mechanism plays only a minor role in explaining segregation trends in urban areas. We also find that black parents have a mild positive response to Hispanic peers (relative to white peers), but Hispanic parents have no response to peers of different races, which highlights important heterogeneity between different minorities that has been largely overlooked. Finally, we document that demographic shocks have been very large in urban areas and the sunbelt but less so in other areas. We collect a variety of evidence that these demographic shocks are almost entirely due to Hispanic immigration.

Although we decompose the causes of school segregation at a relatively coarse level (i.e., into only three mechanisms), our findings are useful in informing policy. For instance, our finding that immigration has played a prominent role in keeping segregation at bay from discriminatory forces suggests that restrictions on immigration may reverse the massive desegregation of predominantly white schools that has been the most widespread and striking trend in US school segregation in recent decades. Moreover, policies to encourage the assimilation of immigrant inflows by adjusting the characteristics of a broad range of schools to immigrants' liking would substantially combat school segregation in cities, since typically these inflows have only a few schools to actually consider when they arrive in the city. Further, reducing discrimination in cities will have a limited impact on reducing current levels of schools segregation, but it would be much more effective in rural areas. A finer understanding of the determinants of school segregation could be possible with more precise data and context-specific research designs. For instance, in a given commuting zone, one might be able to decompose the discriminatory channel into statistical discrimination, taste-based discrimination, and choice frictions[8], or one might be able to decompose the residual channel into specific policies and local investments[9]. Doing so could aid greatly in the design of policies tailored to combat segregation in specific education markets and would complement the findings of this paper.

The remainder of the paper is organized as follows. In Section 2, we describe our data set and document how the levels of school segregation have evolved from 1988 to 2014. In Section 3, we present a conceptual framework to analyze segregation, and in Section 4, we show how it can be taken to data. We present the results of our estimation in Section 5 and decomposition in Section 6. We describe the various robustness checks that we conducted in Section 7 before concluding in Section 8.

2 Data

We obtain enrollment data from the Common Core of Data maintained by the National Center for Education Statistics at the US Department of Education, which covers the entire population of

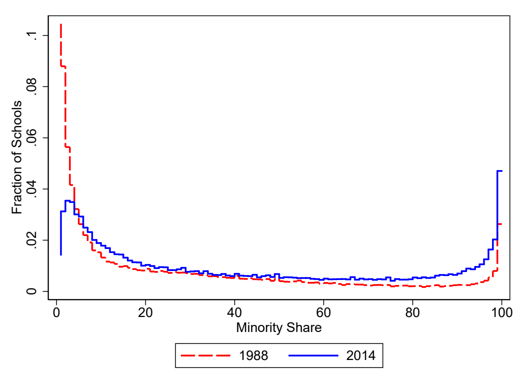
[8]Caetano and Maheshri (2020) attempt to identify discrimination (statistical or taste-based) and choice frictions separately, but to our knowledge, no paper has attempted to empirically identify these different sub-channels in the school or the neighborhood choice setting.

[9]See, for instance, Logan et al. (2008).

American public school students from 1988-2014.[10] We restrict our sample to the 50 states and the District of Columbia and ignore schools in US territories. Enrollment data from a small number of states in some early years of the sample are missing.[11] In total there are 2,410,140 school-year observations. Over this period, the number of schools steadily increased from 61,252 to 95,413.[12] In a typical year, the average school enrolls 488 students. For each school, we observe the numbers of white, black, Hispanic, Asian and native American students enrolled in each year, and we use the term minority to refer to any black or Hispanic student (including white Hispanics) and the term white to refer to any other student.[13]

In Figure 2, we present empirical distributions (PDFs) of the minority share of enrollment in every US school in 1988 and 2014. Each distribution is bi-modal, so the cross-sectional variation among schools is consistent with the Schelling model in which discriminatory responses by parents lead to the proliferation of segregated schools. The distribution in 2014 is clearly shifted to the right relative to 1988. This longitudinal variation among schools is unlikely to be generated by discriminatory responses since they would lead to increases in the density at both extremes. It is, however, consistent with a demographic shift towards a more highly minority national student body.

Figure 2: Empirical Distribution of Minority Share of US Schools, 1988 and 2014

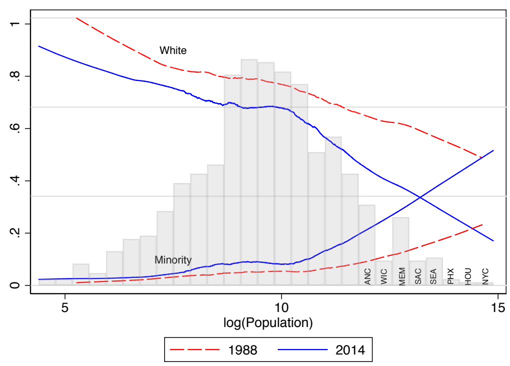


The national trend has unfolded differently across the country. In Figure 3, we present locally weighted least squares regressions of the prevalence of segregated schools in all US commuting

[10] We use 2000 to refer to the 2000-01 academic year and follow this convention throughout the paper.
[11] Detailed documentation of our sample, including the missing data, can be found in Appendix B.
[12] Our sample includes all public charter schools and magnet schools. When we omit these schools from our analysis, all of our results are qualitatively unchanged.
[13] These definitions of white and minority follow from the US Government Accountability Office study GAO-16-345. If we instead define minorities as all non-white students or omit all Asian and Native-American students from our sample, our findings are essentially unchanged.

zones in 1988 and 2014 against the total student populations of each commuting zone (in logs).[14] Over this period, the desegregation of predominantly white schools has occurred everywhere, from sparsely populated rural areas to large urban areas where it is more pronounced. However, increasing minority segregation has been mostly concentrated in large, urban commuting zones, which suggests that we should focus on these areas in particular. This is unsurprising, as there were very few minority students in small commuting zones, particularly in 1988.

Figure 3: Prevalence of Segregated Schools in a Commuting Zone by Student Population, 1988 and 2014



Notes: We present locally weighted least squares regressions of the fractions of segregated schools in commuting zones in 1988 and 2014 against the total student populations (in logs) of each commuting zone (bandwidth = 0.5). We define white-segregated schools as over 75% white, and minority-segregated schools as over 75% minority.

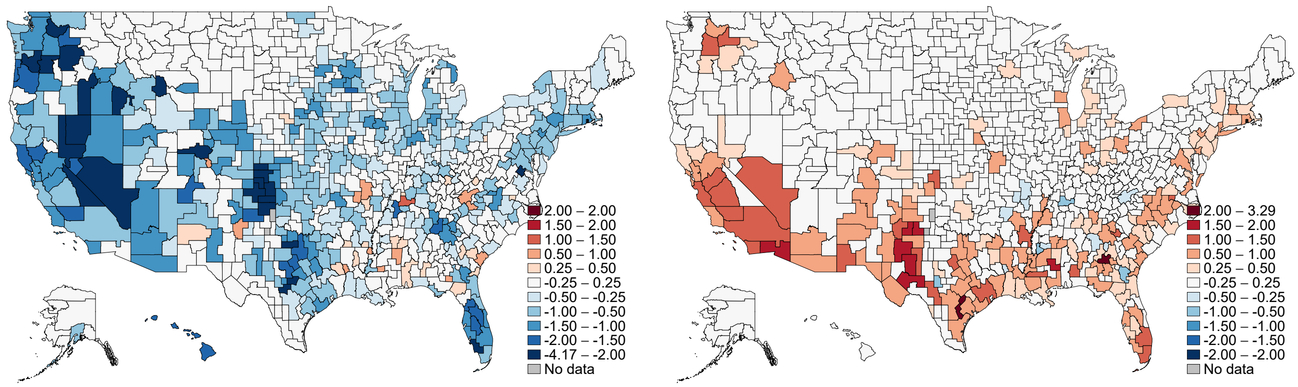
We explore regional patterns of school segregation in Figure 4. The prevalence of white-segregated schools has diminished throughout the country, often at annual rates of 1-4 percentage points, in both highly populated metropolitan areas and relatively less diverse rural areas. Meanwhile, minority-segregated schools have become more prevalent over the sample period throughout the sunbelt (especially along the Southern border) at an annual rate of 0.5-2 percentage points and in urban areas of the Northeast and rust belt at an annual rate of 0.25-1 percentage points. The larger magnitudes and broader geographic scope of the desegregation of white schools relative to the segregation of minority schools has resulted in a public school system that is becoming less segregated overall.[15]

[14]We define a school to be segregated if it is more than 75% white or minority. We find highly similar patterns when we adopt any alternative threshold between 66% and 90% to define a school as segregated. The results of our empirical analysis are also qualitatively unchanged by the use of alternative thresholds.

[15]These findings are consistent with Rivkin (2016), who presents national evidence of recent desegregation in US public schools, and Clotfelter et al. (2006), who documents that segregation levels in Southern schools have remained roughly constant from 1994-2004.

Figure 4: Average Annual Change in Proportion of Segregated Schools, 1988-2014

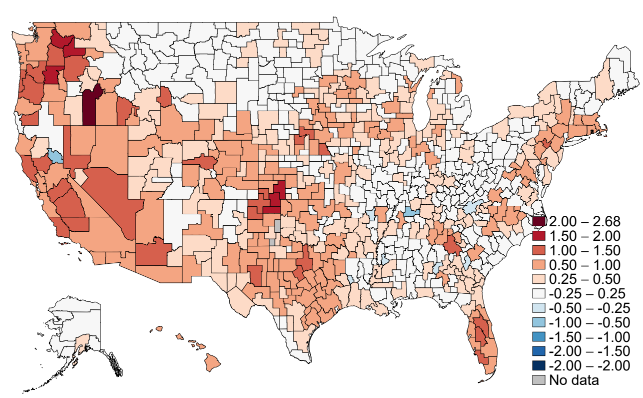
(a) Change in Proportion of Segregated White Schools (b) Change in Proportion of Segregated Minority Schools



Note: We define white-segregated schools as over 75% white, and minority-segregated schools as over 75% minority. Blue (Red) commuting zones have experienced declining (increasing) segregation during this period. Annual changes shown in percentage points.

As a prelude to our analysis, we map demographic change in the aggregate student body in Figure 5 as measured by the average annual change in the minority share of enrollments at the commuting zone level from 1988 to 2014. Thus, in this map we eliminate all sorting across schools within commuting zones, so observed changes in (aggregate) racial composition are attributable only to the demographic mechanism. Demographic change over this period has been widespread, leading to a greater fraction of minority students in all regions of the US except for sparsely populated areas. The association between the spatial distribution of demographic trends in Figure 5 and segregation trends shown in both Figure 2 and Figure 4 is striking and motivates the need for a framework to determine the extent to which this relationship is causal.

Figure 5: Change in Minority Share of Students in Commuting Zone, 1988-2014



Note: Map shows average annual change in the minority share of all students in each commuting zone in percentage points. Red (blue) areas have become more (less) heavily minority.

Remark 1. There are four potential sources of demographic change in aggregate public school enrollments: changes in the racial composition of private school enrollments; changes in fertility rates across races; migration between commuting zones; and immigration. In Appendix C, we present a variety of evidence that leads us to conclude that the demographic change observed during our sample period was largely due to Hispanic immigration. We summarize that evidence here. National private school enrollments of minorities were stable from 1993-2013 while white enrollments decreased slightly (Figure 14); the fertility gap between minorities and whites slightly narrowed from 1971 to 2008[16] (Table 2); black immigration and migration rates were small during the sample period, while Hispanic immigration and migration rates were quite large and widespread (Figure 15); and there was a large observed increase in the absolute number of Hispanic students over the sample period that was not accompanied by a similar change in the numbers of white or black students (Figure 16).

3 Conceptual Framework

We start with a simple model of segregation in the spirit of Schelling (1969) and Becker and Murphy (2000) whereby households observe the characteristics of local schools and then choose where to enroll their children. The key feature of our model is that it explicitly delineates three exhaustive mechanisms through which segregation levels can change over time. For exposition only, we assume that students are either white or minority ($R = \{W, M\}$) in Sections 3 and 4 in order to present the model with two dimensional diagrams. However, in all of our empirical analysis, we allow students to be white, black or Hispanic ($R = \{W, B, H\}$).

Formally, let N_{rt} denote the total number of school-aged children of race $r \in R$ living in a commuting zone with J public schools in year t. For each school j, we define n_{rjt} to be the number of race r students enrolled in year t. The school's racial composition is defined as the minority share

$$s_{jt} = \frac{n_{Mjt}}{n_{Wjt} + n_{Mjt}}. \tag{1}$$

Before the start of each school year, parents observe the characteristics of all public schools in the area (including their historical racial compositions) and then decide where to enroll their child. The race r demand for school j can be written as

[16] Births during this period correspond to students in our sample period.

$$n_{rjt} = N_{rt} \cdot \pi_{rj} \left(\boldsymbol{s_{t-1}}, \boldsymbol{X_t} \right) \tag{2}$$

where the school-race-specific function π_{rj} is the probability that a parent of a given race enrolls their child in a particular school, $\boldsymbol{s_{t-1}}$ is a vector whose jth element is s_{jt-1}, and $\boldsymbol{X_t}$ is a matrix of other school-specific characteristics, whose jth element is vector $\boldsymbol{X_{jt}}$.[17] Together, equations (1) and (2) define how the racial compositions of *all* schools simultaneously evolve from $t-1$ to t; that is, they combine to yield a mapping from $\boldsymbol{s_{t-1}}$ to $\boldsymbol{s_t}$ that defines a J-dimensional dynamic system:

$$s_{jt} = s_{jt}(\boldsymbol{N_t}, \boldsymbol{s_{t-1}}, \boldsymbol{X_t}) \tag{3}$$

where $\boldsymbol{N_t} = (N_{Wt}, N_{Mt})$.

The three arguments in equation (3), $\boldsymbol{N_t}$, $\boldsymbol{s_{t-1}}$, and $\boldsymbol{X_t}$, correspond to three distinct mechanisms underlying these dynamics. First, aggregate demographic changes (i.e., $\boldsymbol{N_t} \neq \boldsymbol{N_{t-1}}$) can cause the racial compositions of individual schools to change simply because all students must enroll somewhere. For example, an influx of minority students into a commuting zone would increase the minority share of at least some schools. We refer to this as the *demographic* mechanism.

Second, parents of different races may respond differently to the racial composition of a school (i.e., $\frac{\partial \pi_{Wj}}{\partial s_{kt-1}} \neq \frac{\partial \pi_{Mj}}{\partial s_{kt-1}}$). If, for instance parents actively pursue segregation, this may lead to dynamic social multiplier effects that can generate the positive feedback loop commonly known as "tipping" (Schelling (1971)). These dynamics will propagate even in the absence of any other changes to the school environment, and we refer to this as the *discriminatory* mechanism. It should be understood as the discriminatory mechanism that fuels school segregation.[18]

Third, segregation may unintentionally arise if parents have different preferences for school or neighborhood characteristics besides their racial compositions (i.e., $\frac{\partial \pi_{Wj}}{\partial x_k} \neq \frac{\partial \pi_{Mj}}{\partial x_k}$ where x_k is a specific characteristic in $\boldsymbol{X_{kt}}$).[19] For instance, if white parents value football more than minority

[17] Hereafter, vectors and matrices are displayed in bold typeface.

[18] This corresponds to the root of racial discrimination as described in Myrdal (1944): "The intensities and proportions in which these conflicting valuations are present vary considerably from one American to another ... are arranged differently in the sphere of valuations of different individuals and groups and bear different intensity coefficients."

[19] Our model of school choice abstracts away from neighborhood choice. To be sure, these choices are likely related to each other. We assume that from the perspective of parents the racial composition of a school is equivalent to the racial composition of its corresponding neighborhood, leaving all other characteristics of the neighborhood to be loaded into the $\boldsymbol{X_{jt}}$ vector. If our assumption is incorrect, then discriminatory responses towards neighbors (beyond any discriminatory responses towards school peers) would be incorrectly attributed to the residual mechanism. In

parents, then all else constant, increases to the football budget of a particular school would be expected to decrease the minority share of enrollment in that school. In contrast to the discriminatory mechanism, changes to these features do not generate a positive feedback loop by themselves. We refer to this as the *residual* mechanism.

We illustrate the dynamics of s_{jt} that arise endogenously from the discriminatory mechanism in Figure 6.[20] In Panel 6a, we plot a *ceteris paribus* curve of s_{jt} on s_{jt-1} holding $\boldsymbol{N_t}$, $\boldsymbol{s_{-jt-1}}$ and $\boldsymbol{X_t}$ fixed[21], which summarizes the evolution of s_{jt} in a canonical "S" curve. Points at which the curve intersects the 45 degree line represent equilibria. In this scenario, we have multiplicity of equilibria because parents intensely discriminate (i.e., $\frac{\partial \pi_{Wj}}{\partial s_{jt-1}} < 0$ or $\frac{\partial \pi_{Mj}}{\partial s_{jt-1}} > 0$ are large in magnitude). In Panel 6b, we plot an alternative *ceteris paribus* curve of s_{jt} on s_{jt-1} if discrimination is weak (i.e., $\frac{\partial \pi_{Wj}}{\partial s_{jt-1}} < 0$ and $\frac{\partial \pi_{Mj}}{\partial s_{jt-1}} > 0$ are small in magnitude). In this scenario, the "S" curve collapses and only intersects the 45 degree line at a single equilibrium. Deducing the dynamics of s_{jt} is straightforward; hypothetically, if the school had a racial composition of s_0, the discriminatory mechanism would result in a racial composition of s_1 one period ahead, s_2 two periods ahead, and so on. The locations of equilibria and the speeds of convergence depend upon $\boldsymbol{N_t}$, $\boldsymbol{s_{-jt-1}}$ and $\boldsymbol{X_t}$ since different values of these would result in shifts and deformations of the curve. This implies that these curves are school-specific (and year-specific). Following the literature (e.g., Bayer and Timmins (2005); Banzhaf and Walsh (2013)), we utilize the "S" curve for the remainder of our exposition.[22]

In order to assess how the demographic (or residual) mechanism interacts with the discriminatory mechanism, we consider the effect of a hypothetical shock in Figure 7. The shock as shown could be an inflow of minorities to the commuting zone (i.e., an increase in N_{Mt}) or a change in some school characteristic or policy that is preferable to minority parents relative to white parents. Panel 7a, depicts a representative school with a racial composition at either point A or B in $t-1$. In the absence of changes, the school at point A would have moved along the solid curve to $A^\star$ through the "baseline" social effect shown as the green arrow (similarly, the school at point B would have moved to $B^\star$). The shock generates an upward shift of the "S" curve to the dashed curve, which

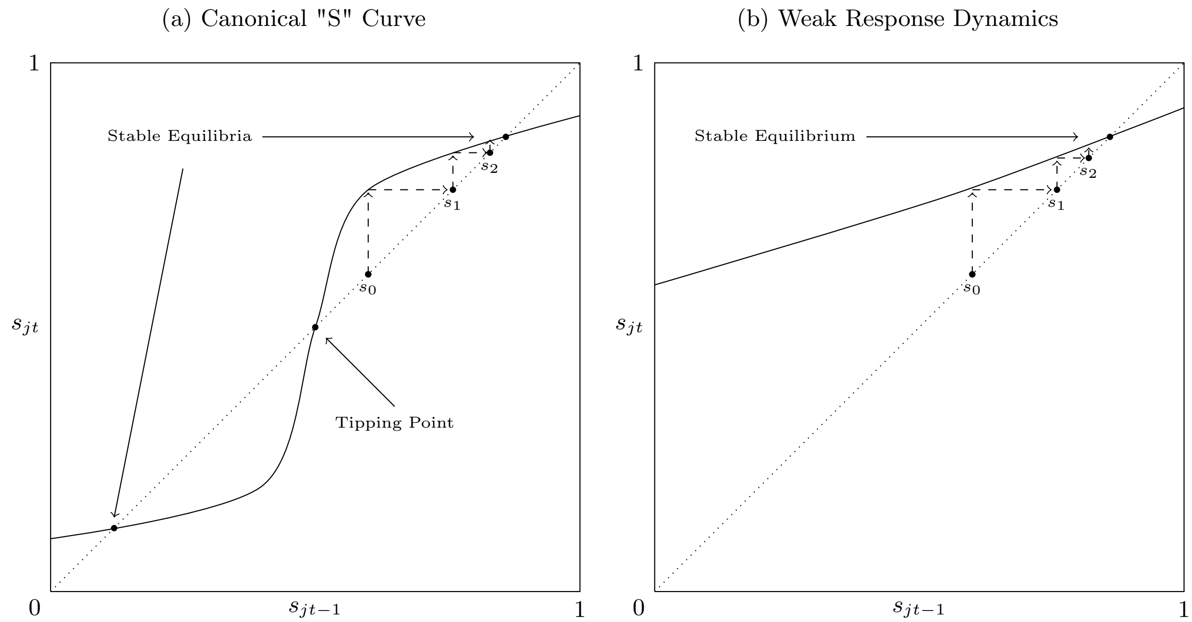
Section 7.1.2, we argue in detail why this is likely not a concern.

[20]To simplify exposition in this section, we assume parents actively pursue segregation, i.e., $\frac{\partial \pi_{Wj}}{\partial s_{jt-1}} < 0$ and $\frac{\partial \pi_{Mj}}{\partial s_{jt-1}} > 0$ when drawing Figure 6. We find robust empirical support for this assumption.

[21]$\boldsymbol{s_{-jt-1}}$ denotes the subvector of $\boldsymbol{s_{t-1}}$ without the element s_{jt-1}.

[22]In practice, we find that some schools have multiple equilibria while others have a single equilibrium. This depends on their commuting zone, neighborhood, grade range and the dynamic profile of their observed racial compositions.

Figure 6: Dynamics of s_{jt}

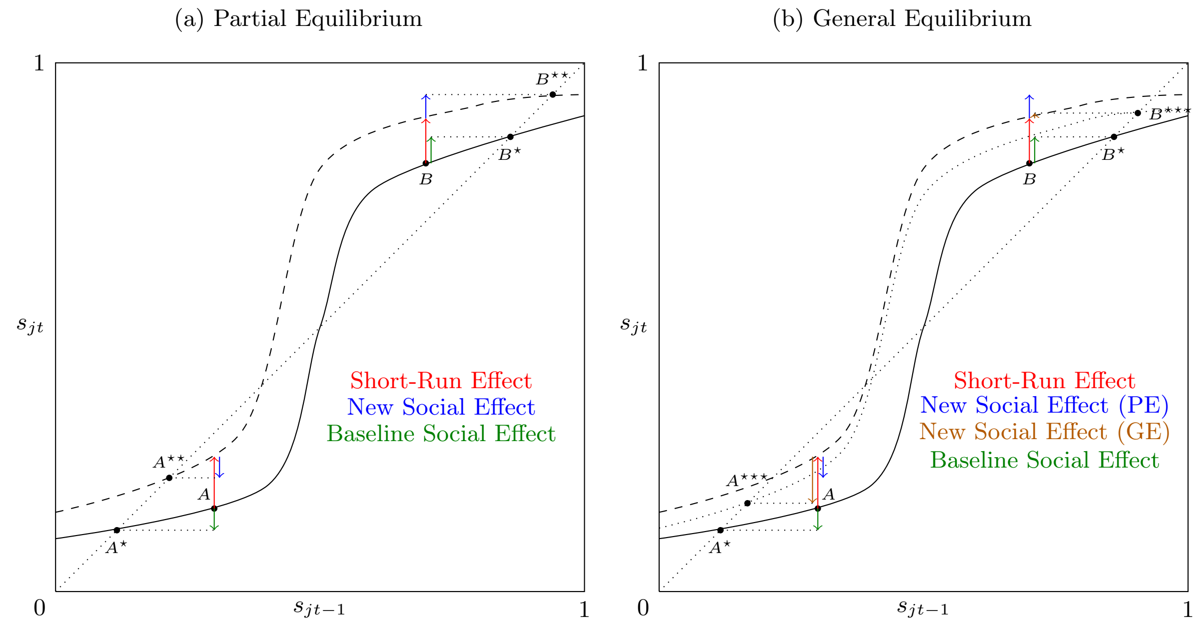


results in new equilibria: $A^{\star\star}$ and $B^{\star\star}$. For the school at point A, the shock from $t-1$ to t generates the short-run effect shown as the red arrow. The discriminatory mechanism then acts as a dynamic social multiplier, generating an additional social effect from t onward shown as the blue arrow. The long-run demographic effect will be equal to the short-run effect plus the new social effect, net of the baseline social effect; this is simply the vertical distance from $A^{\star}$ to $A^{\star\star}$. Similar logic holds for the school at point B. Note that the magnitudes of these effects depend not only on the size of the shock but also on the locations of the stable equilibria and the shapes of the "S" curves, all of which also depend on $\boldsymbol{s_{-jt-1}}$, $\boldsymbol{X_t}$ and the shape of π_{rj} for all r.[23] Moreover, the magnitudes of these effects also depend upon the extent to which schools are out of equilibrium in $t-1$. In the rare case that school j is in equilibrium in $t-1$, the "baseline" social effect would simply be equal to zero. Still, the new social effect would be non-zero, as the shift in the curve would take the school out of equilibrium.

The diagram shown in Figure 7a only shows the dynamics of a single school, so the equilibria as drawn represent "partial" equilibria. However, equation (2) implies that enrollment demand for a single school j is a function of the prior racial compositions of *all* schools in the commuting

[23]The function π_{rj} captures the degree of substitution between school j and the other schools $k \neq j$, and the degrees of complementarity/substitution between the amenities of a given school.

Figure 7: Effects of Changes in Demographics/Other Characteristics on s_{jt}



zones ($\boldsymbol{s_{t-1}}$) depending on substitution patterns across schools. For example, a demographic shock that shifts the "S" curve of school j upward is likely to shift the "S" curve of a school j' that is a close substitute upward as well. All else constant, the associated increase in $s_{j't}$ will make school j relatively less attractive to minority parents and more attractive to white parents in $t+1$ (because a close substitute, j', became disproportionately more attractive to minorities), resulting in a small *downward* shift in the "S" curve of school j. These effects will feed back between these two schools and any others that are substitutes leading to potentially complex general equilibrium effects on the dynamics of other schools.[24] We represent these general equilibrium effects as additional shifts of the "S" curve (shown in Panel 7b) that dampen the effect of the initial shock.[25] This results in a new GE social effect that is smaller than the new social effect from a partial equilibrium perspective.[26]

[24] General equilibrium effects may propagate even in the absence of external shocks if at least one school is out of equilibrium. As the racial composition of that school moves *along* its "S" curve, it becomes differently attractive to schools that are substitutes, inducing *shifts* in their own "S" curves. This shift pushes those schools out of equilibrium, starting the feedback loop anew.

[25] For illustrative purposes only, Figure 7 ignores the fact that the "old" social effect that accounts for general equilibrium effects will generally differ from the partial equilibrium "old" social effect.

[26] In practice, we find that social effects are greatly dampened in general equilibrium, as a naive partial equlbrium analysis yields social effects that are at least three times as large as those presented here.

4 Empirical Approach

We now develop an empirical approach that allows us to take our conceptual framework to data. Our goal is to study how the racial compositions of (all) schools change over time with the understanding that observed changes may be attributable to movements along the "S" curve (i.e., the discriminatory mechanism) towards equilibrium, demographic shocks, or any other exogenous shift in the "S" curve that may or may not change the locations of equilibria. We do so by constructing "S" curves for every school that vary explicitly in $\boldsymbol{s}$ and $\boldsymbol{N}$ and that vary implicitly in $\boldsymbol{X}$ in order to characterize the dynamic system of segregation. This requires us to identify how π_{rj} varies with $\boldsymbol{s_{t-1}}$. Enrollment responses to s_{jt-1} pin down the shape of j's "S" curve — i.e., how movements along the "S" curve occur – while enrollment responses to $\boldsymbol{s_{-jt-1}}$ pin down the general equilibrium effects. These responses can be obtained from a standard discrete choice framework (McFadden (1973); Berry (1994)).[27] Here, we present a simpler and mathematically equivalent reduced-form estimation approach (see Caetano and Maheshri (2017)). For exposition, we describe our approach for a single commuting zone; in practice, it is implemented simultaneously across all commuting zones.

We first specify the log-demand equation for school j by parents of race r as:[28]

$$\log n_{rjt} = \beta_r \cdot s_{jt-1} + \gamma_{rt} + \epsilon_{rjt} \tag{4}$$

The parameter β_r represents the enrollment response to the minority share of the school by parents of each race. The race-year fixed effect γ_{rt} subsumes N_{rt} and encapsulates any demographic changes in the racial composition of aggregate (i.e., commuting zone-level) enrollments (due to fertility, migration, shifts to private schools, etc). Finally, the residual ϵ_{rjt} subsumes $\boldsymbol{X_t}$ and $\boldsymbol{s_{-jt-1}}$ and includes all school-specific characteristics (other than its minority share) that affect the choices of households who already have decided to enroll their child in a public school.[29]

[27] The outside option in our analysis corresponds to enrolling a child in any non-public school. Thus, trends in the proportion of students of each race into and out of the outside option should be understood as part of the demographic channel. As we discuss in Remark 1, nearly all demographic changes during our sample period can be attributed to immigration.

[28] To arrive at this equation, we take logarithms on both sides of equation (2) and assume that $\log \pi_{rj}(\cdot)$ is additively separable in s_{jt-1}. We do not need to assume that $\log \pi_{rj}(\cdot)$ is separable in $s_{j't-1}$ for $j' \neq j$. This allows the function $\pi_{rj}(\cdot)$ to accommodate more complex substitution patterns across schools, as the relationship between $\boldsymbol{X_{jt}}$ and $\boldsymbol{s_{-jt-1}}$ is unrestricted.

[29] The specification presented here corresponds to a choice model in which parents first choose a commuting zone

With causal estimates of the social effects, $\hat{\beta}_r$, we can simulate the evolution of the racial compositions of all schools into the future under different counterfactuals. Equations (1) and (2) have empirical analogs that describe how any counterfactual state vector $\tilde{\boldsymbol{s}}_{\boldsymbol{jt-1}}$ will evolve (given some counterfactual trajectory of the aggregate commuting zone enrollments, $\tilde{\boldsymbol{N}}_{\boldsymbol{t}}$). To simulate this trajectory from t_0, we use the following equations of motion:

$$s_j\left(\tilde{\boldsymbol{N}}_{\boldsymbol{t}}, \tilde{\boldsymbol{s}}_{\boldsymbol{jt-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) = \frac{\hat{n}_{Mj}\left(\tilde{N}_{Mt}, \tilde{\boldsymbol{s}}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right)}{\hat{n}_{Mj}\left(\tilde{N}_{Mt}, \tilde{\boldsymbol{s}}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) + \hat{n}_{Wj}\left(\tilde{N}_{Wt}, \tilde{\boldsymbol{s}}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right)} \ \forall j \tag{5}$$

along with the estimated demand functions

$$\hat{n}_{rj}\left(\tilde{N}_{rt}, \tilde{\boldsymbol{s}}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) = \tilde{N}_{rt} \cdot \hat{\pi}_{rj}\left(\tilde{\boldsymbol{s}}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) \ \forall r, j \tag{6}$$

where the simulated probability of a race r parent choosing school j in t is estimated as

$$\hat{\pi}_{rj}\left(\tilde{\boldsymbol{s}}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) = \frac{\exp\left(\log n_{rjt_0} + \hat{\beta}_r\left(\tilde{s}_{jt-1} - s_{jt_0-1}\right)\right)}{\sum_k \exp\left(\log n_{rkt_0} + \hat{\beta}_r\left(\tilde{s}_{kt-1} - s_{kt_0-1}\right)\right)} \tag{7}$$

and the initial condition $\tilde{\boldsymbol{s}}_{\boldsymbol{t_0-1}} = \boldsymbol{s}_{\boldsymbol{t_0-1}}$ (i.e., the counterfactual value for year $t_0 - 1$ is set to the observed value).[30]

The change in s_j from t_0 to t attributable to the discriminatory mechanism is calculated as

$$\begin{aligned} \Delta^d_{jt_0\to t} &= \hat{s}_j\left(\boldsymbol{N}_{\boldsymbol{t_0}}, \boldsymbol{s}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) - s_{jt_0} \\ &= \hat{s}_j\left(\boldsymbol{N}_{\boldsymbol{t_0}}, \boldsymbol{s}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) - s_j\left(\boldsymbol{N}_{\boldsymbol{t_0}}, \boldsymbol{s}_{\boldsymbol{t_0-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) \end{aligned} \tag{8}$$

$\hat{s}_j\left(\boldsymbol{N}_{\boldsymbol{t_0}}, \boldsymbol{s}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right)$ corresponds to the racial composition of j in t in the absence of any external

to live in and then consider all schools within that commuting zone. However, by specifying the fixed effects γ at narrower levels, e.g. at the neighborhood-race-year level, we would instead estimate a parameter from a choice model in which parents first choose a neighborhood and then consider all schools within that neighborhood. In Section 7.1.2, we present results from alternative formulations of this choice problem and note that our results are insensitive to the specification. This suggests that our estimate of β reflects all relevant discriminatory responses that occur within the commuting zone.

[30]This specific functional form is implied by a discrete choice model whereby parents, having already chosen to enroll their child in a public school in the commuting zone, then choose the school their child will attend. See Caetano and Maheshri (2017).

change to demographics or school characteristics from t_0 to t; hence s_{jt_0} can only change from t_0 to t through the discriminatory channel. The change in s_j from t_0 to t attributable to the demographic mechanism can be calculated as

$$\Delta^D_{jt_0 \to t} \quad = \quad \hat{s}_j \left(\boldsymbol{N_t}, \boldsymbol{s_{t-1}}, \boldsymbol{X_{t_0}} \right) - \hat{s}_j \left(\boldsymbol{N_{t_0}}, \boldsymbol{s_{t-1}}, \boldsymbol{X_{t_0}} \right) \tag{9}$$

since $\hat{s}_{jt} \left(\boldsymbol{N_t}, \boldsymbol{s_{t-1}}, \boldsymbol{X_{t_0}} \right)$ differs from $\hat{s}_{jt} \left(\boldsymbol{N_{t_0}}, \boldsymbol{s_{t-1}}, \boldsymbol{X_{t_0}} \right)$ only in terms of aggregate demographics. Finally, the change in s_j attributable to the residual mechanism can be calculated as

$$\begin{aligned} \Delta^R_{jt_0 \to t} &= s_{jt} - \hat{s}_j \left(\boldsymbol{N_t}, \boldsymbol{s_{t-1}}, \boldsymbol{X_{t_0}} \right) \\ &= s_j \left(\boldsymbol{N_t}, \boldsymbol{s_{t-1}}, \boldsymbol{X_t} \right) - \hat{s}_j \left(\boldsymbol{N_t}, \boldsymbol{s_{t-1}}, \boldsymbol{X_{t_0}} \right) \end{aligned} \tag{10}$$

since $s_{jt} \left(\boldsymbol{N_t}, \boldsymbol{s_{t-1}}, \boldsymbol{X_t} \right)$ differs from $\hat{s}_{jt} \left(\boldsymbol{N_t}, \boldsymbol{s_{t-1}}, \boldsymbol{X_{t_0}} \right)$ only in terms of school characteristics. Note that $\Delta^d_{jt_0 \to t} + \Delta^D_{jt_0 \to t} + \Delta^R_{jt_0 \to t} = s_{jt} - s_{jt_0}$, so they represent a full decomposition of the observed change in racial composition.

Identification of β

Identifying social effects such as β_r is known to be a difficult problem (Manski (1993)). School characteristics that lead parents to chose a particular school in $t-1$ tend to persist into period t. If white and minority parents have different preferences for such characteristics, then the OLS estimate of β_r will be biased upward (in magnitude). This suggests that we may be able to identify β_r with a *transitory* shocks to school characteristics that affected enrollment in $t-1$. By construction, transitory shocks in $t-1$ do not persist into t, so they cannot directly affect enrollment in t onward. Of course, data on transitory variation in school characteristics for all schools in the entire country is infeasible to obtain. We circumvent this obstacle with the identification strategy proposed in Caetano and Maheshri (2017).

In order to isolate exogenous variation in s_{jt-1}, we focus on the component of s_{jt-2} that is orthogonal to determinants of n_{rjt-1}. The cohort structure of schooling presents a natural source of such variation: students enrolled in the second highest grade of school j in $t-2$ no longer enroll in that school in t since they have aged out. Hence, the racial composition of this cohort (the *IV cohort*) mechanically influences s_{jt-1} without directly affecting n_{rjt}. Still, this alone may not be a suitable IV because school characteristics that led students in the IV cohort to choose j may persist into t. We address this issue by controlling for the enrollments of subsequent cohorts of students (the *control cohorts*) in $t-1$.

We present our identification strategy in three steps. First, we index all variables by c so we can analyze parents' enrollment decisions in every commuting zone in the US simultaneously. We then enrich equation (4) to allow school demand to vary by grade:

$$\log n_{rgjct} = \beta_{rg} \cdot s_{jct-1} + \gamma_{rgct} + \epsilon_{rgjct}, \tag{11}$$

n_{rgjct} refers to the number of race r students enrolled in grade g in school j in commuting zone c in year t. The parameter β_{rg} represents the enrollment response of each race to the minority share of the school, and it is now allowed to vary by grade.[31] The race-grade-commuting zone-year fixed effects, γ_{rgct}, encapsulate the demographic effect (disaggregated by grade).[32] Finally, the error term ϵ_{rgjct} incorporates the remainder of the determinants of the school demand.

Second, we add to equation (11) the control vector $C_{rgjct-1}$:

$$\log n_{rgjct} = \gamma_{rgct} + \beta_{rg} s_{jct-1} + \underbrace{\sum_{i=\underline{g}_j}^{\bar{g}_j-1} \left(\alpha_{rigcW} \log n_{Wijct-1} + \alpha_{rigcM} \log n_{Mijct-1}\right)}_{C_{rgjct-1}} + u_{rgjct}, \tag{12}$$

where $\underline{g}_j$ and $\overline{g}_j$ are the lowest and highest grades of instruction of school j, respectively.

Third, we use

$$s_{jct-2}^{\bar{g}_j-1} = \frac{n_{M\bar{g}_j-1jct-2}}{n_{M\bar{g}_j-1jct-2} + n_{W\bar{g}_j-1jct-2}} \tag{13}$$

as an IV for s_{jct-1}. Our IV estimator of β_{rg} is consistent under the following identifying assumption:

[31] In practice, we also allow β_{rg} to vary across commuting zones depending on their student population.

[32] In practice, as a robustness check we also include fixed effects at finer geographic areas than commuting zones such as school districts.

Assumption 1. *Identifying Assumption.* $Cov\left[s_{jt-2}^{\bar{g}_j-1}, u_{rgjct}|C_{rgjct-1}, \gamma_{rgct}\right] = 0.$[33]

That is, if we control for the enrollments of all students in all grades except for the last grade in year $t-1$, then the racial composition of the IV cohort as observed in $t-2$ is a valid IV for the overall racial composition of the school in $t-1$. By controlling for the enrollments of *subsequent* cohorts of students in $t-1$, we effectively control for all school characteristics that persisted from $t-2$ to $t-1$. In words, our identification assumption states that all unobserved school characteristics relevant to prospective parents that persist from $t-2$ to t must have also persisted from $t-2$ to $t-1$. That is, no school characteristic can lose salience to parents in $t-1$ and then suddenly become salient again in t.

For concreteness, we explain our strategy using a 9-12 high school as an example in the diagram below. Our IV is s_{jct-2}^{11}, the minority share of grade 11 (the second highest grade) in $t-2$. (Cohorts age diagonally in this diagram – e.g., the IV cohort is in grade 11 in $t-2$, grade 12 in $t-1$, and out of school in t.) For our IV to be valid, we control for the $t-1$ enrollments of whites and minorities in all grades except for the highest grade (i.e., grades 9, 10 and 11).

	9^{th}	10^{th}	11^{th}	12^{th}
t	Dep. Var.	Dep. Var.	Dep. Var.	Dep. Var.
$t-1$	Control	Control	Control	
$t-2$			IV	
$t-3$		IV		

This IV strategy is feasible for any school that offers at least two grades of instruction. For schools that offer more than two grades of instruction, we can construct additional IVs from the minority shares of the third highest grade in $t-3$ (s_{jct-3}^{10} in the diagram above), the fourth highest grade in $t-4$, etc., which allows us to perform over-identification tests (Hansen (1982)). A detailed discussion of the relevance and validity of our IVs is provided in Appendix A.[34]

[33] This assumption contains an abuse of notation for simplicity. We actually condition on the variables in $\left\{\log n_{rgjt-1}; g = \underline{g}_j, \ldots, \bar{g}_j - 1, r = W, M\right\}$, not on C_{rgjt-1} as written above. In practice, we find that a linear projection of these variables and a more flexible specification of these variables generate the same results.

[34] We should note that our IV strategy differs from the well known IV strategy in Hoxby (2000) that also uses variation in adjacent cohort enrollments. Ours is primarily distinguished by the use of variation only from the oldest cohort and the inclusion of control variables to block grade specific amenities.

Remark 2. As parameters of demand responses, β_{rg} represent how individuals' enrollment *choices* are affected by the prior racial compositions of schools. This should not be conflated with individuals' *preferences* for the past racial composition of a school or any simple transformation thereof. While it is true that β_{rg} is influenced by parents' preferences for the racial composition of schools, it is also comprised of all other environmental considerations that affect the ability of parents to exercise those preferences such as moving costs and the availability of local schools with desired amenities. Hence, the finding of a small value of β_{rg} should not be interpreted as evidence of weak racial discriminatory preferences of race r parents. Instead, it should be interpreted only as weak discriminatory demand *responses*, which is also compatible with strong discriminatory preferences but a weak ability to exercise those preferences. Moreover, as in most of this literature, we do not differentiate whether this parameter reflects taste-based discrimination, statistical discrimination, or some combination of the two.

5 Estimation Results

Our identification strategy requires grade-level enrollment data. Because this is only available starting in 2002, we can only decompose changes in segregation from 2002-2014.[35] In practice, we allow white, black and Hispanic parents to respond differently to their children's peers of each of these three races. We also allow for spatial heterogeneity in their responses by subdividing commuting zones into four groups by the size of their public school population.[36] Thus, equation (12) transforms into the estimation equation

$$\log n_{rgjct} = \gamma_{rgct} + \boldsymbol{\beta_{rgc}}'\boldsymbol{s_{jct-1}} + C_{rgjct-1} + u_{rgjct}, \tag{14}$$

where $\boldsymbol{\beta_{rgc}}$ is now a 2×1 column vector that contains race r parents' responses to the shares of black and Hispanic students in grade g and commuting zone c respectively.[37] Given three races, 13

[35] We discuss how our results from 2002-2014 can inform our understanding of segregation from 1988-2001 in Remark 4.

[36] We grouped commuting zones by first taking logarithms of their total student enrollments and then assigning to group 1 all zones below the mean (the 362 smallest commuting zones), to groups 2 and 3 the zones up to one or two standard deviations above the mean (the 243 and 100 next largest commuting zones respectively), and to group 4 the zones over two standard deviations above the mean (the 15 largest commuting zones in the country). Because larger commuting zones have more schools in them, this subdivision results in four groups that contain a roughly similar number of schools.

[37] The control term $C_{rgjct-1}$ is now equal to $\sum_{i=\underline{g}_j}^{\bar{g}_j-1} (\alpha_{rigcW} \log n_{Wijct-1} + \alpha_{rigcB} \log n_{Bijct-1} + \alpha_{rigcH} \log n_{Hijct-1})$. We use as IVs the 2×1 vector $\boldsymbol{s_{jct-2}^{\bar{g}_j-1}}$ defined for the black and Hispanic shares of enrollments in an analogous

grades, four groups of commuting zones, and two responses (to the black and Hispanic shares of the school) for each race-grade-commuting zone group, $\boldsymbol{\beta_{rgc}}$ corresponds to 312 distinct parameters that capture heterogeneity in enrollment responses between parents of different races, grades and sizes of commuting zones. With such a large number of parameters, we report our results by averaging estimates along different dimensions to highlight relevant heterogeneity in a digestible format.

In Figure 8, we present estimates of white parents' responses to the racial composition of their childrens' school. In Panel (a), we see that white parents with children of all grades respond negatively to both black and Hispanic peers. This response is larger for black peers, though this difference is not always statistically significant. These responses are slightly stronger in earlier grades and in grades K, 6 and 9, which commonly mark transitions into elementary, middle and high school respectively. This is consistent with the notion that the estimates comprise both preferences for peers and constraints on switching schools.[38] In Panels (b) and (c), we aggregate these responses across grades and disaggregate them by commuting zone. This spatial variation is primarily driven by heterogeneity in the sizes of commuting zones.[39] In Panel (b), we find that white parents respond negatively to an increase in black peers in more populous commuting zones, which tend to have sizable black student populations. However, white parents have very small negative responses to black peers in less populous areas. In Panel (c), we find that white parents have extremely small negative responses to Hispanic peers everywhere but slightly larger negative responses in more populous areas.

In Figure 9, we present analogous estimates of black parents' responses to the racial composition of their childrens' school. In Panel (a), we see that black parents respond very strongly and positively to black peers; they exhibit a much weaker positive response to Hispanic peers. As in the case of white parents, the responses spike in grades K, 6 and 9 but to a much greater degree. In Panel (b), we find that black parents respond most positively to black peers in parts of the country where black peers are most scarce. These discriminatory responses exceed black parents' responses in large urban areas by a factor of four on average. In Panel (c), we find that black parents' responses to Hispanic peers are very small in urban areas, and moderate elsewhere.

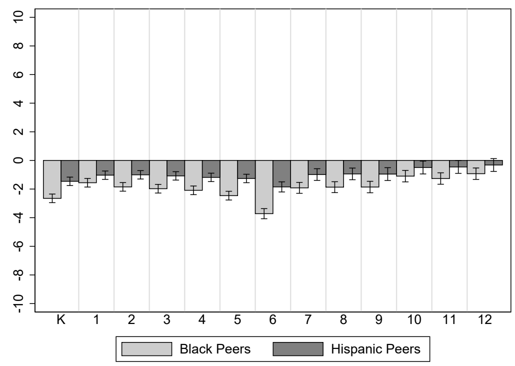
manner to equation (13).

[38]See appendix Figure 13 for the distribution of schools by grade range in the country.

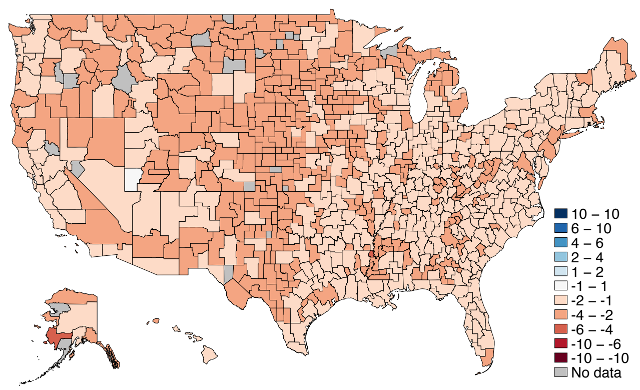
[39]The spatial variation in the maps of parental responses also incorporates variation in the grade structure of schools in different commuting zones.

Figure 8: Estimates of White Parents' Responses to Black and Hispanic Peers, 2005-2014

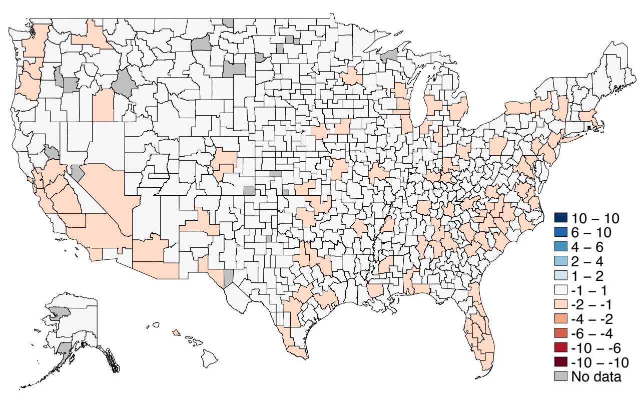
(a) Responses by Grade



(b) Responses to Black Peers by Commuting Zone



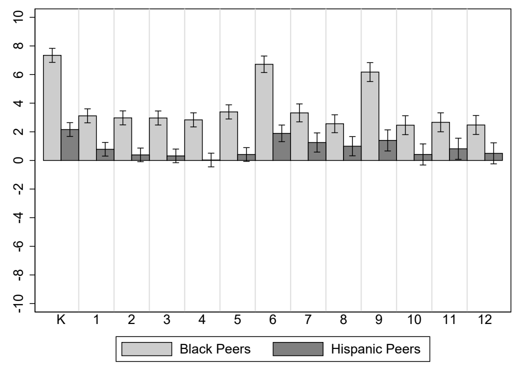
(c) Responses to Hispanic Peers by Commuting Zone



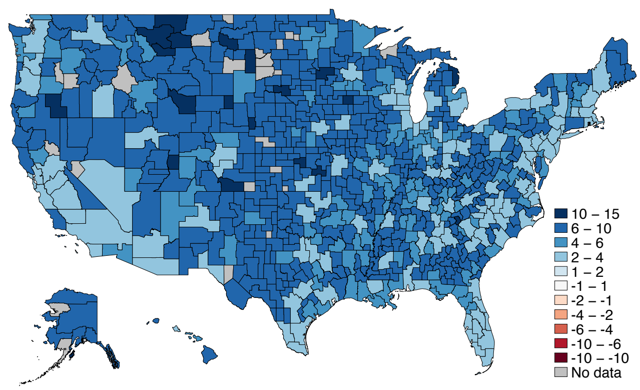
Notes: Estimates obtained from equation (14) are aggregated across commuting zones in Panel (a) and across grades in Panels (b) and (c). In Panel (a), the 95% confidence intervals shown are constructed with standard errors that are clustered at the race-grade-year-commuting zone level. For a few sparsely populated commuting zones, we were unable to estimate responses in Panels (b) and (c) because of a lack of enrollment data. The p-values from F-tests of whether the IVs ($s_{jt-2}^{\bar{g}_j-1}$ and $s_{jt-3}^{\bar{g}_j-2}$) are significant in the first stage regressions are always less than 1%. There are 6,089,772 school-race-grade-year observations in the sample.

Figure 9: Estimates of Black Parents' Responses to Black and Hispanic Peers, 2005-2014

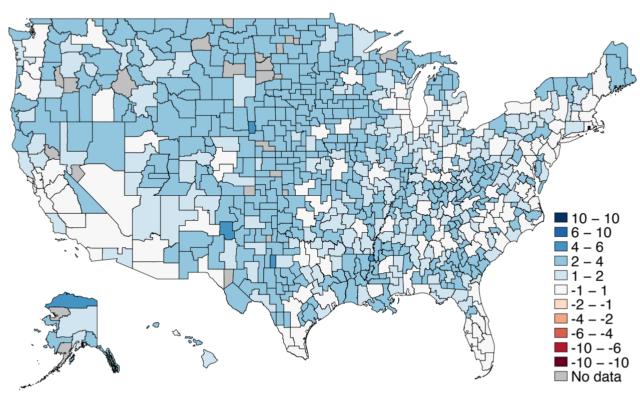
(a) Responses by Grade



(b) Responses to Black Peers by Commuting Zone



(c) Responses to Hispanic Peers by Commuting Zone



Notes: Estimates obtained from equation (14) are aggregated across commuting zones in Panel (a) and across grades in Panels (b) and (c). In Panel (a), the 95% confidence intervals shown are constructed with standard errors that are clustered at the race-grade-year-commuting zone level. For a few sparsely populated commuting zones, we were unable to estimate responses in Panels (b) and (c) because of a lack of enrollment data. The p-values from F-tests of whether the IVs ($s_{jt-2}^{\bar{g}_j-1}$ and $s_{jt-3}^{\bar{g}_j-2}$) are significant in the first stage regressions are always less than 1%. There are 6,089,772 school-race-grade-year observations in the sample.

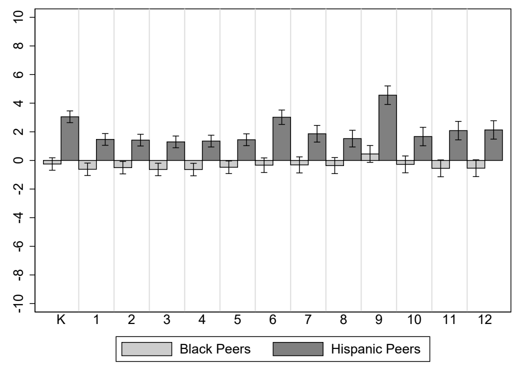
Finally, in Figure 10, we present analogous estimates of Hispanic parents' responses. In Panel (a), we see that Hispanic parents respond positively to Hispanic peers in all grades. These discriminatory responses are smaller in magnitude than those for black parents, but they still spike in grades K, 6 and 9. Hispanic parents exhibit little response to black peers in all grades and all regions of the country (Panel (b)). However, as in the case of black parents, Hispanic parents have weaker positive responses to Hispanic peers in areas with large Hispanic populations and stronger positive responses in the interior of the country, which has a smaller Hispanic population (Panel (c)).

The asymmetric responses of black parents to Hispanic peers (mildly positive) and Hispanic parents to black peers (zero or slightly negative) highlight important heterogeneity across minorities that is often overlooked in this literature. Moreover, this asymmetry supports our claim that the instruments identify racial responses *per se* as opposed to responses to any other variables that are correlated between black and Hispanic households such as income.

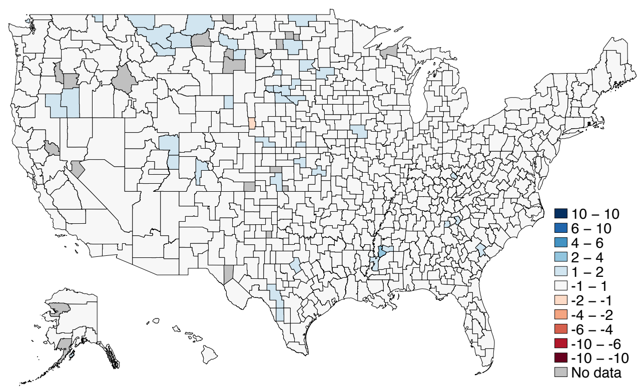
To summarize, (1) white parents react less strongly than minority parents to changes in the racial composition of schools. However, this does not necessarily imply that white parents have less discriminatory preferences than minority parents; it might only reflect the fact that minority parents can more easily translate their discriminatory preferences into choices, e.g., they may have lower moving costs (because they are more likely to be renters) or attendance areas with more minorities may be less expensive to live in. (2) Black and Hispanic parents are strongly attracted to own race peers. This attraction is strongest where own-race peers are scarce, which may reflect the notion of "comfort-in-numbers." (3) Black parents have mildly positive responses to Hispanic peers, but Hispanic parents are unresponsive to peers of any other race. (4) Parents' responses are of roughly similar magnitude across grades but tend to be strongest in grades K, 6 and 9.

Figure 10: Estimates of Hispanic Parents' Responses to Black and Hispanic Peers, 2005-2014

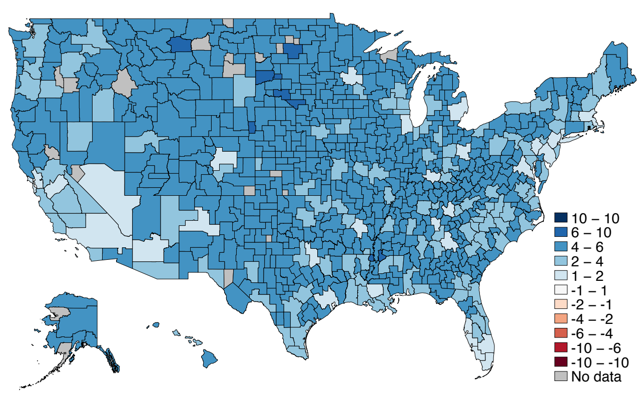
(a) Responses by Grade



(b) Responses to Black Peers by Commuting Zone



(c) Responses to Hispanic Peers by Commuting Zone



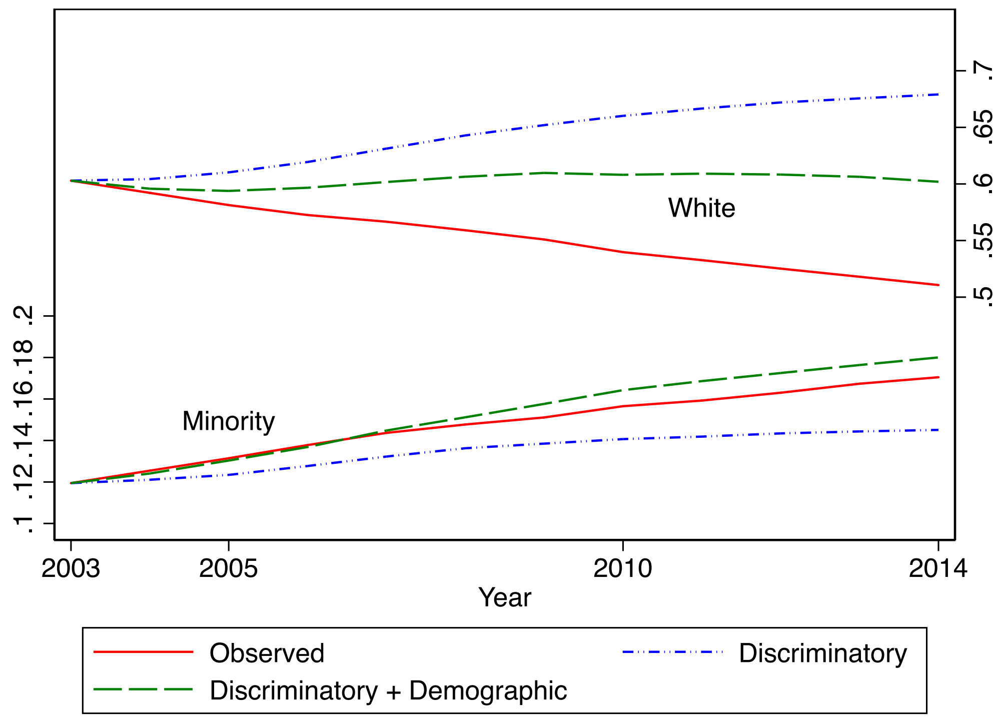
Notes: Estimates obtained from equation (14) are aggregated across commuting zones in Panel (a) and across grades in Panels (b) and (c). In Panel (a), the 95% confidence intervals shown are constructed with standard errors that are clustered at the race-grade-year-commuting zone level. For a few sparsely populated commuting zones, we were unable to estimate responses in Panels (b) and (c) because of a lack of enrollment data. The p-values from F-tests of whether the IVs ($s_{jt-2}^{\bar{g}_j-1}$ and $s_{jt-3}^{\bar{g}_j-2}$) are significant in the first stage regressions are always less than 1%. There are 6,089,772 school-race-grade-year observations in the sample.

6 Simulation Results

We construct various counterfactual time series of s_{jt} over our sample period in order to decompose observed changes in segregation. We first compute how the racial compositions of schools would have evolved in the absence of any demographic shocks, local amenity shocks or policy changes. We denote it as $\tilde{s}^{d}_{jt} = \hat{\Delta}^{d}_{2003\to t}$ as it only reflects changes in s_{jt} due to the discriminatory mechanism. We then compute how the racial compositions of schools would have evolved in the absence of local amenity shocks or policy changes, which we denote as $\tilde{s}^{dD}_{jt} = \hat{\Delta}^{d}_{2003\to t} + \hat{\Delta}^{D}_{2003\to t}$. This time series reflects changes in s_{jt} due to demographic shocks and all subsequent endogenous adjustments to those shocks (due to discrimination). It follows that the remaining change in s_{jt} is attributable to the residual mechanism.

For each counterfactual time series of racial compositions, we calculate how the prevalence of school segregation would have evolved. In Figure 11, we present the proportions of white- and minority-segregated schools that were observed in the data and the proportions of segregated schools that would have existed under the two counterfactuals over a 12 year period. Three results are immediate. First, discriminatory sorting, in the absence of any other changes to the school environment, would have increased the proportion of white- and minority-segregated schools by roughly 12 and 2 percentage points respectively. Second, demographic shocks mitigated over three quarters of the effects of discriminatory sorting for white-segregated schools, but it exacerbated the proliferation of minority-segregated schools. Third, the residual mechanism always reduces segregation. We conjecture that this is because school and neighborhood characteristics may have adjusted to accommodate new inflows of Hispanics. As Hispanics become more prevalent in the country, non-discriminatory sorting might then lead to greater mixing of races in many commuting zones.

Figure 11: Decomposing Observed Changes in the Prevalence of Segregated Schools, 2003-2014



Notes: A white- (minority-) segregated school has over 75% white (minority) enrollment. The decomposition is implemented for all schools who operate in every year from 2003-2014 and averaged annually across the US. The solid red, dotted blue and dashed green paths correspond to segregation levels computed with $\tilde{s}^{A}_{jt}$, $\tilde{s}^{AD}_{jt}$ and s_{jt} respectively. The total vertical change in the dotted blue path corresponds to the change in segregation through the discriminatory channel, the vertical difference between the dashed green path and blue path corresponds to the change in segregation through the demographic channel, and the vertical difference between the solid red path and the dashed green path corresponds to the change in segregation through the residual channel.

As observed in Figure 3, the largest changes in the school segregation occurred in the largest commuting zones, so in Figure 12 we present these counterfactual trajectories against commuting zone population. A histogram of the log(population) of commuting zones and representative cities for the largest bins of commuting zones are provided for context.[40] Discriminatory sorting is essentially zero in very small commuting zones and weak in very large commuting zones, but in mid-size commuting zones, it can be quite large. It always contributes to increasing segregation. The demographic mechanism (as measured by the vertical distance between the dotted blue and dashed green curves) tends to be strong everywhere except for the smallest commuting zones, and it is even stronger in the largest commuting zones. This is consistent with the fact that demographic

[40]NYC= New York, NY; HOU= Houston, TX; PHX=Phoenix, AZ; SEA=Seattle, WA; SAC=Sacramento, CA; MEM=Memphis, TN; WIC=Wichita, KS; ANC=Anchorage, AK.

change has been widespread, except in the most sparsely populated regions of the country, and it has been particularly notable in large urban areas. In all commuting zones, the demographic mechanism has led to desegregation of white schools and segregation of minority schools. Finally, the residual mechanism is weak in the smallest and largest commuting zones but stronger in mid-size commuting zones. It always contributes to desegregation of both white and minority schools with the exception of the largest cities in which it has led to an increase in minority-segregated schools. Indeed, this may help explain why the largest cities have experienced a greater increase in minority-segregated schools than slightly smaller cities as the residual mechanism's contribution to segregation is increasing in population in the right of Panel (b). We conjecture that this reflects the fact that the largest commuting zones have more fragmented schooling markets with multiple large school districts and heterogeneous suburbs. As the suburbs of the largest cities have grown increasingly diverse,[41] certain schools in certain areas might accommodate inflows of new Hispanic students better than others. As discussed in Caetano and Maheshri (2019), this can be understood as a consequence of the "Tyranny of the Market" (Waldfogel (2009)) whereby thicker markets allow minority households to sort more intensely, leading to further segregation.

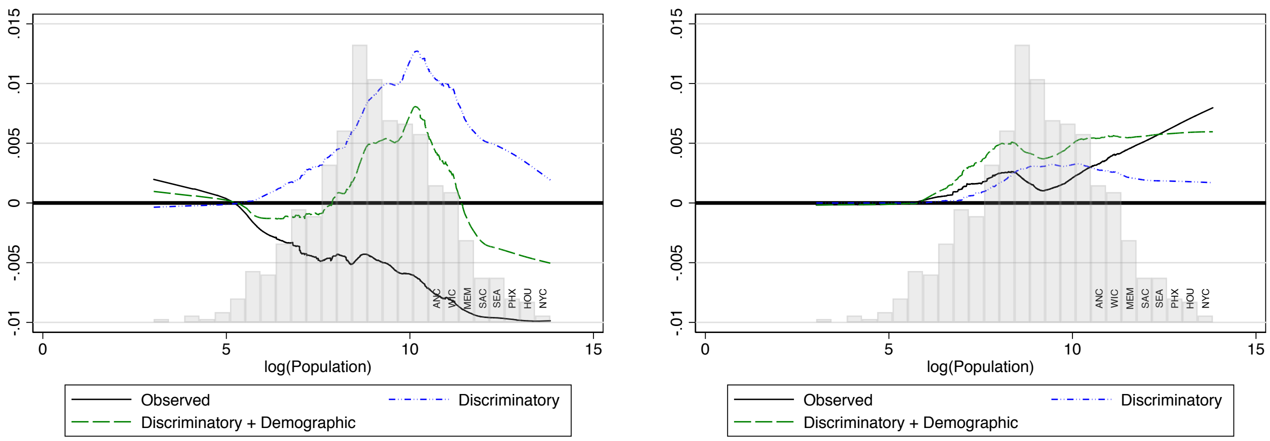
To summarize: All three mechanisms have played roles in explaining the evolution of school segregation from 2003 to 2014, and their relative importance varies systematically. While the discriminatory and residual mechanisms are of similar and large importance for mid-size cities, the demographic mechanism is substantially more important for larger cities where the discriminatory mechanism is extremely weak. In the absence of exogenous changes to schooling markets, discriminatory sorting would have increased all forms of school segregation nearly everywhere, as parents desire to enroll their children with peers of the same race. Residual sorting consisting of exogenous changes to the local amenity mix and other policies has helped to desegregate white schools and dampen the segregation of minority schools almost everywhere except in the largest cities where it has had the opposite effect. Finally, to the extent that we view school segregation as an urban concern, it is critical to recognize that changing demographics have played an immense role in shaping segregation.

[41] See, for example, *American Neighborhood Change in the 21st Century*, April 2019, prepared by the Institute on Metropolitan Opportunity at the University of Minnesota Law School.

Figure 12: Decomposing Observed Changes in the Prevalence of Segregated Schools, 2003-2014

(a) White Segregated Schools

(b) Minority Segregated Schools



Notes: We present locally weighted least squares regressions of each trajectory against the total student populations of each commuting zone in logs (bandwidth=0.3). We overlay a histogram of commuting zones by population along with example cities for the largest bins (see footnote 40 for the city corresponding to each abbreviation). A white- (minority-) segregated school has over 75% white (minority) enrollment. The decomposition is implemented for all schools who operate in every year from 2003 to 2014. The solid red, dotted blue and dashed green paths correspond to segregation levels computed with $\tilde{s}^{A}_{jt}$, $\tilde{s}^{AD}_{jt}$ and s_{jt} respectively. The total vertical change in the dotted blue path corresponds to the change in segregation through the discriminatory channel, the vertical difference between the dashed green path and the dotted blue path corresponds to the change in segregation through the demographic channel, and the vertical difference between the solid red path and the dashed green path corresponds to the change in segregation through the residual channel.

7 Sensitivity Analysis

In this section, we consider many potential empirical concerns with our analysis. First, we focus on the validity of our identification strategy. Next, we focus on other potential concerns that may affect our conclusions. All figures referenced in this section can be found in Appendix D.

7.1 Validity of Identification Strategy

We subject our identification strategy to several robustness checks. First, we compare the OLS estimates with our IV estimates to gauge the extent of bias that would arise if the roles of discriminatory and residual sorting were not separately identified. Next, we consider the possibility that our IV estimates partially incorporate the parental responses to neighborhood peers rather than school peers, and discuss how our approach treats the school choice process. Finally, we consider the possibility that our control variables are insufficient to isolate the transitory variation in the enrollments of IV cohorts.

7.1.1 OLS vs. IV Estimates

In Figure 17, we present a comparison of estimates of β_{rg} from a naive OLS regression of equation (11) (left panels) and from our IV estimates from equation (11) (right panels). In both cases, we allow for heterogeneous estimates by commuting zone groups depending on the population, as discussed in Section 5, and we add fixed effects at the commuting zone-year-race-grade level. Whenever possible, we maintain the same vertical scale in both panels for comparison. These figures suggest OLS estimates are highly positively biased (in magnitude) as expected: OLS estimates are about three to five times larger than IV estimates, which suggests that residual sorting (a confounder in the OLS estimates) is much stronger than discriminatory sorting.

A comparison of OLS and IV estimates indirectly provides more context for the residual mechanism. OLS estimates of the black responses to Hispanic peers (relative to white ones) are positive and much larger than IV estimates. This is expected, since income is a major confounder in this regression (blacks and Hispanics tend to both live in poorer areas than whites do). In contrast, OLS estimates of Hispanic responses to black peers (relative to white peers) are negative in spite of confounders such as income that may have biased estimates upward. This can be reconciled by noting that the share of Hispanic students grew substantially in many commuting zones, whereas the share of black students did not. In parts of the country with relatively few existing Hispanic neighborhoods, Hispanic immigrants settled disproportionately in white neighborhoods, since these areas were less likely to have black neighborhoods to choose from. Meanwhile, in large cities with pre-existing Hispanic neighborhoods, Hispanic immigrants were more likely to settle among their peers.

7.1.2 Neighborhood Choice

As discussed in footnote 19, the racial composition of the school is assumed to perfectly proxy for the racial composition of the neighborhood from the perspective of parents. However, it is possible that this does not hold, in which case some of the discriminatory responses (namely those related to the racial composition of the neighborhood), would be subsumed by the residual mechanism. Based on our findings, we view this concern to be likely unimportant, since the residual mechanism systematically contributes to segregation in the opposite direction of the discriminatory mechanism.

In any case, we attempt to address this concern more directly by presenting IV estimates of β_{rg} from equation (12) specified with different geographic fixed effects. Instead of using **commuting zone**-year-race-grade fixed effects as in our baseline results, we show results with **school district**-year-race-grade fixed effects and, alternatively, **ZIP code**-year-race-grade fixed effects. This effectively corresponds to estimating alternative nested choice models in which parents first choose a given neighborhood (either a school district or a ZIP code) for any reason whatsoever and then consider the s_{jt} and $\boldsymbol{X_{jt}}$ of all schools within that neighborhood before they enroll their child. Because sorting across districts or ZIP codes within the same commuting zone may be disproportionally related to neighborhoods rather than schools, a change in our estimates of β would constitute evidence that part of the discriminatory response to neighbors was not originally identified in the baseline specification using fixed effects at the commuting zone level.

In order to implement this robustness check, we must deal with the fact that specifications with geographically narrower fixed effects rely more heavily on identifying variation from large commuting zones (because smaller areas often have a single school serving a given grade within a district or ZIP code). We thus restrict our attention to the 15 largest commuting zones in the country. A comparison of estimates using more detailed fixed effects (Figure 19) with the baseline results (Figure 18) for this subgroup reveals very similar results. This suggests that the residual mechanism as identified by our simulation is not driven by discrimination towards neighbors.

7.1.3 School choice

Our approach is agnostic to the particulars of the school choice process that underlies the sorting of students to schools. As a result, it accommodates both residential Tiebout sorting to traditional public schools based on attendance areas and less common school choice options such as private, charter and magnet schools, or open enrollment policies. Thus, our analysis incorporates variation in school choice across different commuting zones and school districts in the country. Our results using different fixed effects help illuminate the roles of alternative choice options in explaining changes in segregation. Fixed effects at narrower geographic levels control for many of these other school choice options (at least partially). Based on a comparison of estimates in Figures 18 and 19, these other choice options do not appear to affect the discriminatory mechanism in public schools, although they may affect the residual mechanism as shown in previous work (e.g., Clotfelter et al. (2006);

Bifulco and Ladd (2007)).

7.1.4 Controlling for Persistent Amenities

Even if the logic of our IV is sound, we might be incapable of controlling for all persistent amenities by simply including $C_{rgjct-1}$ in the regression. We address this concern with two additional robustness checks. In our baseline results, we used both $s^{\bar{g}-1}_{jct-2}$ and $s^{\bar{g}-2}_{jct-3}$ as IVs for s_{jct-1}. Intuitively, $s^{\bar{g}-2}_{jct-3}$ is more likely to be valid than $s^{\bar{g}-1}_{jct-2}$ under the logic of our IV because it exploits variation in enrollments in the IV cohorts from farther in the past that is less likely to persist until period t (conditional on controls). Accordingly, the left panels of Figure 20 report the IV estimates using only $s^{\bar{g}-2}_{jct-3}$ as IV. These estimates are very similar to the baseline estimates, which suggests that this does not seem to be a concern. Next, we provide an additional test that addresses the same issue: we modify the IV results from the left panels of Figure 20 by adding further controls of the type $C^{\bar{g}-2}_{rgjct-2}$ to attempt to control for any persistent amenities that may not yet have been controlled by $C_{rgjct-1}$. The results do not change much either, suggesting that $C_{rgjct-1}$ is capable of roughly controlling for persistent amenities[42].

Remark 3. Because we do not have access to an experiment, it is possible that our IV estimates may still be biased in ways that we are unable to detect. It is reassuring that every robustness check that we conducted suggests that a violation of our identifying assumption would result in estimates that are biased upward. This suggests that our primary conclusion that the discriminatory mechanism has been least influential in explaining recent trends in segregation is conservative.

7.2 Other Potential Concerns

7.2.1 Responses Changing Over Time

In our baseline results, we do not allow β_{rgc} to change over time. We relax this restriction and estimate them separately for two sub-periods: 2005-2009 and 2010-2014. Results by grade and race

[42] We attempted to further control for persistent amenities in two other ways and obtained similar results: (i) we added cubic B-spline versions of each element of $C_{rgjct-1}$ to allow for nonlinearities; (ii) we added $s^{\bar{g}-g_j}_{jct-g_j-1}$ as IV with additional controls $C^{\bar{g}-g_j}_{rgjct-g_j}$, where $\bar{g}-g_j$ is the first grade in the grade-range of the school. This latter test is analogous to the test shown in the right panel of Figure 20, but it is plausibly more powerful because we chose the farthest possible IV from period t that we can use for each corresponding school.

are shown in Figure 21. The very small and unsystematic change in β_{rg} across these two sub-periods suggests that our baseline restriction is appropriate.[43]

7.2.2 Alternative Measures of Segregation

Our definitions of segregation may miss important patterns in the way students of different races are distributed across schools in the country. Indeed, a large literature in the social sciences has assessed the advantages and disadvantages of different measures of segregation (see, e.g. Massey and Denton (1988)). Even though no single measure can fully capture all aspects of segregation – isolation, similarity in the racial composition of schools, concentration of racial groups – certain measures are well suited to capture particular aspects of segregation. While our analysis has focused on school-level measures of segregation, alternative commuting zone-level measures of segregation are complementary and reveal a rich perspective on segregation trends. We focus on two widely used measures: isolation indices for white and minority students, and the racial dissimilarity index.[44] In order to facilitate meaningful comparisons, we standardize each measure, so, for example, "0.01" corresponds to an average annual increase of 0.01 standard deviations of the corresponding measure.

In Figure 22, we consider the isolation indices for white and minority students. Briefly, the isolation index reflects the probability that a student will interact with another student of their race in a school. Larger values of isolation reflect greater segregation. In Panels (a) and (b) we simply document observed changes in student isolation from 1988 to 2014. White students have become less isolated nearly everywhere with the greatest changes occurring in areas with rapidly growing Hispanic populations (e.g., South Florida and Las Vegas). However, minority students have become more isolated in much of the country. We decompose these changes in Panel (c) and not surprisingly obtain a strikingly similar pattern as in Figure 11. The causes of the decrease in white student isolation have largely mirrored the causes of the desegregation of predominantly white schools. Similarly, the causes of the increase in minority student isolation track the causes of the

[43] Our finding that white and minority parents exhibit no more or less discriminatory responses towards minority peers in 2005 than in 2014 is consistent with surveys of stated racial attitudes (Bobo et al. (2012)).

[44] In a commuting zone with N^W and N^M total white and minority students distributed across J schools, each of which enrolls n_j^W white students and n_j^M minority students, the race r Isolation Index is calculated as $I_r = \sum_{j=1}^{J} \frac{n_j^r}{N^r} \frac{n_j^r}{(N^W + N^M)}$, and the Dissimilarity Index is calculated as $D = \frac{1}{2} \sum_{j=1}^{J} \left| \frac{n_j^W}{N^W} - \frac{n_j^M}{N^M} \right|$.

increase in prevalence of predominantly minority schools.

In Figure 23, we consider the Dissimilarity Index, which corresponds to the minimal fraction of minority (or white) students in a commuting zone that would have to switch schools in order to obtain a perfectly even allocation of students across all schools. According to this measure, from 1988 to 2014 segregation has increased slightly in the sunbelt while decreasing in other parts of the country. In Panel (b), we decompose the changes in dissimilarity index from 2003 to 2014. Aggregate demographic shocks explain very little of the change in dissimilarity over the sample period, as indicated by the difference between the green and blue lines. This is unsurprising, as the dissimilarity index is a measure of unevenness that is intended to be insensitive to aggregate changes in the environment. Discriminatory sorting would have increased segregation by roughly 25% from 2003 to 2014, but this was entirely offset by the residual mechanism.

Remark 4. Because our identification strategy for β requires grade-level enrollment data, which only became available in 2002, we can only perform a decomposition from 2002-2014. However, we have reasons to believe that these results may inform us about how segregation evolved from 1988 to 2001: (1) Demographic shocks during the 1990s closely resemble demographic shocks during the 2000s (Figure 15); (2) Aggregate trends in the racial composition of national enrollments evolved smoothly over the entire period (Figure 16); (3) Our estimates of β do not change over time from 2005-2014 (Figure 21); (4) We do not observe a qualitatively different pattern of school segregation between the 1988-2001 and 2002-2014 sub-periods (Figure 24).

8 Conclusion

A growing body of research has found adverse short-run and long-run effects of school segregation, particularly for minority students. It is understandable then to be concerned about the increase in the proportion of predominantly minority public schools in the United States. However, policymakers seeking to address segregation would be wise to understand the mechanisms underlying this trend. Those who insist that low minority-share schools are the only acceptable outcome will be disappointed for purely arithmetic reasons; in 2014, the four most populous commuting zones had majority "minority" enrollments.[45]

[45] The minority share of 2014 enrollment of the four largest commuting zones was, in order of size: Los Angeles (70%), New York City (57%), Houston (68%) and Chicago (53%).

Models of segregation predict that when holding all else constant, even mild discriminatory responses will endogenously lead to substantial increases in racial segregation over time. Our findings reveal that all else is not constant. Continuing aggregate demographic shocks, primarily due to Hispanic immigration, have kept segregation at bay over the past quarter century. They have been a key force in desegregating white schools and segregating minority schools, especially in areas that experienced the greatest change in segregation: large, urban commuting zones. Residual, non-discriminatory sorting has reduced the prevalence of both white- and minority-segregated schools in most areas, although there is substantial heterogeneity in these effects across commuting zones. This may reflect the fact that local urban and educational policies to combat segregation have varied considerably throughout the country during this period, e.g., the ending of many desegregation policies in the South that returned control of schools to local authorities and led to an increase in segregation (Lutz (2011)), and the proliferation of school choice (Hoxby (2007)). In any case, we conjecture that much of this residual reduction in segregation may have been an indirect response to changing demographics. As local Hispanic populations increased, the amenities in many schools and neighborhoods that were previously white may have adjusted to attract this large influx of people. This would have contributed to a more diffuse allocation of Hispanics across schools. In principle, this conjecture may become testable as more detailed data on changing characteristics of schools and neighborhoods over a longer horizon become available. If true, then demographic change is an even stronger force for desegregation than what we find in this paper.

Our findings suggest that an understanding of sorting at the local level could be enriched by a greater understanding of sorting at regional levels. Synthesizing a model of migration with a model of segregation might reveal complementarities between broad regional policies regarding immigration or relocation incentives with narrow place-based policies at the school or neighborhood levels. Because the settlement decisions of new immigrants are in part determined by the racial and ethnic composition of potential peers (Munshi (2003)), deeper connections between the discriminatory and demographic mechanisms may be illuminated, though this lies well beyond the scope of this paper. As more precise data on individuals' settlement and enrollment patterns become available, we believe this will become a promising avenue for further inquiry. The recent residential migration of minorities to suburbs in the past two decades may also signal new trends in school segregation that merit closer analysis to complement studies of white flight from 1960-1990 (e.g., Welch and

Light (1987); Boustan (2010); Baum-Snow and Lutz (2011)).

Ultimately, segregation itself should be analyzed in a broader context. While researchers have, with good reason, focused on the negative effects of segregation in predominantly minority schools, exposure to diversity has been found to positively impact white students in other contexts along a variety of outcomes related to educational attainment, cognitive growth, and civic-mindedness.[46] As a result, the ongoing desegregation of white schools may generate widespread pro-social impacts that, while difficult to quantify, shape society in profound ways.

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[46] Most research into the impacts of diversity on white students has been conducted in the context of tertiary education. For instance, Gurin et al. (2002) survey the psychological and sociological theoretical literatures on the exposure to diversity and empirically identify widespread positive effects on white college students across a variety of outcomes related to cognitive growth, identity construction and citizenship in the context of higher education. Boisjoly et al. (2006) find that exposure to black roommates affects the attitudes, immediate behaviors and long term goals of white students in a pro-social direction.

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A Additional Background on Instruments

Relevance: What is the Identifying Variation?

In the context of equation (11), we want to exploit changes in school characteristics that compelled students in the IV cohort to sort towards (or away from) that school in the past (thus changing s_{jct-1}), provided that these changes were transitory and did not affect enrollment decisions in t. To do so, we isolate variation in school characteristics that affect the enrollment of the IV cohort in $t-2$ without affecting any of the enrollments of subsequent cohorts in $t-1$. Although students in the IV cohort will have aged out by period t, they do mechanically contribute to s_{jct-1}. As a result, they plausibly affect the enrollment decisions of subsequent cohorts of students in t purely through the mechanism of interest.[47]

As a concrete example, consider a popular, and well known football coach in a 9-12 high school who retired just before year $t-3$. If football was differentially valued by White and minority parents, then this coach would have affected the enrollments of ninth graders in $t-4$ (who are members of the IV cohort) without directly affecting the enrollments of any subsequent cohorts of students. Still, this coach would have influenced the minority share in $t-1$ (because some members of the IV cohort will continue to enroll in the same school for inertial reasons). Because the IV cohort ages out of the school in t, the only way this coach could affect the enrollment decisions of students in t would be through their response to the minority share in $t-1$, which is the effect we want to identify. Of course, this is just a specific example. In practice, a wide variety of circumstances could lead to some students remaining enrolled in a school despite the fact that the initial attraction is no longer present.

Because we use only enrollment data to isolate this plausibly exogenous variation, our approach is agnostic to the nature of the specific transitory shock in the past that led students to the school. Thus, we do not need to obtain data on any specific shock (such as the quality of football coaches, per the example above). This crucially allows us to perform our analysis nationally and over a relatively long sample period. Moreover, it increases the power of our IV by aggregating all such transitory shocks, including those of which we as researchers are unable to conceive.

[47] Students in the IV cohort might be compelled to remain in the same school from $t-2$ to $t-1$ for inertial reasons, even if the reasons that originally led them to enroll in that school no longer remain.

Validity: Threats to Identification

An unobservable variable (e.g., a school characteristic) violating Assumption 1 would have to satisfy three properties: (1) it affects enrollment decisions in t (i.e., it is included in u_{rgjct}), (2) it correlates to the minority share of students in grade $\bar{g}_j - 1$ in year $t-2$ (i.e., it is correlated to the IV), and (3) it is uncorrelated to changes in the enrollment decisions of students of different races in all other grades in year $t-1$ (i.e., it is not absorbed by $C_{rgjct-1}$). The existence of such a potential confounder is implausible, because it must lie dormant in $t-1$ before becoming relevant again in t, and this return to relevance must be unanticipated by students who enroll in year $t-1$.

To further this logic, consider an unobservable that satisfies properties 1 and 2 above. By construction, this unobservable is either *not* unique to grade $\bar{g}_j$ in $t-1$, or it is unique to grade $\bar{g}_j$ in $t-1$. We will now argue that such unobservable likely does not satisfy property 3 above in both cases.

First, any unobservable that is *not* unique to grade $\bar{g}_j$ in $t-1$ (e.g., a neighborhood or a school-wide unobservable) is valued by at least some students enrolled in some grade $g < \bar{g}_j$ in $t-1$. As a result, it will fail to satisfy the third property. For instance, imagine that a 9-12 high school features a good library in t (property 1), and that the library is valued in $t-2$ by 11th grade students (property 2). As long as the library is valued by students outside of the IV cohort (i.e., students of any race in grades 9, 10 or 11 in $t-1$), property 3 will fail to hold.

Conversely, any school unobservable that is unique to grade $\bar{g}_j$ in $t-1$ will fail to satisfy property 3 if students in some grade $g < \bar{g}_j$ in $t-1$ *anticipate* the unobservable will be present in t. This anticipation is likely because the unobservable must be present in t (property 1), and must have been considered by students in grade $\bar{g}_j - 1$ in $t-2$ (property 2). For instance, in the case of the example of the football coach, property 3 would hold only if the coach was at the school in $t-2$, then left that school in $t-1$, and then later it was announced that they would be reinstated. Moreover, this announcement would have had to occur *after* enrollment decisions were made in $t-1$ (otherwise the control cohorts would have anticipated the return of the coach).[48]

[48] In any case, our approach provides a test for whether there are confounders unique to the last grade of the school, $\bar{g}_j$, and we find that in practice this is of no concern. Because the last grade of the school changes with the school, we can test for whether β_{rgc} inferred by estimates obtained from schools with $\bar{g}_j > g$ is equal to the β_{rgc} inferred by estimates obtained from schools with $\bar{g}_j = g$. While the former subsample of schools may not be affected by this confounder, the latter subsample of schools may be. It turns out has this test also has power to detect another potential concern with our identification approach: some students in the IV cohort might repeat a grade in either

B Data Appendix

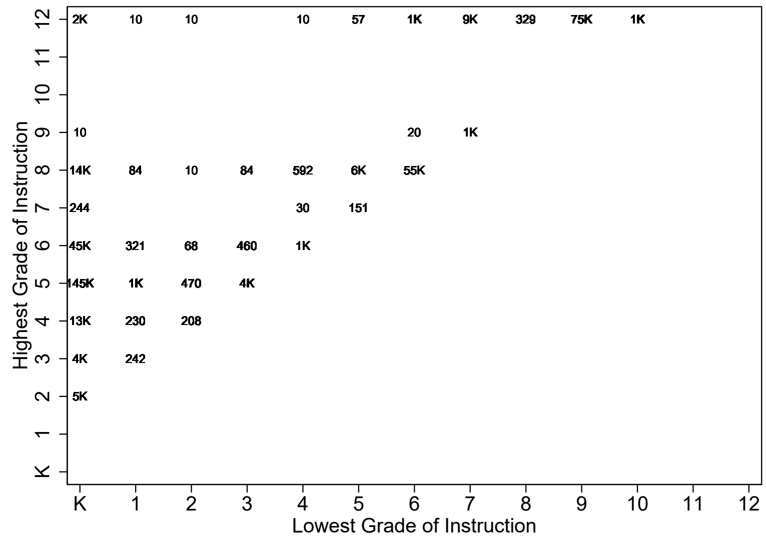
Table 1: Missing Data

State	Years Missing	Fraction of Sample Period Missing
Arizona	1998	4%
Colorado	1998	4%
Georgia	1988-1992	19%
Idaho	1988-2001	44%
Louisiana	1988	4%
Maine	1988-1992	19%
Massachusetts	2000	4%
Minnesota	1998	4%
Missouri	1988-1990	7%
Montana	1988-1989	7%
New Hampshire	1988	4%
New Jersey	1998	4%
New Mexico	1988	4%
New York	1998	4%
Nevada	2004	4%
North Dakota	1998	4%
Oregon	2000	4%
Pennsylvania	1998, 2000-2001	11%
South Dakota	1988-1991	11%
Tennessee	1998-2004	26%
Vermont	1998	4%
Virginia	1988-1991	11%
Washington	1998-2000	11%
West Virginia	1998	4%
Wyoming	1988-1989	7%

Note: Only Nevada and Tennessee have any data missing from 2002-2014, which corresponds to the sample period of our estimation and decomposition subsample. We have recalculated all results omitting these states, and our findings are qualitatively unchanged.

$t-2$ or $t-1$, leading them to still attend the school in t, thus potentially contaminating our estimate of β_{rgc} for $\bar{g}_j = g$. In practice, we find no evidence of such contamination.

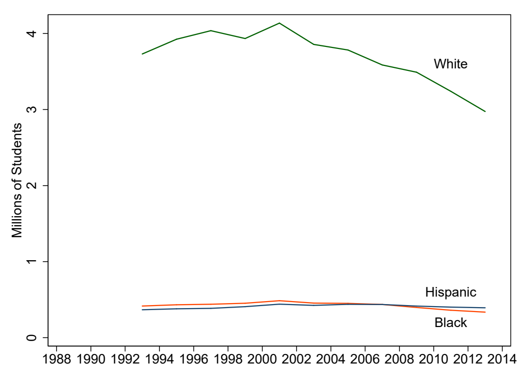
Figure 13: Distribution of Grade Range Across All Schools



Note: For each $\underline{g}$ in the horizontal axis and $\overline{g}$ in the vertical axis, this plot shows the number of schools in our sample that are of a given grade range $(\underline{g}, \overline{g})$. $1K$ represents 1,000 schools.

C Determinants of Demographic Change: Figures

Figure 14: Private School Enrollments by Race, 1993-2013



Note: Private school enrollment data are obtained from Private School Universe Surveys, 1993-1994 through 2013-2014 maintained by the National Center for Education Statistics. Our estimation period (2002-2014) coincides with a decline in white private school enrollment and stable minority enrollment.

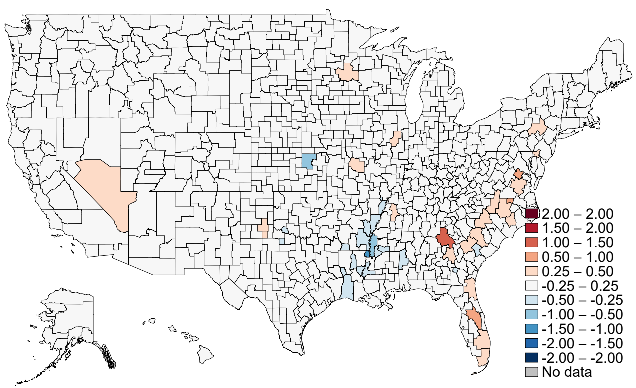
Table 2: Fertility Rates by Race, Selected Years

	White	Black	Hispanic
1971[1]	77.3	109.7	N/A
1989	60.5	84.8	104.9
2008	59.4	71.1	98.8

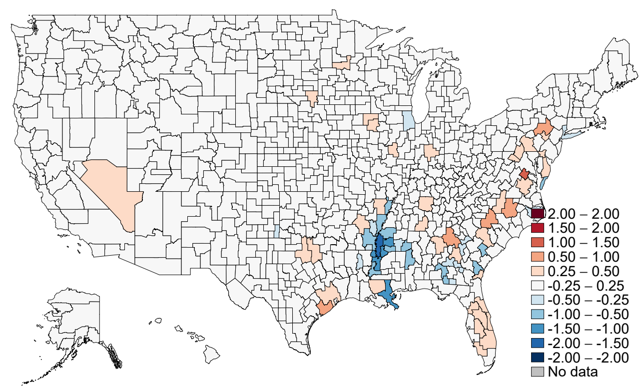
Notes: Fertility rates are defined as total births per 1,000 women aged 15-44. Details on Hispanic status of mothers not available until 1989. [1]: In this year, Hispanic white and Hispanic black mothers were classified as white and black respectively. Sources: Vital Statistics of the United States, 2003, Volume 1: Natality, and National Vital Statistics Reports, Vol. 56, No. 6, December 5, 2007. Children in our sample correspond to those born between 1984 and 2009, the majority of whom were born between 1989 and 2008. White fertility has decreased about 2% over this period, while black and Hispanic fertility rates have decreased 16% and 6%, respectively.

Figure 15: Average Annual Change in Black/Hispanic Share of School-Age Population due to Immigration and Migration

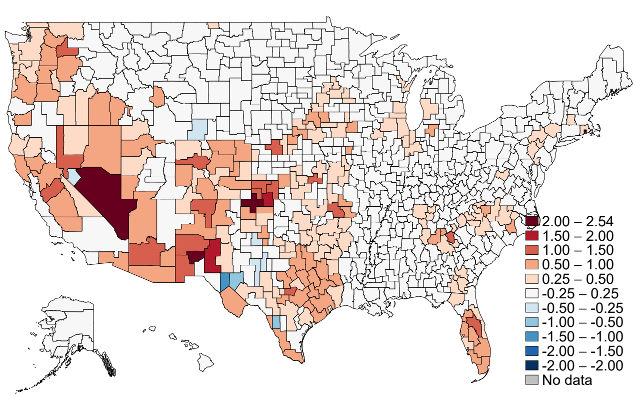
(a) Change in Black Share, 1990s



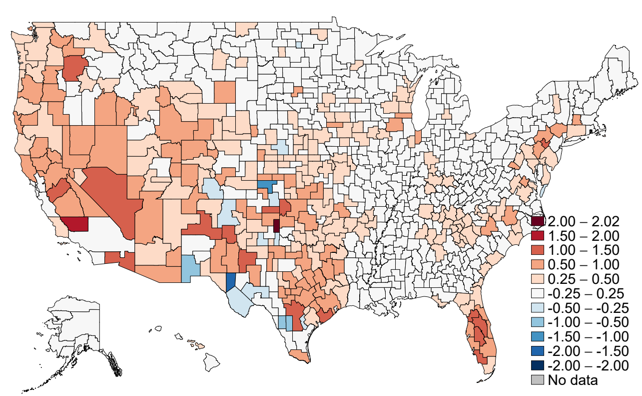
(b) Change in Black Share, 2000s



(c) Change in Hispanic Share, 1990s

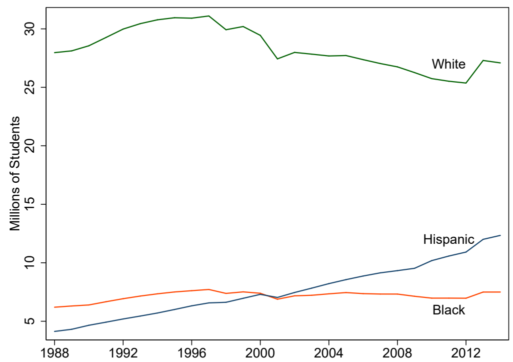


(d) Change in Hispanic Share, 2000s



Note: Map shows the average annual change in the age 5-14 population of a given race in a commuting zone due to migration or immigration. Data obtained from Winkler et al. (2013). Because most of the regions of the country have experienced inflows of Hispanics and only few have experienced small outflows, this is suggestive of Hispanic immigration.

Figure 16: National Public School Enrollments by Race, 1988-2013

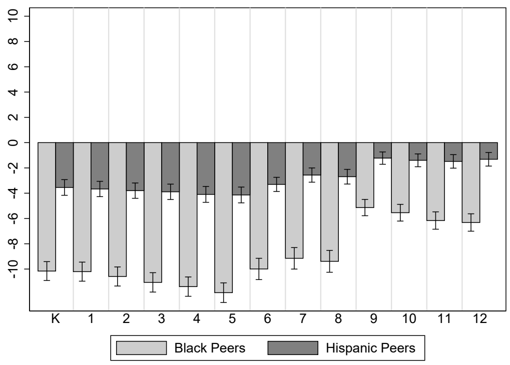


Note: Missing data (see appendix B) is linearly interpolated and extrapolated to create this figure. Hispanic enrollment in public schools has gone up substantially during this period, while white and black enrollment has been mostly stable.

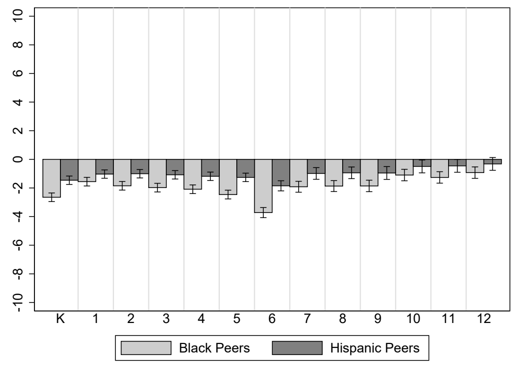
D Sensitivity Analysis: Figures and Tables

Figure 17: Estimates of β_{rg}, 2005-2014: OLS vs. IV

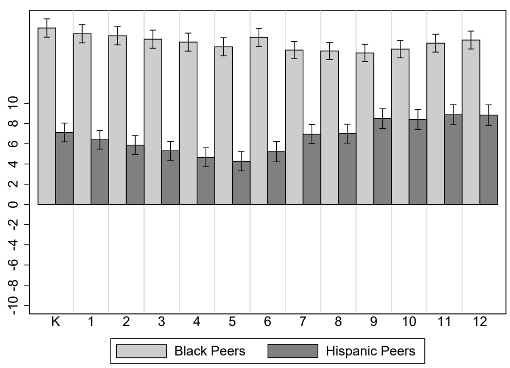
(a) White Responses, OLS



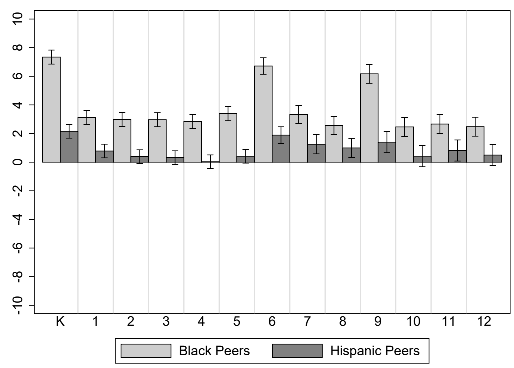
(b) White Responses, IV



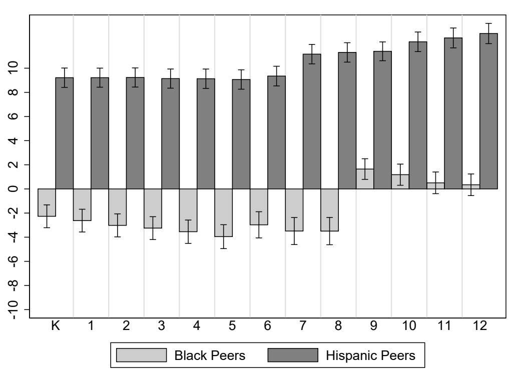
(c) Black Responses, OLS



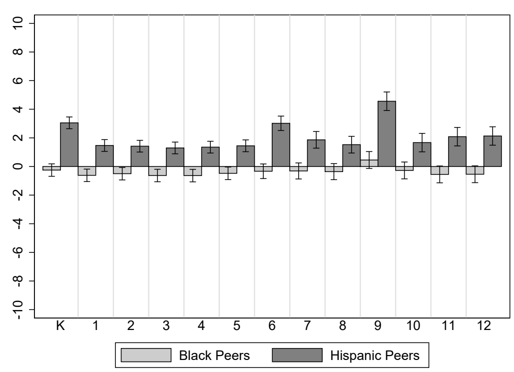
(d) Black Responses, IV



(e) Hispanic Responses, OLS



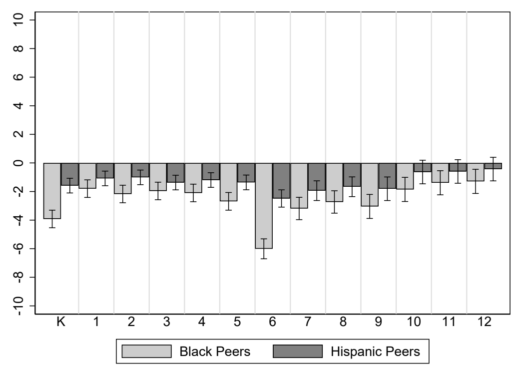
(f) Hispanic Responses, IV



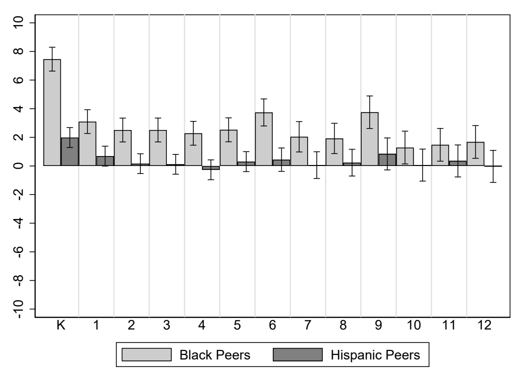
Notes: OLS (left panels) and IV (right panels) estimates of equation (11) are aggregated across commuting zones. The 95% confidence intervals shown are constructed with standard errors that are clustered at the commuting zone-year-race-grade level. The p-values from F-tests of whether the IVs ($s_{jt-2}^{\bar{g}_j-1}$ and $s_{jt-3}^{\bar{g}_j-2}$) are significant in the first stage regressions are always less than 1%. There are 6,089,772 school-race-grade-year observations in the sample.

Figure 18: Estimates of β_{rg}, 2005-2014: Commuting Zone FEs, Large Cities

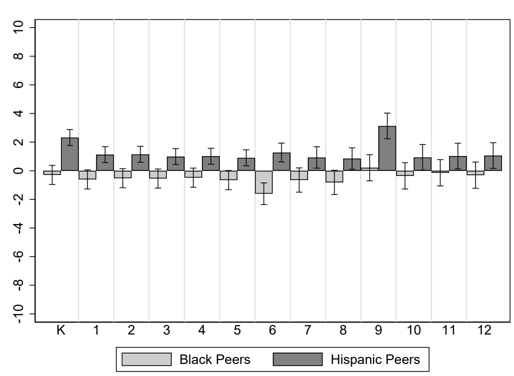
(a) White Responses, **Commuting Zone**-Year-Race-Grade FEs



(b) Black Responses, **Commuting Zone**-Year-Race-Grade FEs



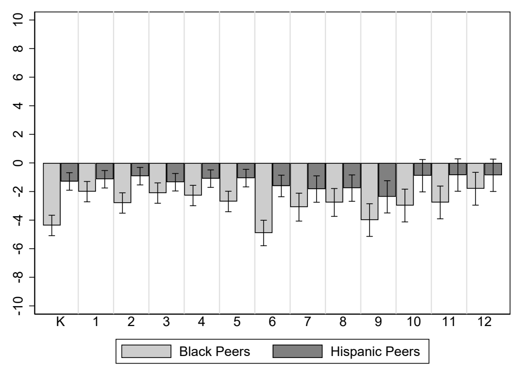
(c) Hispanic Responses, **Commuting Zone**-Year-Race-Grade FEs



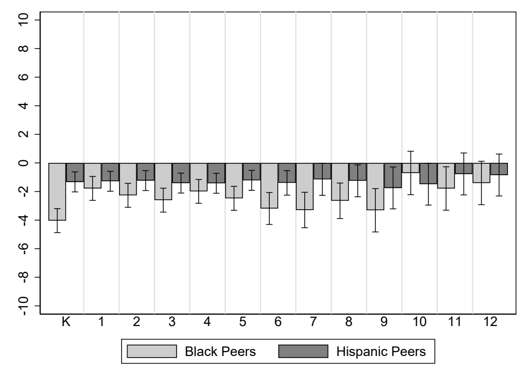
Notes: IV estimates from equation (11) are aggregated only across the 15 largest commuting zones. They include fixed effects at the commuting zone-year-race-grade level. The 95% confidence intervals shown are constructed with standard errors that are clustered at the commuting zone-year-race-grade level. The p-values from F-tests of whether the IVs ($s^{\bar{g}_j-1}_{jt-2}$ and $s^{\bar{g}_j-2}_{jt-3}$) are significant in the first stage regressions are always less than 1%. There are 1,601,547 school-race-grade-year observations in the sub-sample used for this figure.

Figure 19: Estimates of β_{rg}, 2005-2014: Neighborhood FEs, Large Cities

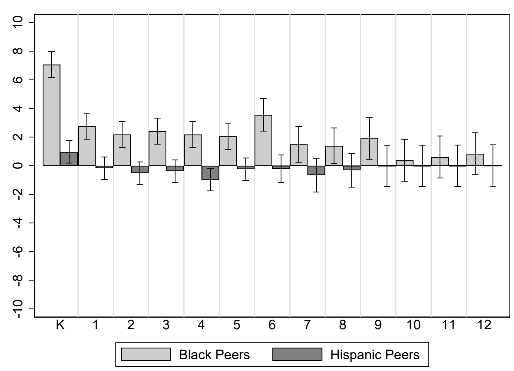
(a) White Responses, **School District**-Year-Race-Grade FEs



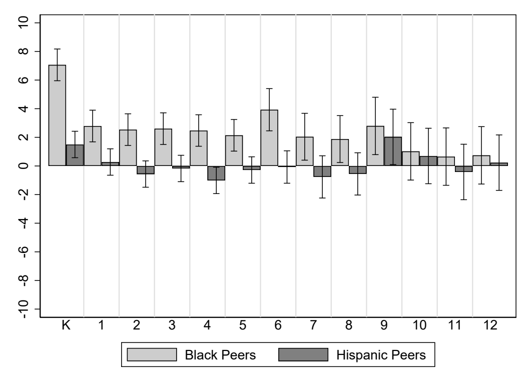
(b) White Responses, **ZIP Code**-Year-Race-Grade FEs



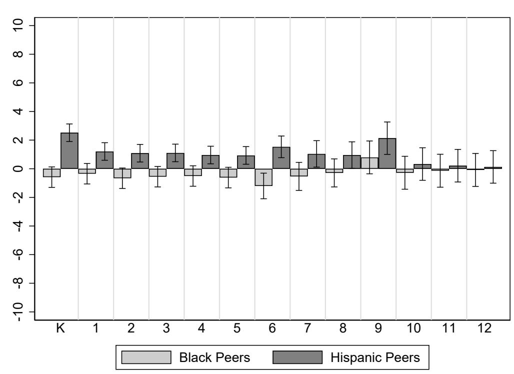
(c) Black Responses, **School District**-Year-Race-Grade FEs



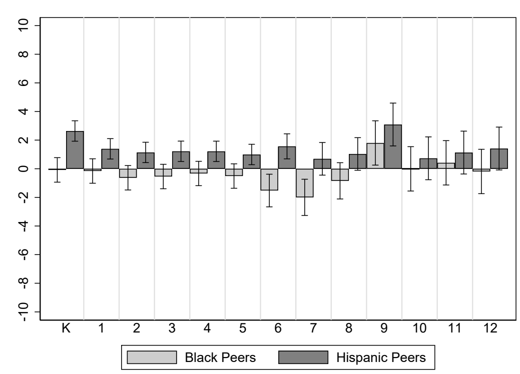
(d) Black Responses, **ZIP Code**-Year-Race-Grade FEs



(e) Hispanic Responses, **School District**-Year-Race-Grade FEs



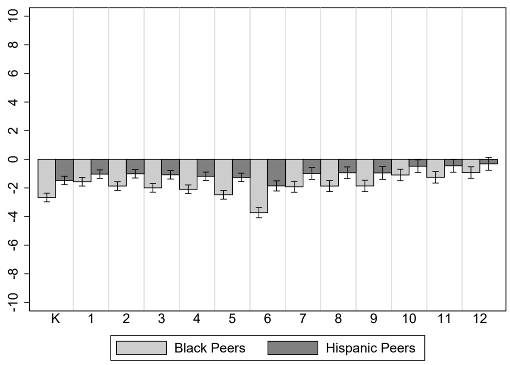
(f) Hispanic Responses, **ZIP Code**-Year-Race-Grade FEs



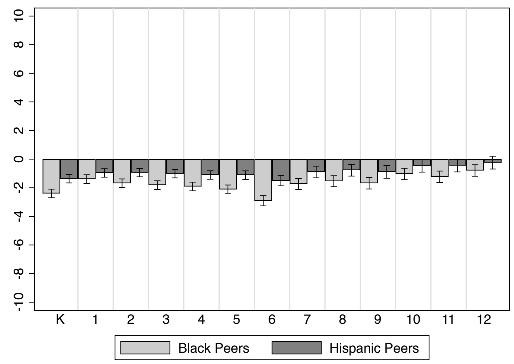
Notes: IV estimates from equation (11) are aggregated only across the 15 largest commuting zones. The left panels include fixed effects at the school district-year-race-grade level while the right panels include fixed effects at the ZIP code-year-race-grade level. In contrast, the baseline results were estimated with fixed effects at the commuting zone-year-race-grade level. The 95% confidence intervals shown are constructed with standard errors that are clustered at the commuting zone-year-race-grade level. The p-values from F-tests of whether the IVs ($s_{jt-2}^{\bar{g}_j-1}$ and $s_{jt-3}^{\bar{g}_j-2}$) are significant in the first stage regressions are always less than 1%. There are 1,601,547 school-race-grade-year observations in the sub-sample used for this figure.

Figure 20: Estimates of β_{rg}, 2005-2014: Adding Further Controls to Absorb Persistent Amenities

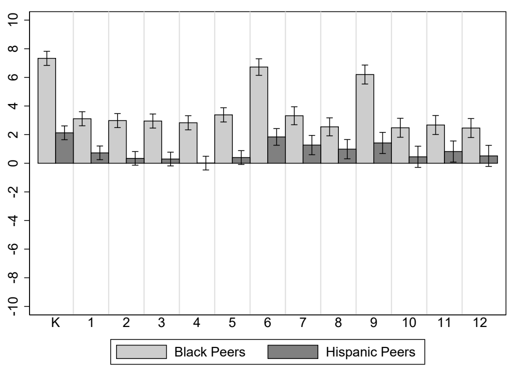
(a) White Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV



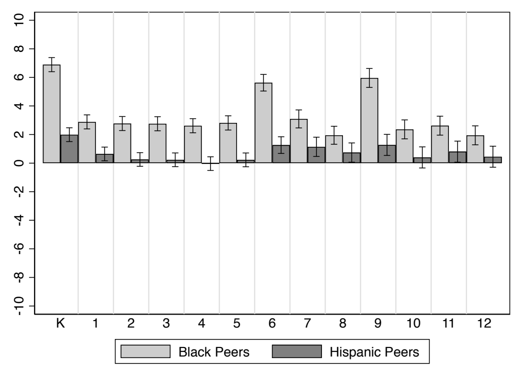
(b) White Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV plus additional controls



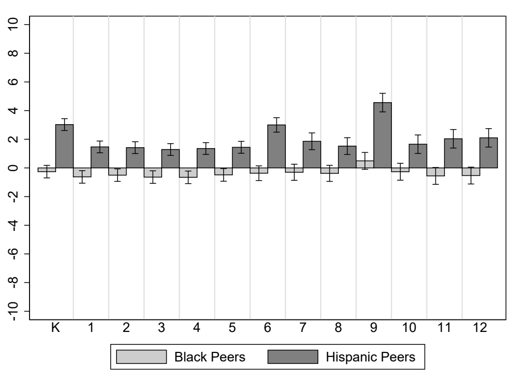
(c) Black Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV



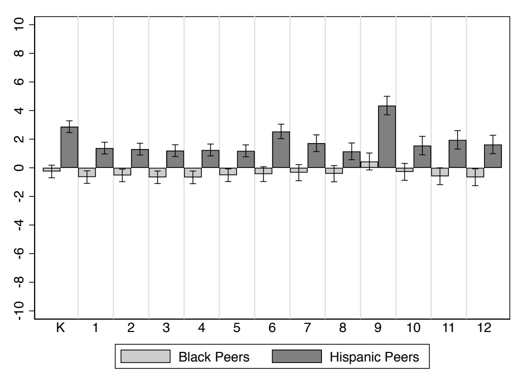
(d) Black Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV plus additional controls



(e) Hispanic Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV



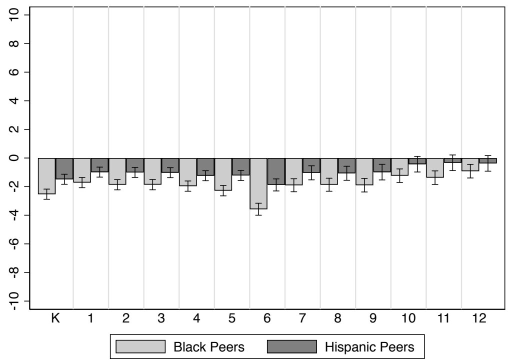
(f) Hispanic Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV plus additional controls



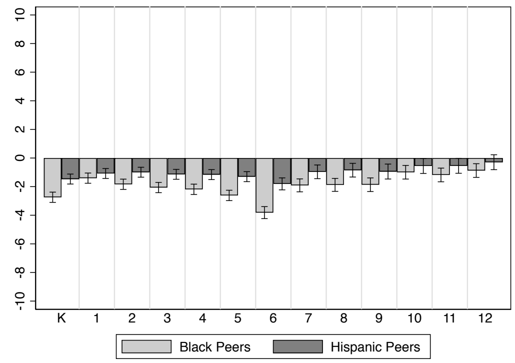
Notes: IV estimates from equation (11) are aggregated across commuting zones. Only $s^{\bar{g}-2}_{jct-3}$ are used as IVs in this case (as opposed to previous results, which use both $s^{\bar{g}-1}_{jct-2}$ and $s^{\bar{g}-2}_{jct-3}$ as IVs). In the right panels, $C^{\bar{g}-2}_{rgjct-2}$ are also added as controls (beyond $C_{rgjct-1}$ and fixed effects at the commuting zone-year-race-grade level). The 95% confidence intervals shown are constructed with standard errors that are clustered at the commuting zone-year-race-grade level. The p-values from F-tests of whether the IV ($s^{\bar{g}_j-2}_{jt-3}$) is significant in the first stage regressions are always less than 1%. There are 6,089,772 school-race-grade-year observations in the sample.

Figure 21: Estimates of β_{rg}, 2005-2009 vs. 2010-2014

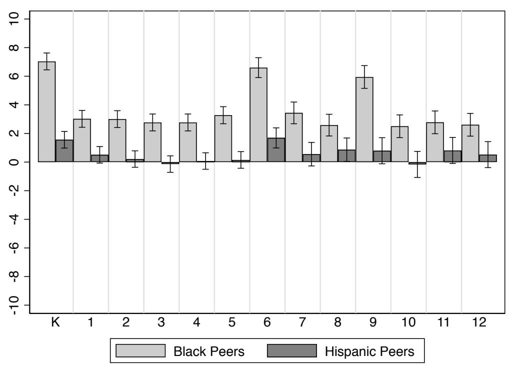
(a) White Responses, 2005-2009



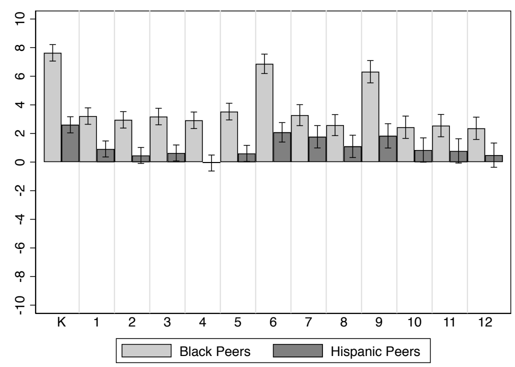
(b) White Responses, 2010-2014



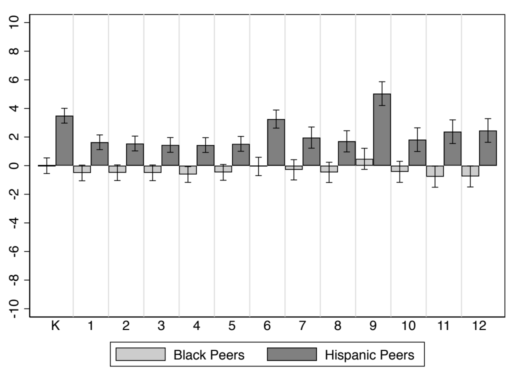
(c) Black Responses, 2005-2009



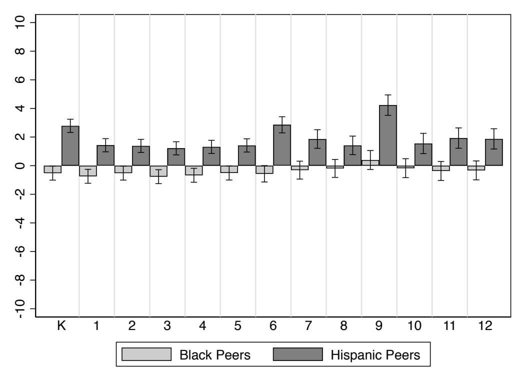
(d) Black Responses, 2010-2014



(e) Hispanic Responses, 2005-2009



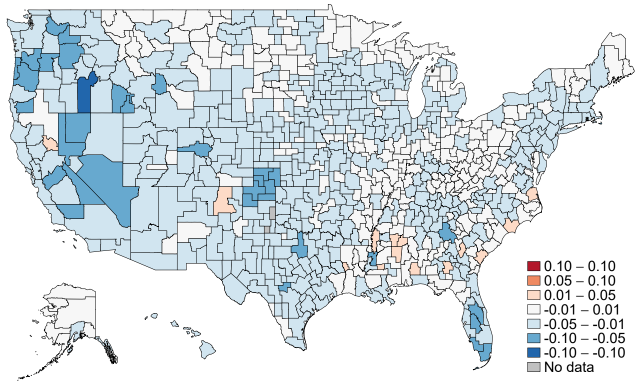
(f) Hispanic Responses, 2010-2014



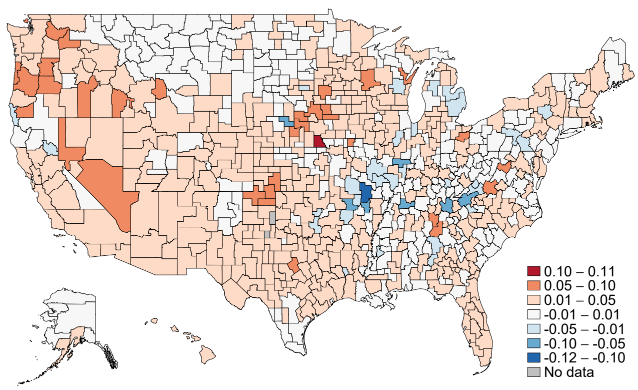
Notes: IV estimates from equation (11) are aggregated across commuting zones. In the left panels, the sample is restricted to 2005-2009, and in the right panels the sample is restricted to 2010-1014. The 95% confidence intervals shown are constructed with standard errors that are clustered at the commuting zone-year-race-grade level. The p-values from F-tests of whether the IVs ($s_{jt-2}^{\bar{g}_j-1}$ and $s_{jt-3}^{\bar{g}_j-2}$) are significant in the first stage regressions are always less than 1%. There are 2,949,714 and 3,140,058 school-race-grade-year observations in the samples 2005-2009 and 2010-2014 respectively.

Figure 22: White and Minority Isolation Indices

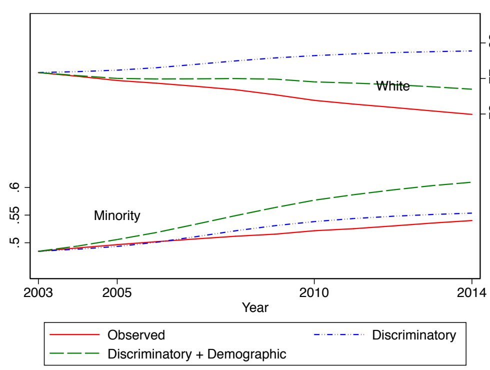
(a) Observed Change in White Isolation, 1988-2014



(b) Observed Change in Minority Isolation, 1988-2014



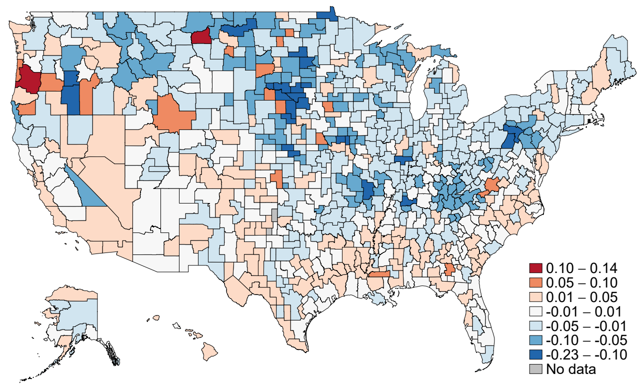
(c) Decomposition of Isolation Indices, 2003-2014



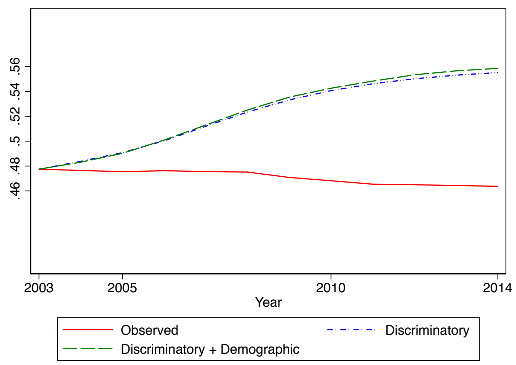
Note: Maps in Panels (a) and (b) show the average annual change in standardized isolation indices, so "0.01" corresponds to an average annual increase of 0.01 standard deviations. Red (blue) areas have become more (less) segregated. Details on the construction of these measure can be found in footnote 44. The decomposition shown in Panel (c) is implemented for all schools who operate in each year from 2003-2014, and national averages of commuting zone level measures weighted by population are reported on the vertical axis.

Figure 23: Dissimilarity Index

(a) Observed Change in Racial Dissimilarity, 1988-2014



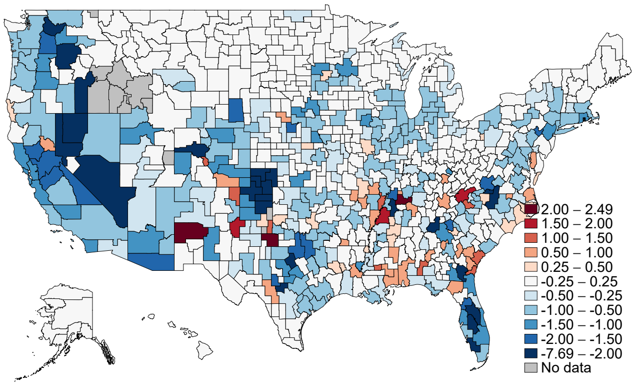
(b) Decomposition of Dissimilarity, 2003-2014



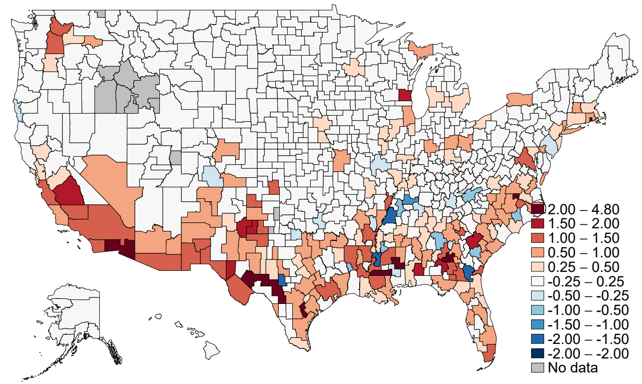
Notes: The map in Panel (a) shows the average annual change in the dissimilarity index, so "0.01" corresponds to an average annual increase of 0.01 standard deviations. Red (blue) areas have become more (less) segregated. The decomposition shown in Panel (b) is implemented for all schools who operate in each year from 2003-2014, and national averages of commuting zone level measures weighted by population are reported on the vertical axis. Details on the construction of these measure can be found in footnote 44.

Figure 24: Average Annual Change in Proportion of Segregated Schools, 1988-2001 and 2002-2014

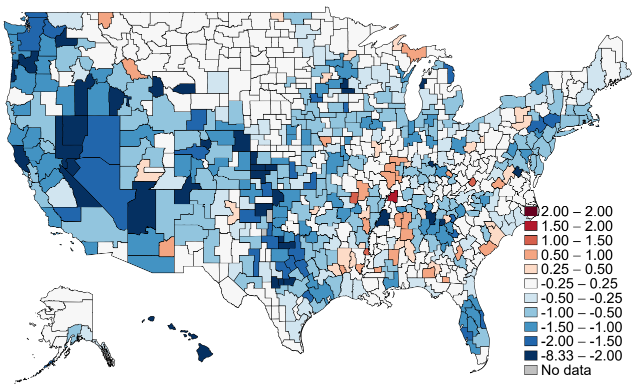
(a) Change in Proportion of Segregated White Schools, 1988-2001



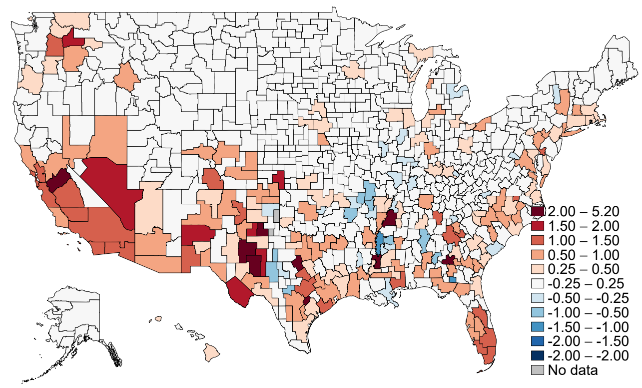
(b) Change in Proportion of Segregated Minority Schools, 1988-2001



(c) Change in Proportion of Segregated White Schools, 2002-2014



(d) Change in Proportion of Segregated Minority Schools, 2002-2014



Note: We define white-segregated schools as over 75% white, and minority-segregated schools as over 75% minority. Blue (Red) commuting zones have experienced declining (increasing) segregation during this period. Annual changes shown in percentage points.