# Explaining Recent Trends in US School Segregation

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**Abstract**

From 2002 to 2018, the fraction of minority-segregated public schools in the US 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 even though minority students have become more isolated. 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 endogenous, demographic and residual channels. The endogenous channel is fueled by parents choosing schools on the basis of the racial compositions of their student bodies; this channel can in principle dwarf all other determinants of segregation over time due to social multiplier effects. However, it has actually been the least important in explaining recent trends. Instead, demographic change, mostly 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 racial gaps 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 from 2002 to 2018 to document how local school segregation has evolved and understand its determinants.

Three mechanisms shape the racial compositions of schools and in turn the overall level of school segregation. First, parents may sort toward (or away from) specific schools because of their racial compositions. This mechanism generates the *endogenous* feedback loop 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 initial inflows of minorities into a school may lead to more (fewer) minority (White) students enrolling in that school next year, which in turn will trigger subsequent net inflows of minorities in the future. This ultimately leads to a highly segregated school system (Becker and Murphy (2000)). Second, the racial compositions of schools may change in response to 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. Finally, parents of different races may seek different schools for other *residual* reasons such as other school and neighborhood characteristics.

As pointed out by Manski (1993), distinguishing between endogenous effects and effects arising from other sources is potentially invaluable to policymakers, because the feedback loop that arises from the endogenous mechanism generates dynamic treatment effects of one-shot policies that may far exceed their short-run effects. In our setup, we allow for external shocks (due either to the demographic or residual mechanisms) to reverberate into the future because of the feedback loop generated by the endogenous mechanism. In previous work, 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 endogenous 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 dismissals of desegregation policies on school segregation, which falls under the residual mechanism. However, no prior study has assessed the relative importance of these mechanisms against one another.

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

The interplay between these three mechanisms raises several practical obstacles to a proper decomposition of observed changes in segregation. Identifying how segregation changes endogenously requires us to identify how parents' choices are influenced by the racial compositions of schools versus other school and neighborhood features (including unobserved ones). Moreover, the endogenous mechanism implies that effects arising from all three mechanisms are dynamic. For instance, any shock to a school today may affect enrollments of White and minority students differently; in turn, the ensuing change in racial composition may trigger further enrollment responses. As this feedback loop continues, that original shock may potentially generate much larger effects on segregation in the long run. This is further complicated by the necessity to account for the consequences of multiple schools being affected by the same shocks at the same time (for example, an aggregated demographic shock in a metropolitan area that simultaneously affects many schools). The responses to these shocks in any 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 these three channels for all public schools in the United States. Our approach makes three innovations over existing approaches, each of which is found to be empirically important. 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 propagate to other nearby schools. We find that neglecting these general equilibrium concerns leads to a dramatic overstatement of the role of the demographic mechanism in explaining segregation. Third, we conduct our analysis at a much larger scale than previous work in the literature. The breadth of our analysis – the entire country over a long period of time – is critical since the United States is a large, diverse country. While some urban centers have recently experienced major inflows of immigrants, others have not. In addition, different states, cities and rural areas may differ in racial attitudes and have had unique past experiences with segregation.

To briefly preview our results, during 2003-2018 the endogenous mechanism has been the least important and the demographic mechanism has been the most important. However, the relative roles of each mechanism vary 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 other two mechanisms play larger roles.

The results of our decomposition follow from several empirical fundamentals. We find that White parents tend to sort away from minority peers throughout the country, but these responses are moderate in size and of higher intensity in densely populated areas. In contrast, we find that Black and Hispanic parents strongly seek same-race 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 such peers for their children less intensely. As a result, the endogenous channel is limited 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 respond similarly to peers of all other 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 Sun Belt but less so in other areas. We collect a variety of evidence that these demographic shocks are mostly due to Hispanic immigration.

In choosing to conduct our analysis at scale, we must 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). A rich literature has shown that these local differences 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 separating these effects entirely into a residual channel. This allows us to explore the importance of the other two channels (endogenous and demographic) 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.

Although we coarsely decompose the causes of school segregation into only three mechanisms, our findings are useful to inform policy. For instance, our finding that immigration has played a prominent role in keeping segregation at bay from endogenous forces suggests that restrictions on immigration may slow or even reverse the massive desegregation of predominantly White schools, which has been the most widespread and striking trend in US school segregation in recent decades. Further, the impact of any policy on segregation is likely going to be very different in the short-run and in the long-run because of the endogenous mechanism, since its effects are gradual but accumulate over time even if no other actions are taken. This is especially true in midsize cities, where we find the endogenous mechanism to be strongest. 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 endogenous channel further to better understand the role of choice frictions in preventing sorting[3], or one might be able to decompose the residual channel into specific policies and local investments[4]. 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 present a conceptual framework to analyze segregation, and in Section 3, we explain how it can be taken to data. In Section 4, we describe our data set and document how the levels of school segregation have evolved recently. We present our estimation results in Section 5 and decomposition results in Section 6 before concluding in Section 7. We include a detailed sensitivity analysis of our findings and additional supporting results in the supplementary appendix.

## 2 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, in Sections 2 and 3 we assume that students are either White or minority ($R = \{W, M\}$) in order to present the model with two dimensional diagrams. In 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

[3] Caetano and Maheshri (2021) analyze the dynamic implications of choice frictions on segregation in San Francisco Bay Area neighborhoods.

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

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

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

where the school-race-specific function $\pi_{rj}$ 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 $j$th element is $s_{jt-1}$, and $\boldsymbol{X_t}$ is a matrix of other school-specific characteristics, whose $j$th element is vector $\boldsymbol{X_{jt}}$.[5] 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., $\frac{\partial \pi_{Wj}}{\partial s_{kt-1}} \neq \frac{\partial \pi_{Mj}}{\partial s_{kt-1}}$). This is a response to the racial share and whatever else may be caused by it. It includes responses to preferences to live around others of the same race, but it also includes responses to changes in expectations triggered by changes in the racial share. For instance, a change in $s_{jt-1}$ may signal to households today that the characteristics of the school (or associated

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

neighborhood) will change in the future, and some households may choose or avoid that school and neighborhood today because of the ensuing changes in expectations. This may lead to dynamic social multiplier effects that can generate the positive feedback loop commonly known as "tipping" (Schelling (1971)), as any change in $s_{jt-1}$ triggers further sorting, which further changes the racial share leading to yet more sorting, and so on. Because these dynamics will continue to propagate even in the absence of any other changes to the school environment, we refer to this as the *endogenous* mechanism following Manski (1993).

Third, segregation may arise if parents of different races have systematically different preferences for any other 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 $\boldsymbol{X_{kt}}$). If, for instance, Hispanic parents valued bilingual education more than White parents on average, then all else constant, improvements in bilingual education at a particular school would be expected to increase the minority share of enrollment in that school. More generally, the effects of any school or neighborhood characteristics that are not affected by the racial shares of schools would fall under this mechanism.[6] Importantly, such changes to these characteristics do not generate a positive feedback loop by themselves. We refer to this as the *residual* mechanism.

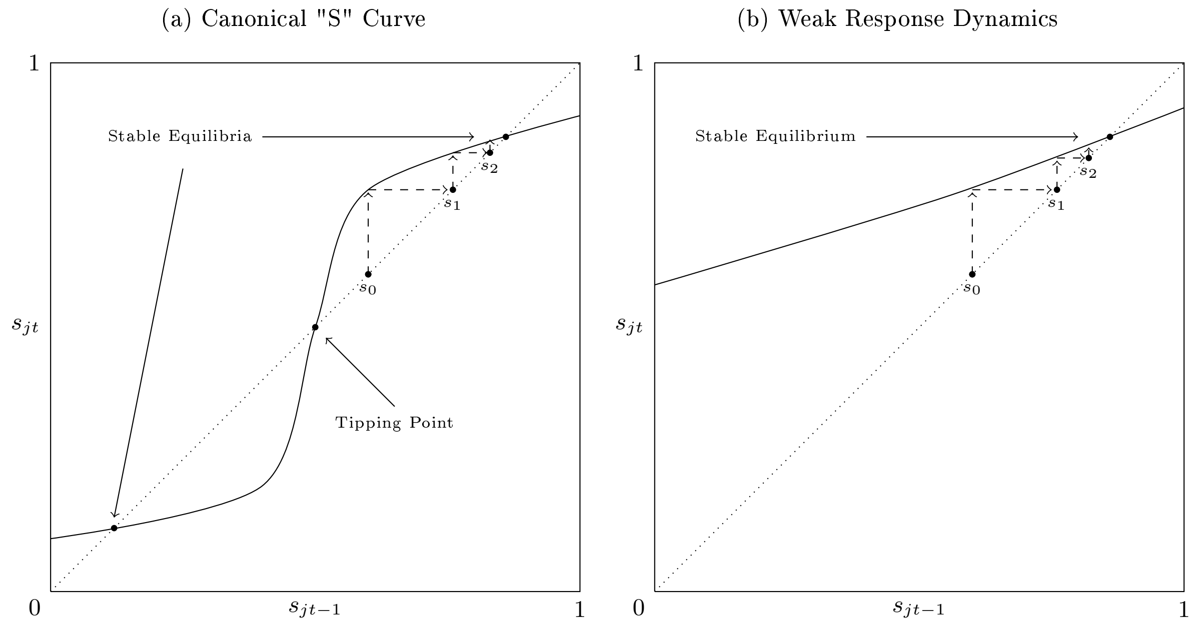
We illustrate the dynamics of $s_{jt}$ that arise from the endogenous mechanism in Figure 1.[7] In Panel 1a, we plot a *ceteris paribus* curve of $s_{jt}$ on $s_{jt-1}$ holding $\boldsymbol{N_t}$, $\boldsymbol{s_{-jt-1}}$ and $\boldsymbol{X_t}$ fixed[8], which summarizes the evolution of $s_{jt}$ in 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 $\frac{\partial \pi_{Wj}}{\partial s_{jt-1}} < 0$ or $\frac{\partial \pi_{Mj}}{\partial s_{jt-1}} > 0$ are large in magnitude. In Panel 1b, we plot an alternative *ceteris paribus* curve of $s_{jt}$ on $s_{jt-1}$ if $\frac{\partial \pi_{Wj}}{\partial s_{jt-1}} < 0$ 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 endogenous mechanism would result in a racial composition of $s_1$ one period ahead, $s_2$ two periods ahead, and

[6] Changes in $s_{jt-1}$ may also signal future *neighborhood* changes. For instance, a reduction in the Hispanic share of a school may lead White households to expect that this neighborhood will become more attractive to them for whatever reason (e.g., they may expect local venues to change in the near future to cater to their preferences). In this example the effects of $s_{jt-1}$ on demand through expected neighborhood changes are included in the endogenous mechanism. To the extent that neighborhood amenities are expected to change beyond what is implied by changes to the school's racial composition, they are loaded onto the $\boldsymbol{X_{jt}}$ vector.

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

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

Figure 1: Dynamics of $s_{jt}$

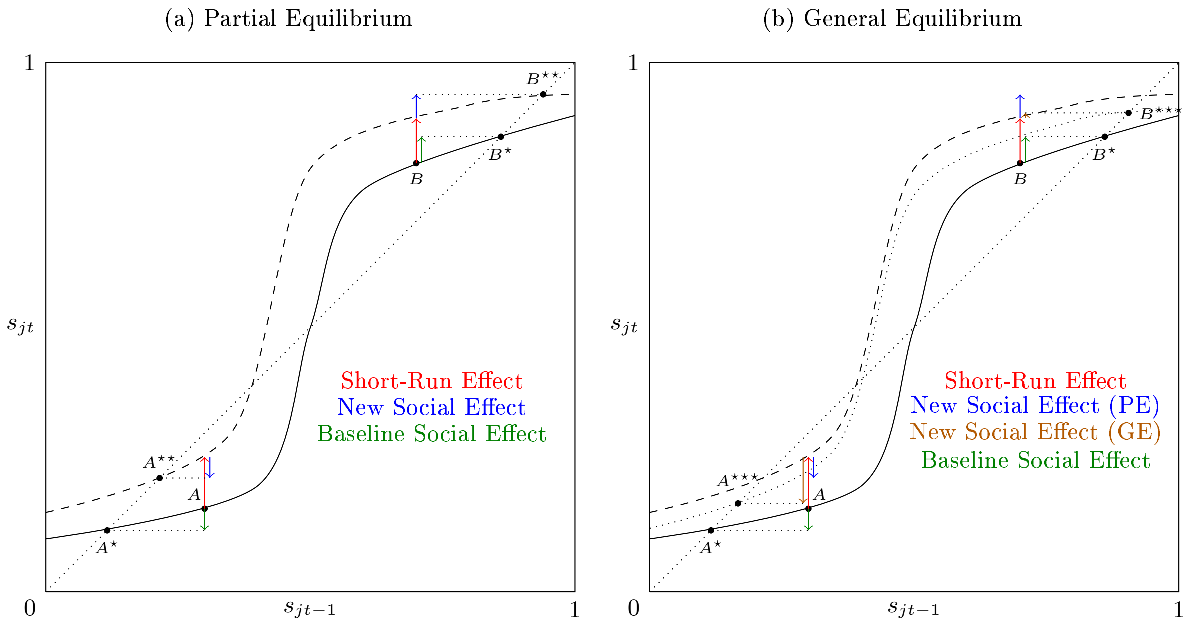



so on. The locations of equilibria and the speeds of convergence depend upon $\boldsymbol{N_t}$, $\boldsymbol{s_{-jt-1}}$ and $\boldsymbol{X_t}$ since different values of these would result in shifts and deformations of the curve. This implies that these curves are school-specific (and year-specific). Following the literature (e.g., Bayer and Timmins (2005); Banzhaf and Walsh (2013)), we utilize the "S" curve for the remainder of our exposition.[9]

In order to assess how the demographic (or residual) mechanism interacts with the endogenous mechanism, we consider the effect of a hypothetical shock in Figure 2. 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 2a, 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 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 endogenous mechanism then acts as a dynamic

[9]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 2: Effects of Changes in Demographics/Other Characteristics on $s_{jt}$




social multiplier, generating an additional social effect from $t$ onward shown as the blue arrow. The long-run demographic (or residual) 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 $\pi_{rj}$ for all $r$.[10] 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 zero. Still, the new social effect would be non-zero since the shift in the curve would take the school out of equilibrium.

The diagram shown in Figure 2a 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 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

[10]The function $\pi_{rj}$ 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.

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 feedback between these two schools and any others that are substitutes leading to potentially complex general equilibrium effects on the dynamics of other schools.[11] We represent these general equilibrium effects as additional shifts of the "S" curve (shown in Panel 2b) that dampen the effect of the initial shock.[12] This results in a new GE social effect that is smaller than the new social effect from a partial equilibrium perspective.[13]

Finally, we should contrast the effects of changes to demographics or other characteristics of schools with the effects of desegregation policies that simply re-allocate students of different races across schools (e.g., busing). These re-allocations can be modeled as movements *along* the "S" curves of schools, so the locations of equilibria are unchanged. As a result, such policies will have no effect in the long-run (unless a reallocation is so dramatic that the racial composition of a school crosses a tipping point.)

# 3 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 schools change over time with the understanding that observed changes may be attributable to movements along the "S" curve toward equilibrium (i.e., the endogenous mechanism), demographic shocks, or any other 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 $\pi_{rj}$ 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

[11] 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.

[12] For illustrative purposes only, Figure 2 ignores the fact that the "old" social effect that accounts for general equilibrium effects will generally differ from the partial equilibrium "old" social effect.

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

obtained from a standard discrete choice framework (McFadden (1973); Berry (1994)).[14] 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, we implement it simultaneously for all commuting zones.

We first specify the log-demand equation for school $j$ by parents of race $r$ as:[15]

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

The parameter $\beta_r$ represents the enrollment response to the minority share of the school by race $r$ parents. The race-year fixed effect $\gamma_{rt}$ subsumes $N_{rt}$ and encapsulates any demographic changes in the racial composition of aggregate enrollments due to fertility, migration, shifts to private schools, etc. Finally, the residual $\epsilon_{rjt}$ subsumes $\boldsymbol{X_t}$ and $\boldsymbol{s_{-jt-1}}$ and includes all school (and associated neighborhood) characteristics other than $s_{jt-1}$ that affect the choices of households who already have decided to enroll their child in a public school.[16]

With causal estimates of $\hat{\beta}_r$, 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 $\boldsymbol{\tilde{s}_{jt-1}}$ will evolve (given some counterfactual trajectory of the aggregate commuting zone enrollments, $\boldsymbol{\tilde{N}_t}$). To simulate this trajectory from $t_0$, we use the following equations of motion:

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

[14] 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 3, nearly all demographic changes during our sample period can be attributed to immigration.

[15] 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 since the relationship between $\boldsymbol{X_{jt}}$ and $\boldsymbol{s_{-jt-1}}$ is unrestricted.

[16] The specification presented here corresponds to a choice model in which parents first choose whether to send their children to a public school in a commuting zone and then consider all schools within that commuting zone. In selecting a school, parents consider the school-level racial composition as opposed to the grade-specific racial composition, as the latter information is more salient to parents. However, by specifying the fixed effects $\gamma$ at narrower levels, e.g. at the neighborhood-race-year level, we would instead estimate a parameter from a different choice model in which parents first choose a neighborhood and then consider all schools within that neighborhood. In Appendix C, we present results from alternative formulations of this choice problem and show that our results are insensitive to the specification. This suggests that our estimate of $\beta$ reflects all relevant endogenous responses that occur within the commuting zone.

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).[17]

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

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

$\hat{s}_j\left(\boldsymbol{N}_{\boldsymbol{t_0}}, \boldsymbol{s}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right)$ corresponds to the racial composition of $j$ in $t$ in the absence of any external change to demographics or school and neighborhood characteristics from $t_0$ to $t$; hence $s_{jt_0}$ can only change from $t_0$ to $t$ through the endogenous channel. The change in $s_j$ from $t_0$ to $t$ attributable to the demographic mechanism is calculated as

$$\Delta^D_{jt_0\rightarrow t} = \hat{s}_j\left(\boldsymbol{N}_{\boldsymbol{t}}, \boldsymbol{s}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) - \hat{s}_j\left(\boldsymbol{N}_{\boldsymbol{t_0}}, \boldsymbol{s}_{\boldsymbol{t-1}}, \boldsymbol{X}_{\boldsymbol{t_0}}\right) \tag{9}$$

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

[17] 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).

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

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 other school and neighborhood characteristics, which are subsumed in the residual. 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 this represents a full decomposition of the observed change in racial composition.

### Identification of $\beta$

Identifying endogenous effects such as $\beta_r$ 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 the current period $t$. If White and minority parents have different preferences for such characteristics, then the OLS estimate of $\beta_r$ will be biased upward (in magnitude). As such, we employ the IV strategy proposed in Caetano and Maheshri (2017).

Intuitively, this IV strategy exploits an asymmetry between the information sets of parents who choose where to enroll their children today and parents who chose where to enroll their children in the past. Any difference in these information sets implies the existence of some previous *transitory* shock to parents' information sets that was relevant to decision makers in the past but it is no longer relevant to decision makers today. By construction, such shocks do not persist into $t$, so they cannot directly affect enrollment in $t$. However, frictions (e.g., moving costs) may "lock" some children into their school even though it is no longer as attractive to them. These children are enrolled in their current school "by accident" in a sense, since the reasons for their initial sorting decision are no longer relevant. However, these children still contribute to the racial composition $s_{jt-1}$. This suggests that if we could isolate the variation in enrollments in $t$ that is only due to *ex post* "accidental" enrollments in the past, we could use it to obtain causal estimates of $\beta$.

Of course, comprehensive data on transitory shocks to school characteristics for all schools in the entire country is not available. We circumvent this obstacle with an approach that relies solely on enrollment data. We isolate exogenous variation in $s_{jt-1}$ by focusing on the component of $s_{jt-2}$ that is orthogonal to $n_{rjt-1}$. 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*) influences $s_{jt-1}$ without directly affecting $n_{rjt}$. To isolate the transitory component, we control for the enrollments of subsequent cohorts of students (the *control cohorts*) in $t-1$. The variation in the IV from $t-2$ that is orthogonal to the enrollments of the control cohorts in $t-1$ is the component that is likely irrelevant to choices in $t$.

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 $\beta_{rg}$ represents the enrollment response of each race to the minority share of the school, and it is now allowed to vary by grade.[18] The race-grade-commuting zone-year fixed effects, $\gamma_{rgct}$, encapsulate the demographic effect (disaggregated by grade).[19] Finally, the error term, $\epsilon_{rgjct}$, incorporates the remainder of the determinants of the school demand.

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

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

where $\underline{g}_j$ and $\bar{g}_j$ are the lowest and highest grades of instruction of school $j$, respectively, and $\alpha$ represents regression coefficients.

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 $s_{jct-1}$ in equation (13). Our IV estimator of $\beta_{rg}$ is consistent under the following

[18]We also allow $\beta_{rg}$ to vary across commuting zones depending on their student population. See equation (14).

[19]As a robustness check we also include fixed effects at finer geographic areas than commuting zones such as school districts. See Appendix C.

identifying assumption:

**Assumption 1.** *Identifying Assumption.* $Cov\left[s_{jt-2}^{\bar{g}_j-1}, u_{rgjct}|C_{rgjct-1}, \gamma_{rgct}\right] = 0.$[20]

In words, our identification assumption states that unobserved school characteristics that affected parents' enrollment decisions in the past ($s_{jt-2}^{\bar{g}_j-1}$) but do not affect enrollment decisions in $t-1$ ($C_{rgjct-1}$) cannot suddenly reappear and affect enrollment decisions in $t$.[21] To help explain how we implement this IV strategy, consider a 9-12 high school as an example in the diagram below. 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 $t$. Our IV is $s_{jct-2}^{11}$, and to absorb persistent (confounding) school characteristics we control for the $t-1$ enrollments of Whites and minorities in all grades except for the highest grade. For schools that offer more than two grades of instruction, we can construct additional instruments from the IV cohort observed in earlier grades such as $s_{jct-3}^{10}$ and $s_{jct-4}^{9}$, which permits over-identification tests (Hansen (1982)).[22]

| | $9^{th}$ | $10^{th}$ | $11^{th}$ | $12^{th}$ |
|---|---|---|---|---|
| $t$ | Dep. Var. | Dep. Var. | Dep. Var. | Dep. Var. |
| $t-1$ | Control | Control | Control | |
| $t-2$ | | | IV | |
| $t-3$ | | IV | | |
| $t-4$ | IV | | | |

**Relevance: What is the Identifying Variation?**

We identify $\beta$ by using all changes in school characteristics that (1) compelled students in the IV cohort to sort towards a school in the past (thus changing $s_{jct-1}$), and (2) did not affect enrollment decisions in $t$. Because we cannot observe – or even enumerate – all of these shocks, our strategy relies on the fact that their effects are observed in enrollment data. We provide a concrete example of a shock here for intuition. Consider a popular and well known ESL teacher in a 9-12 high school

[20]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.

[21]See Appendix C for a description of many robustness checks where we weaken this assumption and obtain similar results.

[22]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.

who retired just before year $t-3$. On average, ESL instruction is plausibly valued more by Hispanic parents than by other parents, so this teacher would have affected the racial composition of ninth graders in $t-4$ (who are members of the IV cohort) without directly affecting the enrollments of any subsequent cohorts of students. Despite retiring, the teacher would have still influenced the minority share in $t-1$ since some members of the IV cohort remain in the same school simply due to inertia. However, the IV cohort aged out of the school by $t$, so the only way the teacher could affect the enrollment decisions of students in $t$ would be through parents' enrollment response to the minority share in $t-1$. This is precisely the effect that we seek to identify.

Of course, this is just a single example that is not meant to be representative. However, we conjecture that 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. Indeed, any forecast error on the part of households who sorted in the past – perhaps they expected school and neighborhood amenities to trend in a certain way, which went unrealized in actuality – will generate identifying variation for us. Importantly, we can test our conjecture directly: if parents' information sets did not change from $t-2$ to $t-1$ (or if they did change, but no children remained in the school due to inertia) then we would not have a first stage. 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 specific shocks. Parents' expectations of the future trajectories of schools may differ from one another as they are formed through conversations with other parents, real estate agents, online reviews, etc. Whatever these expectations are, they lead to the choices which we observe in the data. 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 that are unobservable or even inconceivable to us as researchers.

*Remark* 1. $\beta_{rg}$ represents 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 $\beta_{rg}$ 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, the availability of local schools with desired amenities, and even supply-side restrictions that might steer households of different races toward certain neighborhoods (Christensen and Timmins (2019)). Hence, the finding of a small value of $\beta_{rg}$ should not be interpreted as evidence of weak racial preferences of race $r$ parents. Instead, it should be interpreted only as weak demand responses, which is compatible with strong racial preferences and a weak ability to exercise those preferences.

*Remark* 2. Note that *discrimination*, commonly understood as the tendency of people to avoid associating with others of different types, may fall within each of the three mechanisms we delineate. Naturally, all of the endogenous mechanism can be understood as discriminatory whether for taste-based or for statistical reasons, but the demographic and residual mechanisms likely include a discriminatory component as well. For instance, households of a given race may sort to certain cities because they contain a large proportion of same-race residents, which would fall under the demographic mechanism, and discrimination in the real estate market (that is orthogonal to the racial composition of schools) would fall under the residual mechanism.

## 4 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 American public school students from 1988-2018.[23] We restrict our sample to the 50 states and the District of Columbia and ignore schools in US territories. From 1988-2001, enrollment data was only available at the school-race level of disaggregation; in 2002, enrollment data was made available at the school-grade-race level of disaggregation. As such, our estimation uses the 2002-2018 subsample of our data, and our simulation analysis only uses the 2003-2018 subsample of our data. Nevertheless, for greater context, we present background data from the entire sample in this section only. Enrollment data from a small number of states in some early years of the sample are missing, but this is a minor issue in the post 2002 subsample that we use for our analysis.[24] Our sample includes all public charter schools and magnet schools. For each school, we observe the

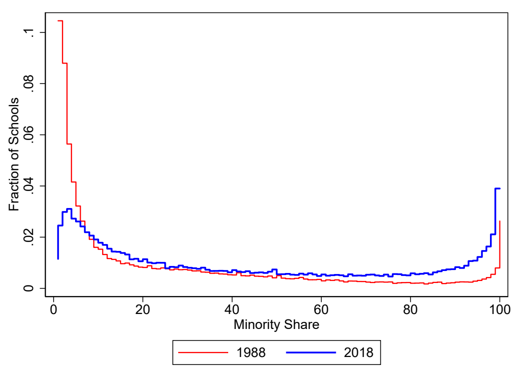
[23]We use 2000 to refer to the 2000-01 academic year and follow this convention throughout the paper.

[24]Detailed documentation of our sample, including the missing data, can be found in Appendix A. For our main analysis, only Tennessee enrollment data from 2002-2004 and Nevada enrollment data from 2004 is not available in the Common Core of Data.

numbers of White, Black, Hispanic, Asian and Native American students enrolled in each grade 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.[25]

In Figure 3, we present empirical distributions (PDFs) of the minority share of enrollment in every US school in 1988 and 2018. The cross-sectional variation among schools is inconsistent with the endogenous channel being the main driver of school segregation. While minority segregated schools (in the right tails of the distributions) became more prevalent over time, White segregated schools (in the left tails of the distributions) became less prevalent at a faster rate. If the endogenous channel was the main determinant of school segregation over this period, we would instead expect both tails to fatten over time. Instead, this figure is more consistent with an aggregate increase in the minority share of public school students, which would fall under the demographic channel.

Figure 3: Empirical Distribution of Minority Share of US Schools, 1988 and 2018




The national trend has unfolded differently across the country. In Figure 4, we present locally weighted least squares regressions of the prevalence of segregated schools in all US commuting zones in 1988 and 2018 against the total student populations of each commuting zone.[26] A histogram of the log(population) of commuting zones and representative cities for the largest bins of commuting zones is provided for context.[27] Over this period, the desegregation of predominantly White schools

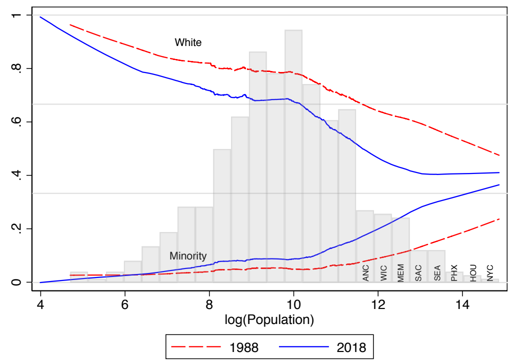
[25]These definitions of White and minority follow from US Government Accountability Office study GAO-16-345. If we instead classify Native Americans as minorities instead, define minorities as all non-White students, or omit all Asian and Native American students from our sample entirely, our findings are essentially unchanged. Starting in 2015, students were separately classified as being of two races, though the specific races were not reported. Because of this ambiguity, we omitted them from our analysis entirely. However, when we replicate our entire analysis using the 2002-2014 subsample, our findings are again essentially unchanged.

[26]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.

[27]NYC= New York, NY; PHX=Phoenix, AZ; SEA=Seattle, WA; SAC=Sacramento, CA; MEM=Memphis, TN;

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.

Figure 4: Prevalence of Segregated Schools in a Commuting Zone by Student Population, 1988 and 2018




Notes: We present locally weighted least squares regressions of the fractions of segregated schools in commuting zones in 1988 and 2018 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. "White" includes non-Hispanic Whites, Asians and Native Americans (see Footnote 25).

Regional patterns of school segregation can be found in appendix Figure 9. 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 Sun Belt, 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.[28]

For additional context, demographic changes in the aggregate student body can be found in appendix Figure 10 as measured by the average annual change in the minority share of enrollments at the commuting zone level from 1988 to 2018. Thus, in this map we eliminate all sorting across schools within commuting zones, so observed changes in (aggregate) racial composition are attributable only

WIC=Wichita, KS; ANC=Anchorage, AK.

[28]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.

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 and segregation trends is striking and motivates the need to determine the extent to which this relationship is causal.

*Remark* 3. There are four potential sources of demographic change in aggregate public school enrollments: changes in the racial composition of school enrollments outside of the public school system (i.e., private school or homeschooling); changes in fertility rates across races; migration between commuting zones; and immigration. In Appendix B, 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 1993-2018 while White enrollments decreased slightly (Figure 11);[29] the fertility gap between minorities and Whites slightly narrowed from 1971 to 2018 (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 12); 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 13).

## 5 Estimation Results

For our empirical analysis, we generalize from the two race model in Section 2 and 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.[30] Thus, equation (12) transforms into the estimation equation

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

[29]The percentage of the school-age population that is homeschooled increased from 1.7% in 1999 to 3.4% in 2012 (Source: US Department of Education), so this is unlikely to substantially affect the general trends we observe in public schooling.

[30]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.

where $\boldsymbol{\beta_{rgc}}$ is now a $2 \times 1$ column vector that contains race $r$ parents' responses to the shares of Black and Hispanic students in grade $g$ and commuting zone $c$ respectively.[31] Given three races, 13 grades, four groups of commuting zones, and two responses (to the Black and Hispanic shares of the school), $\boldsymbol{\beta_{rgc}}$ contains 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.[32]

In Figure 5, we present estimates of parents' responses to the racial composition of their children's 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 to Black peers, though this difference is not always statistically significant.[33] In Panel (b), we see that Black parents respond very strongly and positively to Black peers; they exhibit a much weaker positive response to Hispanic peers relative to White peers. Analogously, in Panel (c), we see that Hispanic parents respond positively to Hispanic peers in all grades, though these responses are smaller in magnitude than those of Black parents. Hispanic parents exhibit little response to Black peers in all grades.

These responses are stronger 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 (Remark 1).[34]

In Appendix Figures 20-22, we aggregate these responses across grades and disaggregate them by commuting zone to highlight spatial variation, which is primarily driven by heterogeneity in the sizes of commuting zones.[35] We find that White parents respond negatively to an increase in Black

[31] The control term $C_{rgjct-1}$ is now equal to $\sum_{i=\underline{g}_j}^{\bar{g}_j-1} \left(\alpha_{rigcW} \log n_{Wijct-1} + \alpha_{rigcB} \log n_{Bijct-1} + \alpha_{rigcH} \log n_{Hijct-1}\right)$. We use as IVs the $2 \times 1$ vector $\boldsymbol{s_{jct-2}^{\bar{g}_j-1}}$ defined for the Black and Hispanic shares of enrollments in an analogous manner to equation (13).

[32] Because of the large numbers of endogenous variables and instruments, we do not report detailed first stage results in the paper, though they are available upon request. The joint F-stat for each endogenous variable ranges from $1.6 \times 10^5$ to $4.1 \times 10^5$, and we are able to reject the null hypothesis of joint insignificance of all instruments at the 99% level using both the Cragg-Donald and the Kleinbergen-Paap weak identification tests. We have also studied the possibility that the variation we use may not be representative, leading to a LATE that is very different from the ATE under heterogeneous treatment effects. We find that our first stage is uniformly strong in different regions of the country, in schools with different grade spans, in schools located in cities with varying densities, and in schools with varying levels of racial compositions.

[33] This is consistent with Fairlie and Resch (2002), who find evidence of White parents avoiding Black peers in public schools but report less clear evidence of White response to Hispanic peers.

[34] See Figure 8 (Appendix A) for the distribution of schools by grade range in the country.

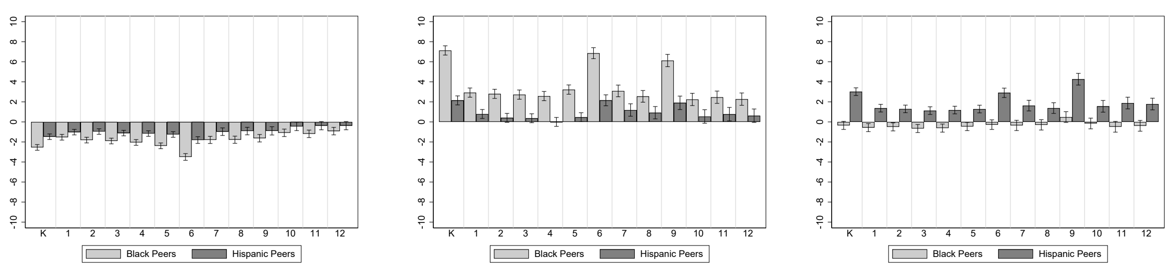
[35] The spatial variation in the maps of parental responses also incorporates variation in the grade structure of schools in different commuting zones.

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. White parents have extremely small negative responses to Hispanic peers everywhere but slightly larger negative responses in more populous areas. Black parents respond most positively to Black peers in parts of the country where Black peers are most scarce. These responses exceed Black parents' responses in large urban areas by a factor of four on average. Similarly, 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.

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.

Figure 5: Estimates of Parents' Responses to Peers by Grade, 2005-2018

(a) White Parents' Responses (b) Black Parents' Responses (c) Hispanic Parents' Responses




Notes: Estimates obtained from equation (14) are aggregated across commuting zones. The 95% confidence intervals shown are constructed with standard errors that are clustered at the race-grade-year-commuting zone 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 7,578,789 school-race-grade-year observations in the sample.

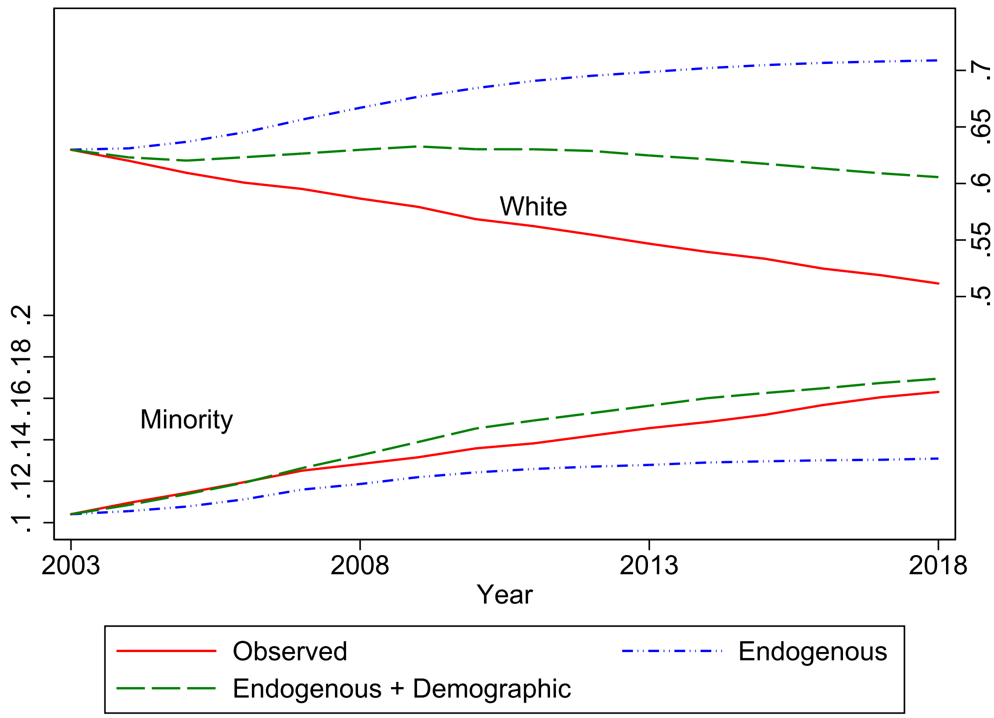
In Appendix C, we perform a detailed sensitivity analysis and present the results of a number of additional tests to ensure the robustness of our results.

## 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 $\tilde{s}_{jt}^{E} = \hat{\Delta}_{2003\to t}^{E}$ as it only reflects changes in $s_{jt}$ due to the endogenous 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 $\tilde{s}_{jt}^{DE} = \hat{\Delta}_{2003\to t}^{D} + \hat{\Delta}_{2003\to t}^{E}$. This time series reflects changes in $s_{jt}$ due to demographic shocks and all subsequent endogenous adjustments to those shocks. 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 6, 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 16 year period. Three results are immediate. First, endogenous 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 8 and 2 percentage points respectively. Second, demographic shocks more than offset the endogenous effects for White-segregated schools, but it exacerbated the proliferation of minority-segregated schools by roughly three times as much as the endogenous effect. Third, the residual mechanism (the vertical distance between the solid red line and the dashed green line) 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, residual sorting might then lead to greater mixing of races in many commuting zones.

Figure 6: Decomposing Observed Changes in the Prevalence of Segregated Schools, 2003-2018



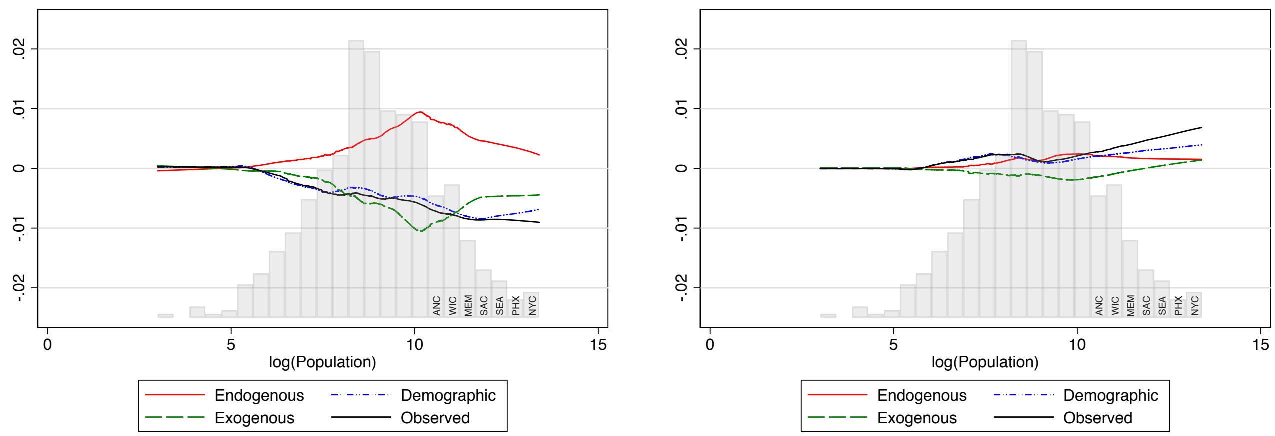

Notes: A White- (minority-) segregated school has over 75% White (minority) enrollment. The decomposition is implemented for all schools who operate in every year from 2003-2018 and averaged annually across the US. The solid red, dotted blue and dashed green paths correspond to segregation levels computed with $\tilde{s}^{D}_{jt}$, $\tilde{s}^{DE}_{jt}$ and $s_{jt}$ respectively. The total vertical change in the dotted blue path corresponds to the change in segregation through the endogenous 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.

Because the largest changes in the school segregation have occurred in the largest commuting zones (see Figure 4), we present these counterfactual trajectories against commuting zone population in Figure 7. The endogenous mechanism (solid red) has essentially no effect in very small commuting zones and is weak in very large commuting zones, but in midsize commuting zones, it can be quite large. As expected, this mechanism always contributes to increasing segregation. The demographic mechanism (dotted blue) 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 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 types of commuting zones, the demographic mechanism has led to desegregation of White schools and segregation of minority schools. Finally, the residual mechanism (dashed green) is weak in the smallest and largest commuting zones but stronger in midsize 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).

To summarize: All three mechanisms have played roles in explaining the evolution of school segregation from 2003 to 2018, and their relative importance varies systematically. While the endogenous and residual mechanisms are of similar and large importance for midsize cities, the demographic mechanism is substantially more important for larger cities where the endogenous mechanism is weak. In the absence of exogenous changes to schooling markets, endogenous sorting would have increased all forms of school segregation nearly everywhere, as parents desire to enroll their children in schools with peers of the same race. Residual sorting 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.

Figure 7: Decomposing Observed Changes in the Prevalence of Segregated Schools, 2003-2018

(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 27 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 2018. The solid red, dotted blue and dashed green paths correspond to segregation levels computed with $\tilde{s}^E_{jt}$, $\tilde{s}^D_{jt}$ and $s^X_{jt}$ respectively. The total vertical change in the dotted blue path corresponds to the change in segregation through the endogenous 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 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 2018, the four most populous commuting zones had majority "minority" enrollments.[36]

Models of segregation predict that when holding all else constant, even mild endogenous responses will 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

[36]The minority share of 2018 enrollment of the four largest commuting zones was, in order of size: Los Angeles (71%), New York City (58%), Houston (68%) and Chicago (52%).

in desegregating White schools and segregating minority schools, especially in areas that experienced the greatest change in segregation: large, urban commuting zones. Exogenous changes to the schooling environment (and the sorting of students that resulted from those changes) have 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 some of this reduction in segregation may have been an indirect response to changing demographics if, for example, neighborhood amenities adjusted to cater to new Hispanic residents into previously predominantly White attendance areas. 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 endogenous 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.[37]

[37] Most research into the impacts of diversity on White students has been conducted in the context of tertiary

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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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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# Online Appendices

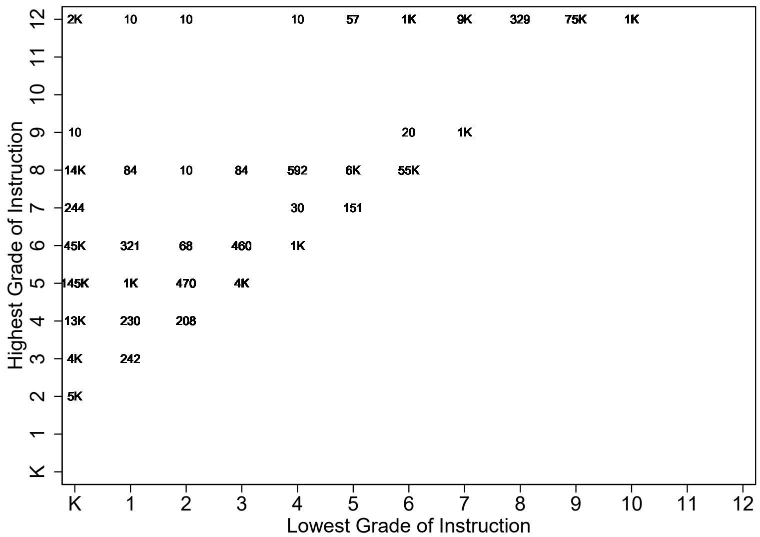
## A Data Appendix

Table 1: Missing Data

| State | Years Missing |
|---|---|
| Arizona | 1998 |
| Colorado | 1998 |
| Georgia | 1988-1992 |
| Idaho | 1988-2001 |
| Louisiana | 1988 |
| Maine | 1988-1992 |
| Massachusetts | 2000 |
| Minnesota | 1998 |
| Missouri | 1988-1990 |
| Montana | 1988-1989 |
| New Hampshire | 1988 |
| New Jersey | 1998 |
| New Mexico | 1988 |
| New York | 1998 |
| Nevada | 2004 |
| North Dakota | 1998 |
| Oregon | 2000 |
| Pennsylvania | 1998, 2000-2001 |
| South Dakota | 1988-1991 |
| Tennessee | 1998-2004 |
| Vermont | 1998 |
| Virginia | 1988-1991 |
| Washington | 1998-2000 |
| West Virginia | 1998 |
| Wyoming | 1988-1989 |

Note: Only Nevada and Tennessee have any data missing from 2002-2018, 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.

Figure 8: Distribution of Grade Range Across All Schools



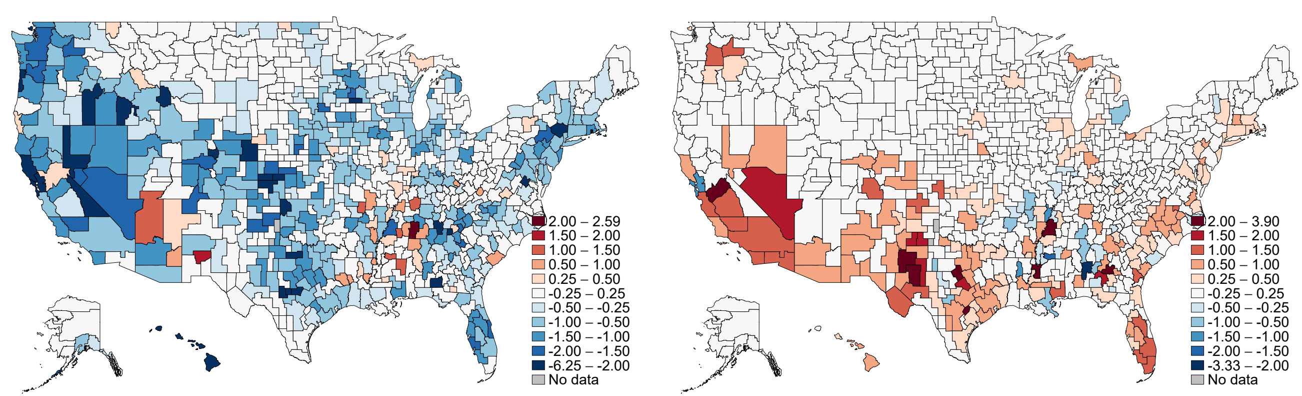

Note: For each $\underline{g}$ in the horizontal axis and $\overline{g}$ in the vertical axis, this plot shows the number of schools in our sample that are of a given grade range $(\underline{g}, \overline{g})$. $1K$ represents 1,000 schools.

# B Demographic Change: Figures

Figure 9: Average Annual Change in Proportion of Segregated Schools, 1988-2018

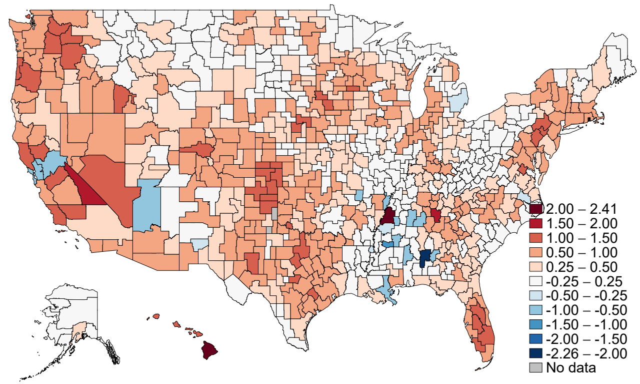
(a) Change in Proportion of Segregated White Schools

(b) Change in Proportion of Segregated Minority Schools



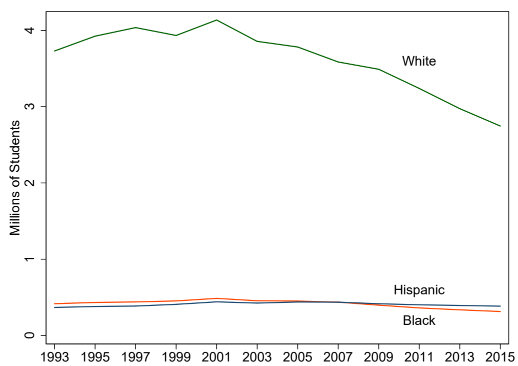

Note: We define White-segregated schools as over 75% White, and minority-segregated schools as over 75% minority. Blue (Red) commuting zones have experienced declining (increasing) segregation during this period. Annual changes shown in percentage points.

Figure 10: Change in Minority Share of Students in Commuting Zone, 1988-2018




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.

Figure 11: Private School Enrollments by Race, 1993-2015




Note: Private school enrollment data are obtained from Private School Universe Surveys, 1993-1994 through 2015-2016 maintained by the National Center for Education Statistics. Our sample period coincides with a decline in White private school enrollment and stable minority enrollment.

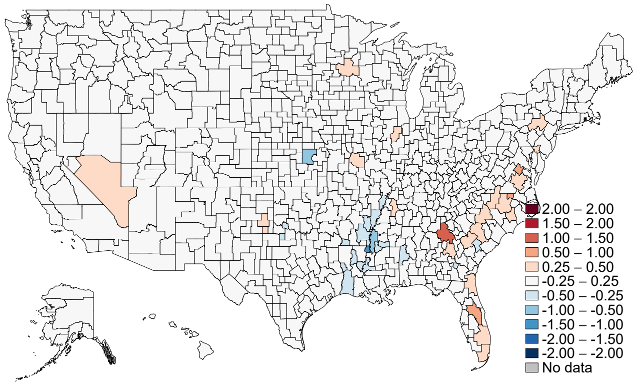
Table 2: Fertility Rates by Race, Selected Years

| | 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 |
| 2018 | 56.3 | 62.0 | 65.9 |

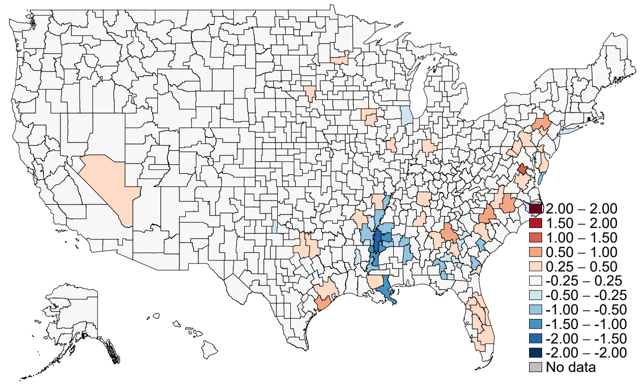
Notes: Fertility rates are defined as total births per 1,000 women aged 15-44. Details on Hispanic status of mothers not available until 1989.[1]: In this year, Hispanic White and Hispanic Black mothers were classified as White and Black respectively. Sources: Vital Statistics of the United States, 2019.

Figure 12: Average Annual Change in Black/Hispanic Share of School-Age Population due to Immigration and Migration

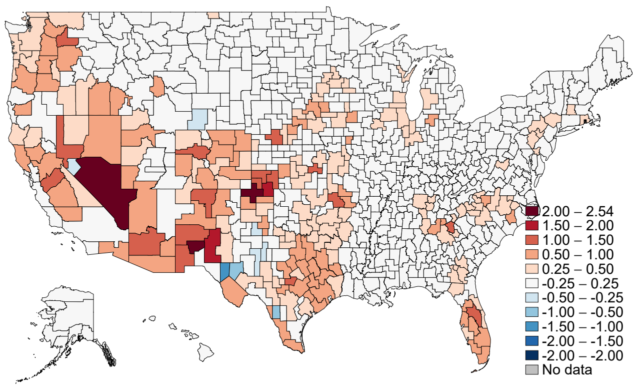
(a) Change in Black Share, 1990s



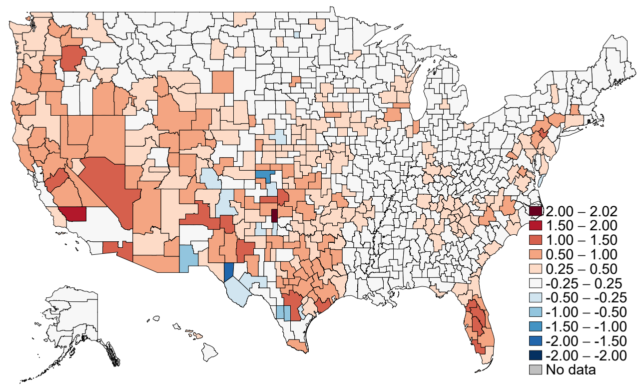

(b) Change in Black Share, 2000s




(c) Change in Hispanic Share, 1990s

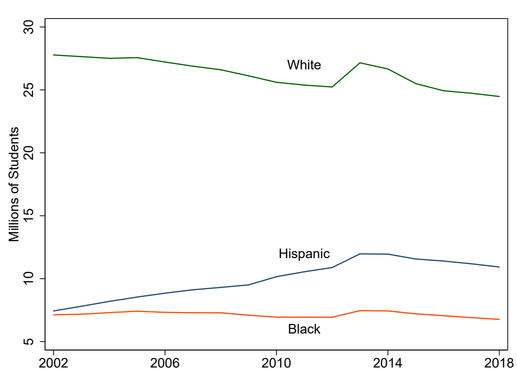



(d) Change in Hispanic Share, 2000s




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 13: National Public School Enrollments by Race, 2002-2018




Note: Missing data (see Table 1) is linearly interpolated and extrapolated to create this figure.

# C Sensitivity Analysis

In this appendix, 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.

## C.1 Validity of Identification Strategy

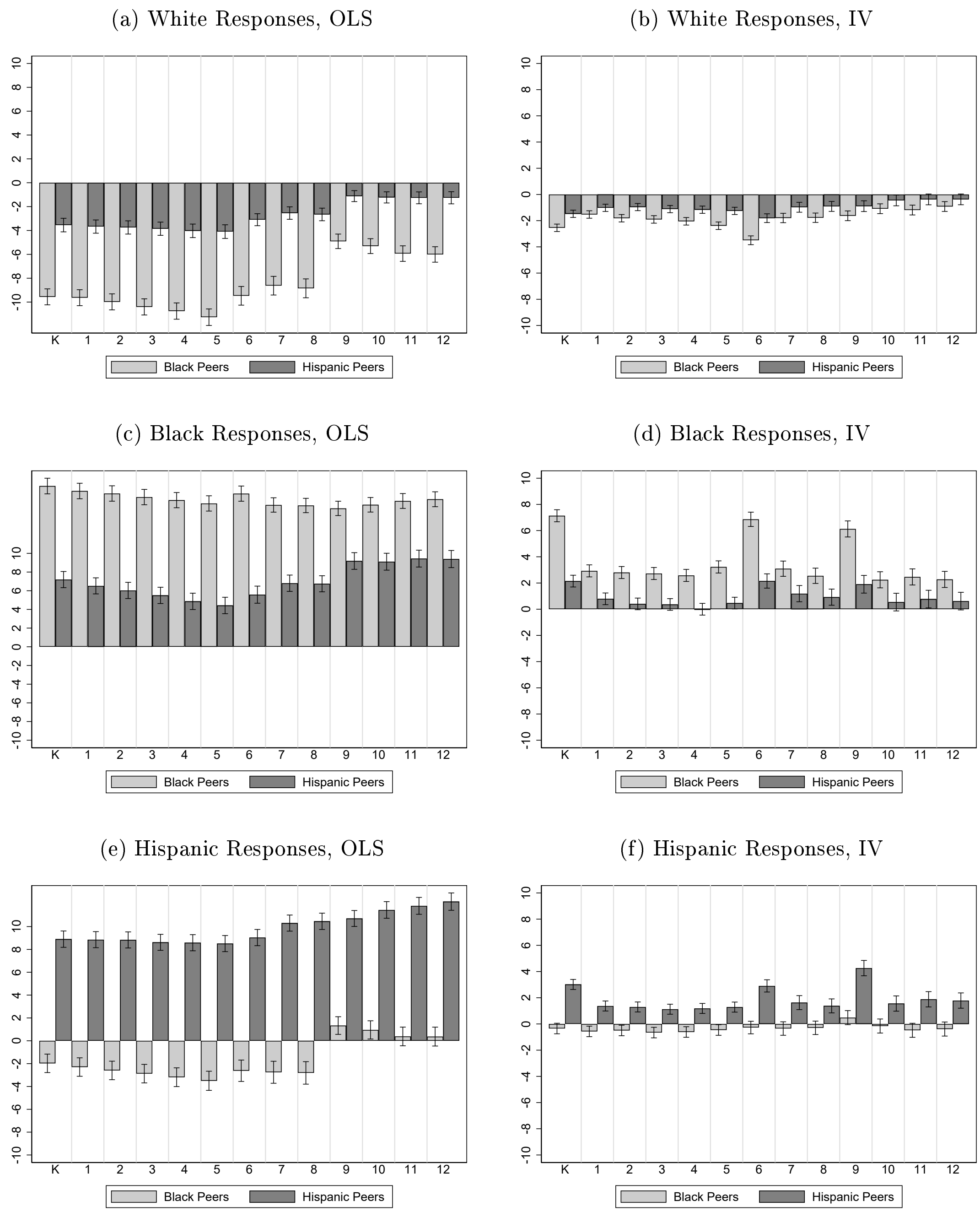
We subject our identification strategy to several robustness checks. First, we compare the OLS estimates with our IV estimates to gauge the extent of bias that would arise if the roles of endogenous and residual sorting were not separately identified. Next, we consider the possibility that our IV estimates 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.

### C.1.1 OLS vs. IV Estimates

In Figure 14, we present a comparison of estimates of $\beta_{rg}$ 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 endogenous sorting.[38]

[38] Our OLS estimates of White responses to the Black share of peers in 8th grade are of the same order of magnitude as the correlations reported in Saporito and Lareau (1999). We find the OLS response to Black peers to be three times the size of the response to Hispanic peers, whereas they find it to be twice the size of the response to Hispanic peers.

Figure 14: Estimates of $\beta_{rg}$, 2005-2018: OLS vs. 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 7,578,789 school-race-grade-year observations in the sample.

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 Hispanic neighborhoods to choose from. Meanwhile, in large cities with pre-existing Hispanic neighborhoods, Hispanic immigrants were more likely to settle among Hispanic peers.

### C.1.2 Neighborhood Choice

Parents may respond to changes in $s_{jt-1}$ for several reasons. One reason is that a change in $s_{jt-1}$ may signal to parents that the amenities of a neighborhood will change in the future. This is helpful to us since we want to incorporate all endogenous effects, including those that operate through neighborhoods and not schools. Of course, there is still a chance that some effect that should be attributed to the endogenous mechanism gets misattributed to the residual mechanism, i.e., households could respond further to the component of the racial composition of a neighborhood that is orthogonal to the racial composition of its school. We view this concern as likely unimportant since the residual mechanism systematically contributes to segregation in the opposite direction of the endogenous mechanism.[39]

In any case, we attempt to address this concern more directly by presenting IV estimates of $\beta_{rg}$ 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

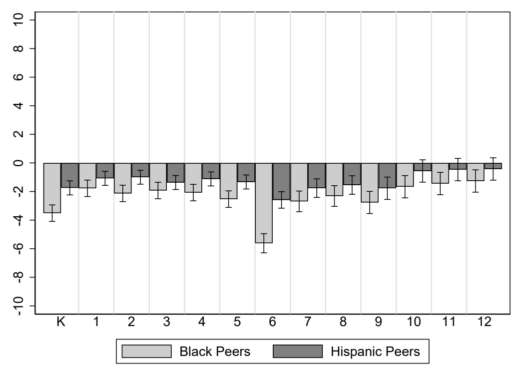
[39]This is consistent with the findings of Candipan (2019) and Candipan (2020), which document increasing gaps in the racial compositions of public schools and neighborhoods, particularly in the most rapidly gentrifying areas.

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 $\beta$ would constitute evidence that part of the endogenous response to neighbors was not originally identified in the baseline specification using fixed effects at the commuting zone level.

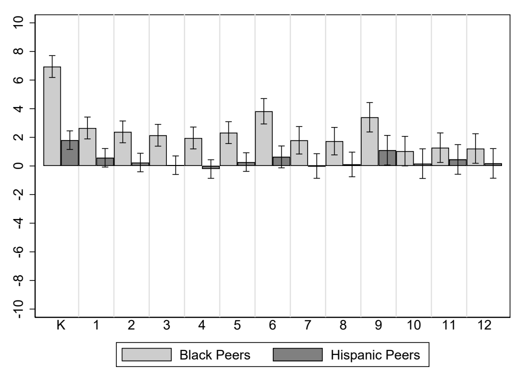
In order to implement this robustness check, we must deal with the fact that specifications with geographically narrower fixed effects rely more heavily on identifying variation from large commuting zones (because smaller areas often have a single school serving a given grade within a district or ZIP 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 16) with the baseline results (Figure 15) for this subgroup reveals very similar results. This suggests that the residual mechanism as identified by our simulation is not driven by endogenous responses toward neighbors.

Figure 15: Estimates of $\beta_{rg}$, 2005-2018: Commuting Zone FEs, Large Cities

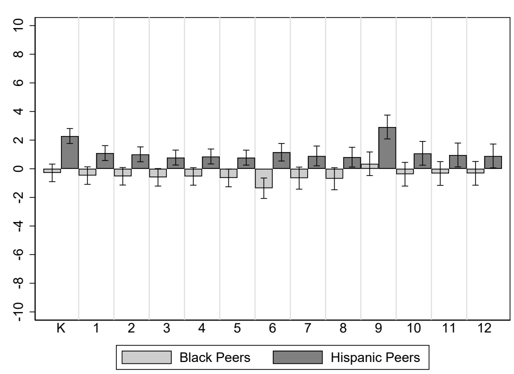
(a) White Responses, **Commuting Zone**-Year-Race-Grade FEs




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



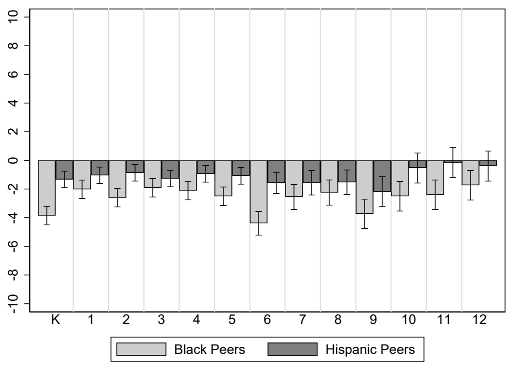

(c) Hispanic Responses, **Commuting Zone**-Year-Race-Grade FEs



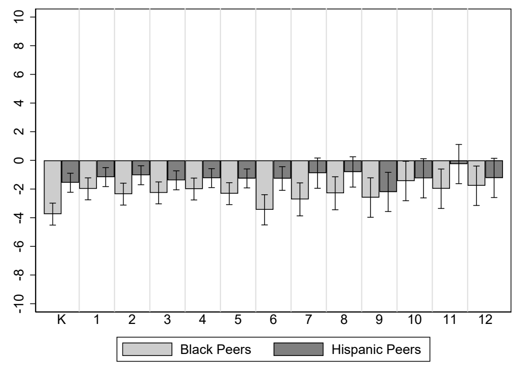

Notes: IV estimates from equation (11) are aggregated only across the 15 largest commuting zones. They include fixed effects at the commuting zone-year-race-grade level. The 95% confidence intervals shown are constructed with standard errors that are clustered at the commuting zone-year-race-grade level. The p-values from F-tests of whether the IVs ($s_{jt-2}^{\bar{g}_j-1}$ and $s_{jt-3}^{\bar{g}_j-2}$) are significant in the first stage regressions are always less than 1%. There are 1,988,634 school-race-grade-year observations in the sub-sample used for this figure.

Figure 16: Estimates of $\beta_{rg}$, 2005-2018: Neighborhood FEs, Large Cities

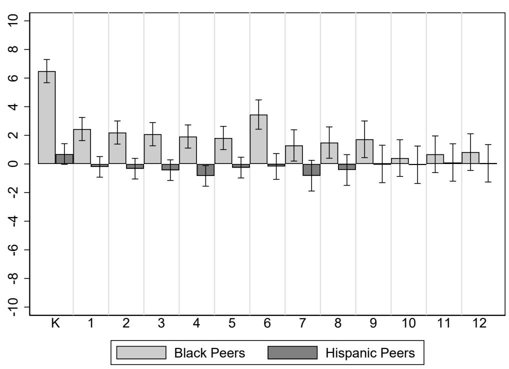
(a) White Responses, **School District**-Year-Race-Grade FEs



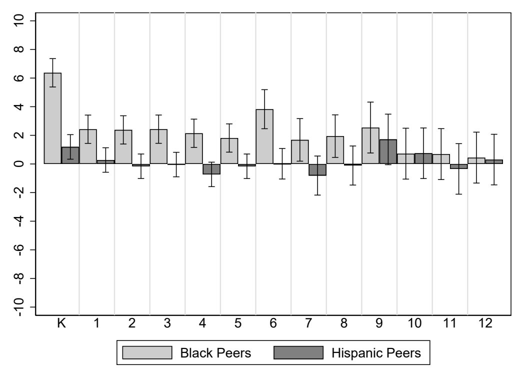

(b) White Responses, **ZIP Code**-Year-Race-Grade FEs



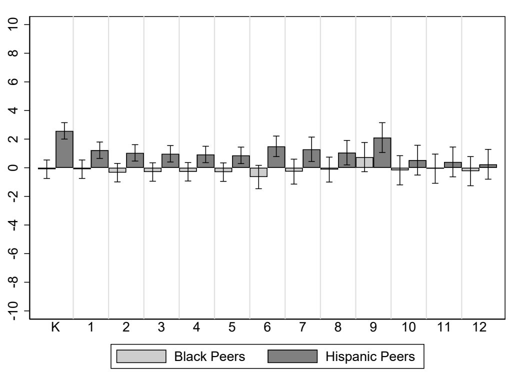

(c) Black Responses, **School District**-Year-Race-Grade FEs



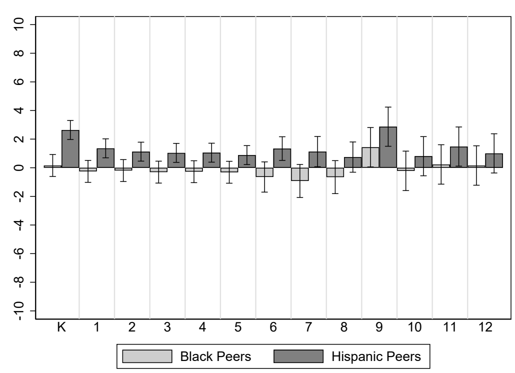

(d) Black Responses, **ZIP Code**-Year-Race-Grade FEs




(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 1,988,634 school-race-grade-year observations in the sub-sample used for this figure.

### C.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, open enrollment policies or homeschooling. For instance, consider a White ninth grader who attends a local public school. An increase in the minority share of this local public school may trigger them to enroll in a private school. This will be observed as a reduction in $\log n_{jt}^{gr}$ in tenth grade enrollment of the public school that the child would have attended, so the response is included in the $\beta$ coefficient. More generally, whenever White parents respond to the racial share of their neighborhood public school by exercising school choice via some mechanism other than standard residential assignment via attendance area (i.e., a private school, a charter or magnet school, another public school via open enrollment, or homeschooling), $\beta$ would include this endogenous response because we would observe a reduction in White enrollment in the public school that was assigned to those parents.

Our results using different fixed effects help illuminate the roles of these alternative choice options. Recall that in our baseline estimates of $\beta$ we use **commuting zone**-year-race-grade fixed effects. Fixed effects at narrower geographic levels (**school district**-year-race-grade fixed effects or, alternatively, **ZIP code**-year-race-grade fixed effects) partially control for many of these other school choice options because parents tend to exercise these options only if they are located sufficiently close to their residence. For instance, private schools tend to be located in areas within commuting zones that have sufficient demand for private schooling (e.g., Downes and Greenstein (1996)). If this margin was important, we would expect endogenous responses of parents in districts (or ZIP codes) with nearby private schools to be larger than the responses of those without nearby private schools. Thus, our estimates of $\beta$ would be systematically larger when controlling for commuting zone-year-race-grade fixed effects versus when controlling for either school district-year-race-grade or ZIP code-year-race-grade fixed effects since these geographically finer fixed effects would absorb some of the endogenous response. As noted in Section C.1.2, our estimates of $\beta$ estimates are similar when controlling for all three sets of fixed effects.[40]

[40] When we omit charter and magnet schools from our analysis, all of our $\beta$ estimates are essentially unchanged. This is further evidence that the most important margin along which parents individually respond to the racial shares

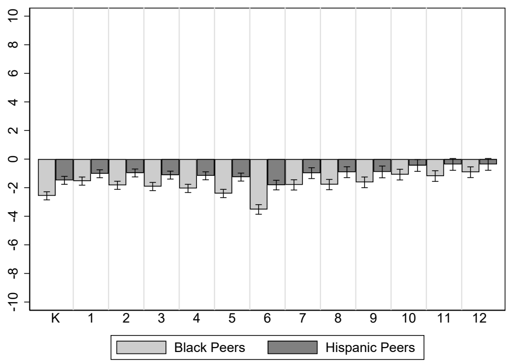
### C.1.4 Controlling for Persistent Amenities

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 a few additional robustness checks. In our baseline results, we used both $s_{jct-2}^{\bar{g}-1}$ and $s_{jct-3}^{\bar{g}-2}$ as IVs for $s_{jct-1}$. Intuitively, $s_{jct-3}^{\bar{g}-2}$ is more likely to be valid than $s_{jct-2}^{\bar{g}-1}$ 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 17 report the IV estimates using only $s_{jct-3}^{\bar{g}-2}$ 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 17 by adding further controls of the type $C_{rgjct-2}^{\bar{g}-2}$ 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. We attempt to further control for persistent amenities in two other ways and obtain similar results: (1) we include cubic B-splines of each element of $C_{rgjct-1}$ to allow for nonlinearities in the controls; and (2) we use $s_{jct-g_j-1}^{\bar{g}-g_j}$ as an IV with additional controls $C_{rgjct-g_j}^{\bar{g}-g_j}$, where $\bar{g}-g_j$ is the first grade of instruction offered in school $j$. The test implied by (2) is analogous to the test shown in the right panel of Figure 17, but it is plausibly more powerful because we use the farthest possible IV from period $t$ that is available for each school.

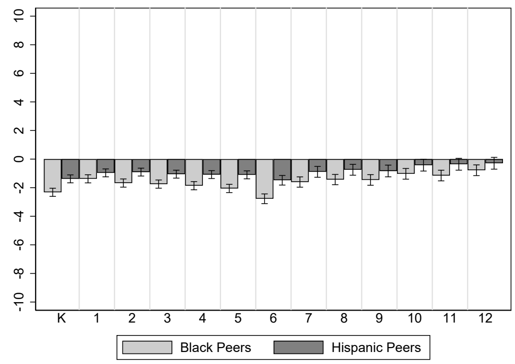
of schools is by sorting across neighborhood public schools.

Figure 17: Estimates of $\beta_{rg}$, 2005-2018: Adding Further Controls to Absorb Persistent Amenities

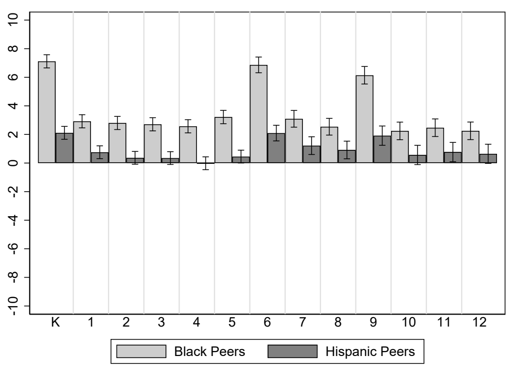
(a) White Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV



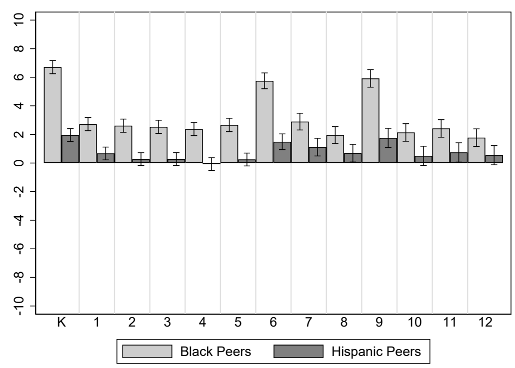

(b) White Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV plus additional controls



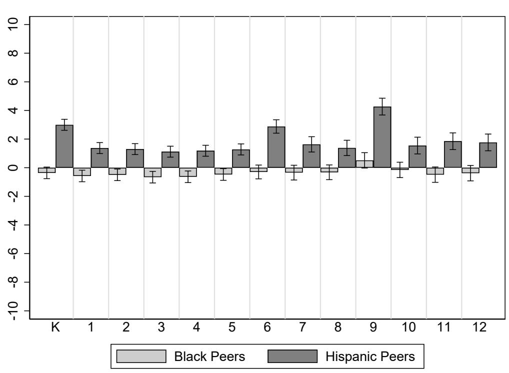

(c) Black Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV



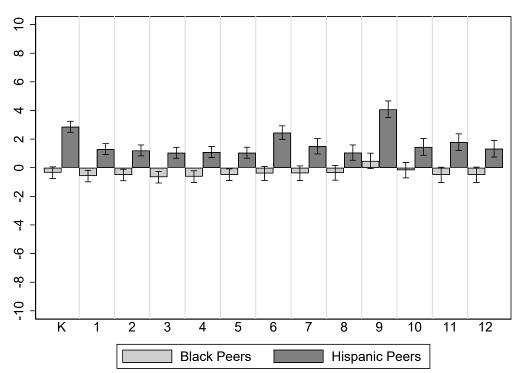

(d) Black Responses, only $s^{\bar{g}-2}_{jct-3}$ as IV plus additional controls




(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 7,578,789 school-race-grade-year observations in the sample.

*Remark* 4. 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 endogenous mechanism has been least influential in explaining recent trends in segregation is conservative.

## C.2 Other Potential Concerns

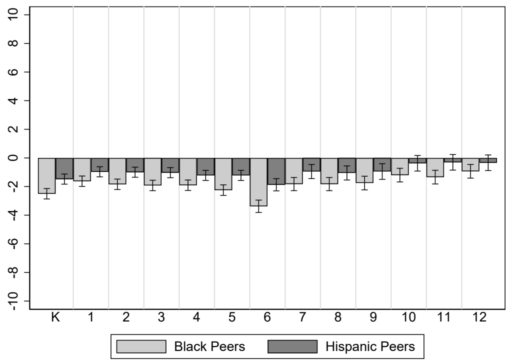
### C.2.1 Responses Changing Over Time

In our baseline results, we do not allow $\beta_{rgc}$ to change over time. We relax this restriction and estimate them separately for two sub-periods before and after 2010. Results by grade and race are shown in Figure 18. The very small and unsystematic change in $\beta_{rg}$ across these two sub-periods suggests that our baseline restriction is appropriate.[41]

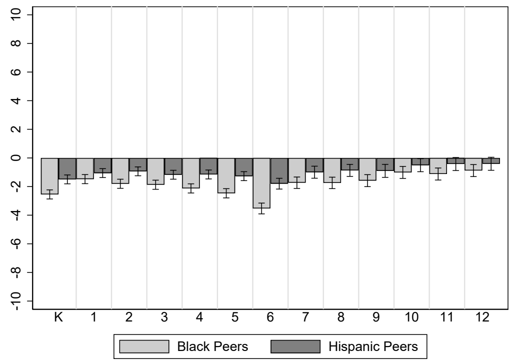
[41] Our finding that White and minority parents exhibit similar responses toward minority peers in 2005 than in 2018 is consistent with surveys of stated racial attitudes (Bobo et al. (2012)).

Figure 18: Estimates of $\beta_{rg}$, 2005-2009 vs. 2010-2018

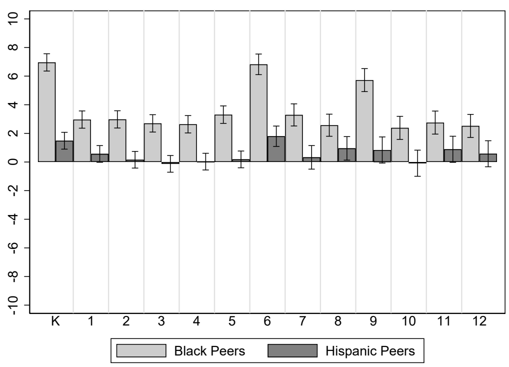
(a) White Responses, 2005-2009



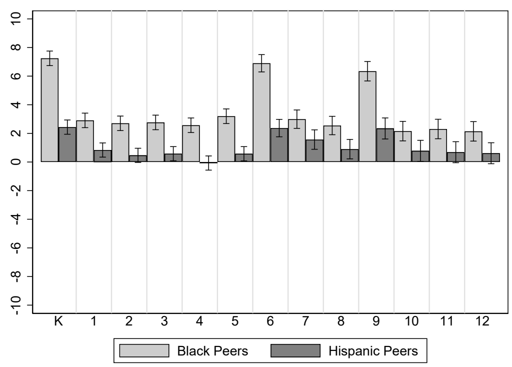

(b) White Responses, 2010-2018



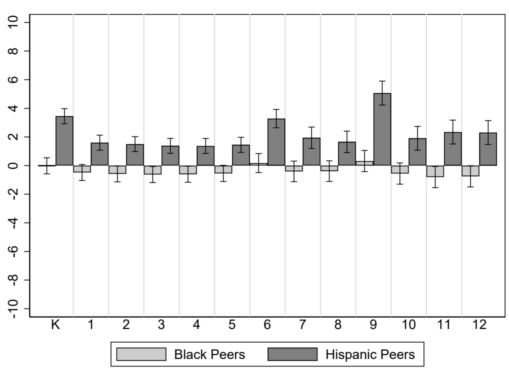

(c) Black Responses, 2005-2009



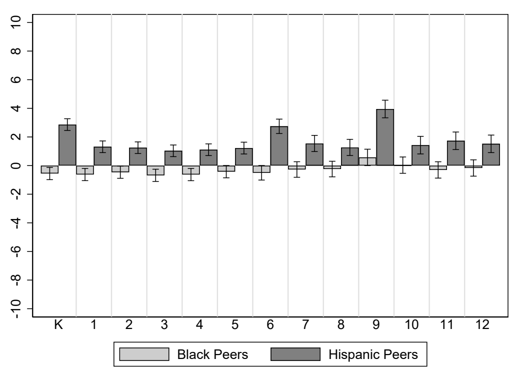

(d) Black Responses, 2010-2018




(e) Hispanic Responses, 2005-2009




(f) Hispanic Responses, 2010-2018




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 2010-1018. 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 4,629,075 school-race-grade-year observations in the samples 2005-2009 and 2010-2018 respectively.

### C.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.[42] 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 23, 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 2018. 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 6. 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 increase in prevalence of predominantly minority schools.

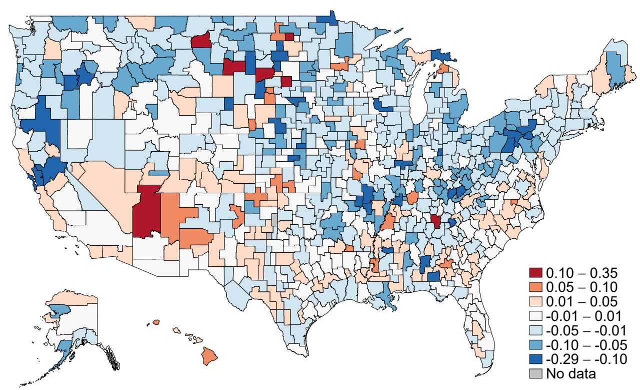
In Figure 19, we consider the Dissimilarity Index, which corresponds to the minimal fraction of minority (or White) students in a commuting zone that would have to switch schools in order to obtain a perfectly even allocation of students across all schools. According to this measure, from

[42] 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 $D = \frac{1}{2} \sum_{j=1}^{J} \left| \frac{n_j^W}{N^W} - \frac{n_j^M}{N^M} \right|$.

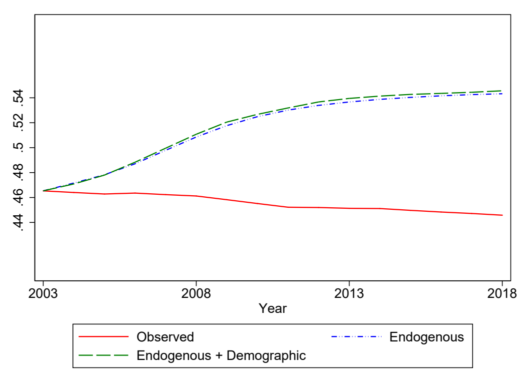
1988 to 2018 segregation has increased slightly in the Sun Belt while decreasing in other parts of the country. In Panel (b), we decompose the changes in dissimilarity index from 2003 to 2018. Aggregate demographic shocks explain very little of the change in dissimilarity over the sample period, as indicated 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, which are precisely the changes that would be arise from demographic shocks. The endogenous mechanism would have increased segregation by roughly 25% from 2003 to 2018, but this would be entirely offset by the residual mechanism.

Figure 19: Dissimilarity Index

(a) Observed Change in Racial Dissimilarity, 1988-2018




(b) Decomposition of Dissimilarity, 2003-2018

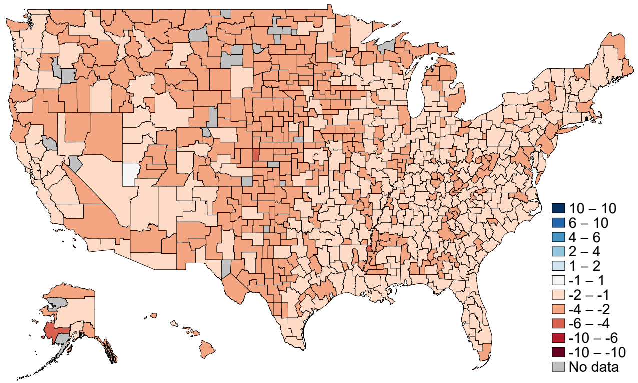



Notes: The map in Panel (a) shows the average annual change in the dissimilarity index, so "0.01" corresponds to an average annual increase of 0.01 standard deviations. Red (blue) areas have become more (less) segregated. The decomposition shown in Panel (b) is implemented for all schools who operate in each year from 2003-2018, 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 42.

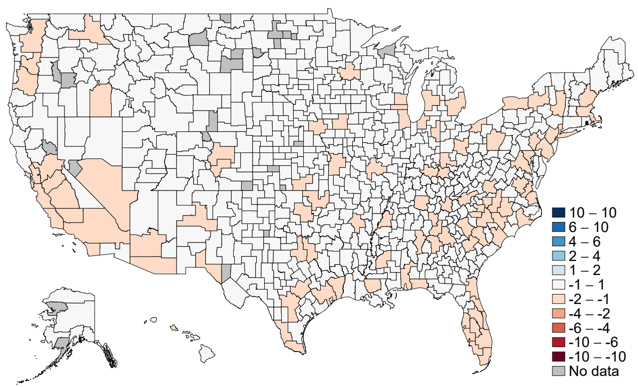
# D Additional Figures

Figure 20: Estimates of White Parents' Responses to Black and Hispanic Peers, 2005-2018

(a) Responses to Black Peers by Commuting Zone



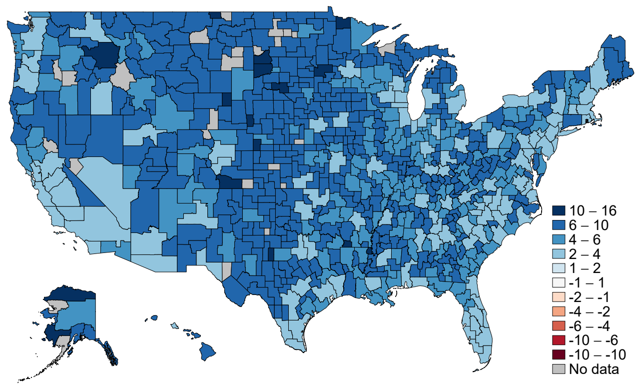

(b) Responses to Hispanic Peers by Commuting Zone



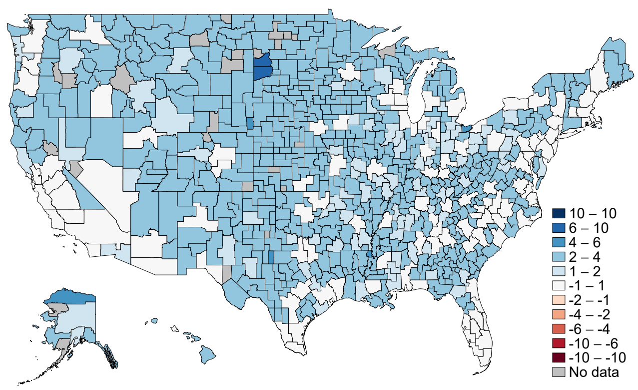

Notes: Estimates obtained from equation (14) are aggregated across grades. For a few sparsely populated commuting zones, we were unable to estimate responses because of a lack of enrollment data. The p-values from F-tests of whether the IVs ($s_{jt-2}^{\bar{g}_j-1}$ and $s_{jt-3}^{\bar{g}_j-2}$) are significant in the first stage regressions are always less than 1%. There are 7,578,789 school-race-grade-year observations in the sample.

Figure 21: Estimates of Black Parents' Responses to Black and Hispanic Peers, 2005-2018

(a) Responses to Black Peers by Commuting Zone



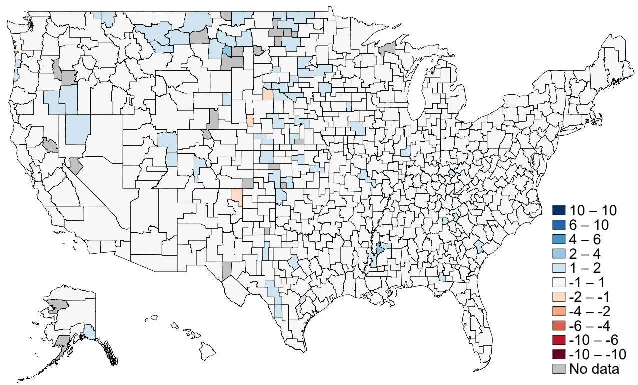

(b) Responses to Hispanic Peers by Commuting Zone



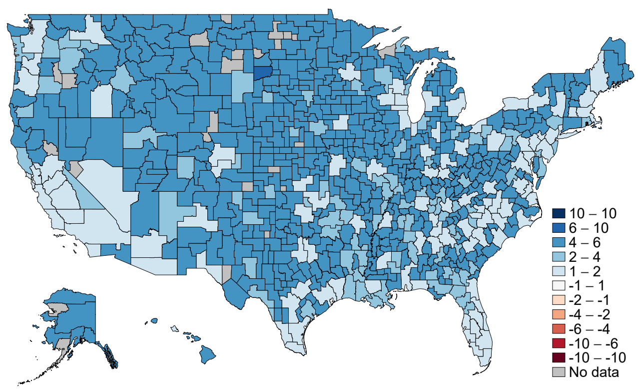

Notes: Estimates obtained from equation (14) are aggregated across grades. For a few sparsely populated commuting zones, we were unable to estimate responses because of a lack of enrollment data. The p-values from F-tests of whether the IVs ($s^{\bar{g}_j-1}_{jt-2}$ and $s^{\bar{g}_j-2}_{jt-3}$) are significant in the first stage regressions are always less than 1%. There are 7,578,789 school-race-grade-year observations in the sample.

Figure 22: Estimates of Hispanic Parents' Responses to Black and Hispanic Peers, 2005-2018

(a) Responses to Black Peers by Commuting Zone



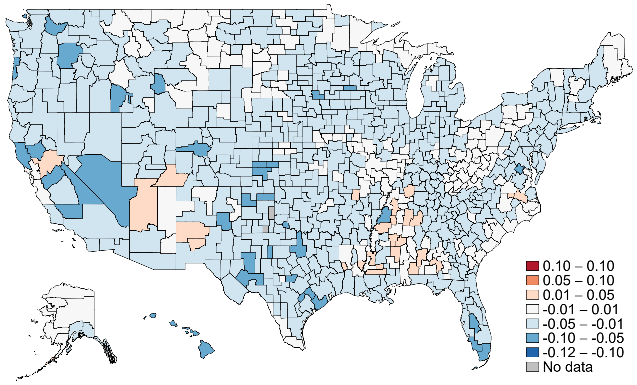

(b) Responses to Hispanic Peers by Commuting Zone



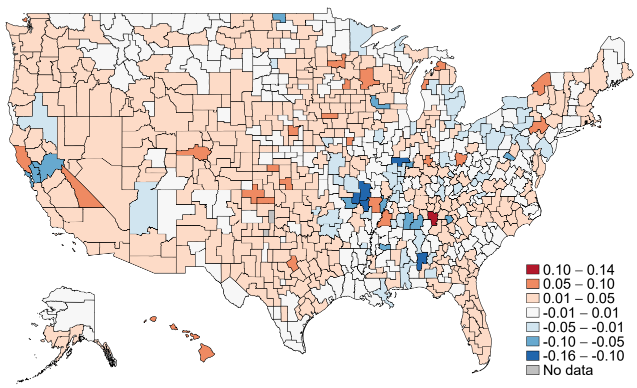

Notes: Estimates obtained from equation (14) are aggregated across grades in Panels (b) and (c). For a few sparsely populated commuting zones, we were unable to estimate responses because of a lack of enrollment data. The p-values from F-tests of whether the IVs ($s^{\bar{g}_j-1}_{jt-2}$ and $s^{\bar{g}_j-2}_{jt-3}$) are significant in the first stage regressions are always less than 1%. There are 7,578,789 school-race-grade-year observations in the sample.

Figure 23: White and Minority Isolation Indices

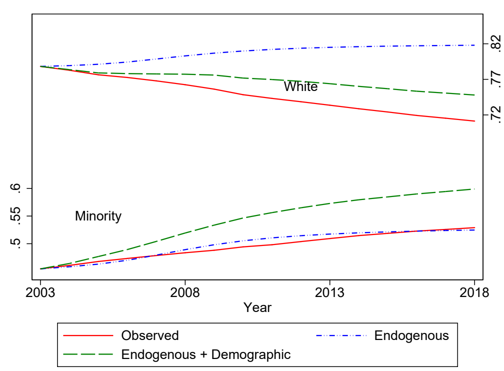
(a) Observed Change in White Isolation, 1988-2018




(b) Observed Change in Minority Isolation, 1988-2018




(c) Decomposition of Isolation Indices, 2003-2018




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 measures can be found in footnote 42. The decomposition shown in Panel (c) is implemented for all schools who operate in each year from 2003-2018, and national averages of commuting zone level measures weighted by population are reported on the vertical axis.