Explaining Recent Trends in US School Segregation: 1988-2014

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Abstract

We document and analyze trends in public school segregation throughout the United States from 1988 to 2014. While predominantly minority schools have increased in prevalence, predominantly white schools have decreased in prevalence at a faster rate. Overall, the majority of commuting zones in the US have experienced decreasing levels of school segregation measured in a variety of ways, and regional patterns in these trends point to changing demographics primarily due to Hispanic immigration as an important cause. We develop an empirical framework to analyze segregation in a non-stationary environment (e.g., one that is undergoing demographic change) that explicitly accounts for general equilibrium effects and endogenous social effects due to discrimination, and we conclude that 90% of the observed desegregation of White schools and 59% of the observed segregation of minority schools can be attributed to the immediate effects of demographic shocks. Recently, the gradual discriminatory process of segregation has been dwarfed by systematic inflows of minorities throughout the country and has been dampened by general equilibrium effects within local schooling markets. Without demographic change (e.g., under immigration restrictions), we find that school segregation would eventually increase substantially in most regions. *JEL Codes: R13, J15, I20*

1 Introduction

School segregation has occupied a prominent role in the public sphere ever since the landmark *Brown v. Board of Education* (1954) ruling and the Elementary and Secondary Education Act (1966), which identified the reduction of school segregation as a primary goal of federal policy. Policymakers that aim to improve student achievement, graduation rates, and long-run outcomes in the labor market (and, importantly, reduce racial gaps in these outcomes) have good reason to

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target school segregation, as a high concentration of minority students has been repeatedly found to reduce minority achievement .[1] More broadly, segregated schools have been linked to long-run adverse effects on the occupational aspirations, expectations, and attainment of minority students at least in part through social network effects.[2]

Recent well-publicized studies[3] have advanced the idea that schools have been growing more segregated with an increasing proportion of minority students enrolling in segregated minority schools.[4] This has led many observers in the popular press to conclude that we have entered into a new era of discrimination.[5] To better understand the determinants of these important trends, we argue that these findings should be viewed in the context of a broader trend: In 1988, 9% of schools were minority-segregated (over 75% minority); by 2014, 23% of schools were. At the same time, in 1988, 68% of schools were White-segregated (over 75% White), but by 2014, only 47% were. Hence, segregated White schools have been disappearing faster than segregated minority schools have been appearing. Discriminatory preferences for peers are unlikely to generate such a pattern by themselves, as theory predicts that such preferences would lead to an increase in both White and minority segregated schools. Instead, this pattern is more suggestive of a different cause: demographic change in the aggregate.

In this paper, we study how the changing demographic composition of students in the US has affected school segregation. Minority students have steadily and systematically flowed into most commuting zones in the US over the past quarter century, primarily due to Hispanic immigration. These inflows have in turn affected all schools within those areas either directly or indirectly, leading to the concomitant increase in the number of segregated minority schools and reduction in the number of segregated White schools. Identifying these effects is made difficult as aggregate demographic

[1]See, for example, Guryan (2004); Card and Rothstein (2007); Hanushek et al. (2009); Fryer Jr (2010).

[2]See, for example, the sociology literature that has followed from Granovetter (1986); Julius (1987); Wells and Crain (1994)

[3]See, for example, GAO-16-345 ("Better Use of Information Could Help Agencies Identify Disparities and Address Racial Discrimination," April 2016, Government Accounting Office) and Orfield et al. (2014).

[4]Throughout this paper, we will follow GAO nomenclature and use the term "minority" to refer only to Black and Hispanic students (including white Hispanics), and "White" to refer to all other students. Our results are essentially unchanged if we consider all non-Whites to be minorities or if we omit all students who are not White, Black or Hispanic.

[5]See, for example, Strauss, Valerie, "School segregation sharply increasing, studies show," *The Washington Post*, 9/22/12; Bouie, Jamelle, "Still Separate and Unequal," *Slate,* 5/15/14; Toppo, Greg, "GAO Study: Segregation worsening in U.S. schools," *USA Today*, 5/17/16. In contrast, Rivkin (2016) presents national evidence of recent desegregation in US public schools, and Clotfelter et al. (2006) document that segregation levels in Southern schools have remained roughly constant from 1994-2004.

changes can continue to affect the racial composition of school enrollments over many periods due to the dynamic social multiplier effects first described in the seminal Schelling model of segregation.[6] If, for example, parents prefer their children to attend schools with more peers of the same race, then inflows of minorities may lead to a positive feedback loop in which successively more (fewer) minority (White) students enroll in some schools, while the opposite may occur in other schools, ultimately leading to highly segregated schools through a process colloquially known as "tipping". Hence a given demographic shock may have very different short-run and long-run effects, which also makes it difficult to disentangle the effects of current demographic shocks from past demographic shocks.

This complication is compounded by the fact that demographic shocks by their very aggregate nature affect many schools in a local market simultaneously, and the adjustments to the racial composition of one school in response to these shocks may in turn affect the racial composition of other schools. For example, an aggregate demographic shock that hits one school likely also hits schools that are viewed by prospective parents as close substitutes in a similar way. In addition, an enrollment response to the change in the racial composition of one school may propagate to other nearby schools as well, potentially setting the racial compositions of those schools off on different trajectories. Theory suggests that general equilibrium effects likely dampen the immediate effects of demographic change on segregation, so ignoring them may lead to overestimates of the full effects of demographic shocks that are subject to a dynamic social multiplier.

Building on Caetano and Maheshri (2017), we develop a new empirical approach that is sensitive to these concerns and apply it to the universe of American public schools. First, we use the complex panel structure of school enrollment data to construct plausible instrumental variables (IV) for estimating causal demand responses of parents of each race to changes in the racial compositions of schools. The IVs exploit variation in the past racial composition of school enrollments that were influenced by school amenities that are no longer relevant today. These amenities can only affect current enrollment decisions through the mechanism of interest. Next, we use these estimates to simulate (in general equilibrium) the future trajectory of all schools in each commuting zone under two counterfactuals: (a) no demographic shocks, and (b) the immediate demographic shocks

[6] We use the phrase "Schelling model" to refer to the seminal model of segregation put forth in Schelling (1969), Schelling (1971) and Schelling (2006).

as observed in the data. This allows us to identify the extent to which demographic shocks and discriminatory sorting have impacted segregation in the short- and the long-run.

We find clear evidence of discriminatory sorting.[7] All else constant, White parents tend to leave schools that are increasing in Black or Hispanic share, whereas Black and Hispanic parents tend to enroll their children in schools with more peers of the same race.[8] These patterns of discriminatory school demand responses change depending on the region of the country, but they have not changed over time.[9] All else constant, the discriminatory responses that we estimate would increase the prevalence of White and minority segregated schools in the long-run. Of course, all else has not been constant in the US over the past quarter century. In a non-stationary environment with large and systematic inflows of minorities into commuting zones, the gradual increases in segregation that are due to discriminatory sorting take time to accumulate and are partially offset by demographic shocks and general equilibrium responses. Indeed, the immediate effects of demographic change can explain 90% and 59% of the observed changes in White and minority school segregation respectively. In addition, we find that neglecting general equilibrium effects would lead us to overstate the long-run impacts of demographic change on segregation by 220% for White-segregated schools and 316% for minority-segregated schools.

In the absence of demographic change, we find that segregation would increase substantially for both predominantly White and predominantly minority schools. The fact that this stands in stark contrast to observed trends in segregation leads us to conclude that demographic change has been a powerful force in reducing segregation. Without minority inflows that systematically disrupt local schooling markets and prevent schools from reaching highly segregated equilibria, endogenous discriminatory forces would dramatically reduce the exposure of students to peers of different races. We believe that these effects should be taken into account in a full assessment of alternative immigration policies.

The remainder of the paper is organized as follows. In Section 2, we describe our data set

[7] Although the enrollment responses that we estimate are consistent with discriminatory preferences, they do not only reflect preferences; they also reflect the ability of parents to exercise their preferences.

[8] These findings of homophilic racial responses complement the extensive literature in economics that has estimated revealed racial preferences in housing markets (Bajari and Kahn (2005)), dating and marriage markets (Fisman et al. (2008)), and friendships (Currarini et al. (2010)). Similarly to these papers, we are agnostic as to whether these responses are due to statistical discrimination or taste-based discrimination.

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

and document how the levels of school segregation have evolved from 1988 to 2014. In Section 3, we present a theoretical model of segregation that highlights the role of demographic shocks and discriminatory responses in determining the racial composition of schools in both the short- and the long-run, and we show how this model can be taken to the data. In Section 4, we describe how we identify the demand responses to changes in the school racial composition. We present our empirical results in Section 5 before concluding in Section 6.

2 National and Regional Trends in School Segregation

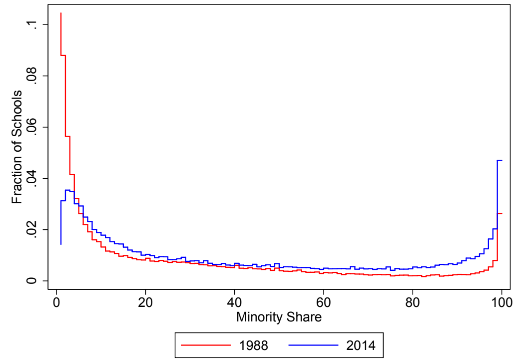
Our sample consists of all students enrolled in all public schools in the United States from 1988-2014.[10] In total there are 2,410,140 school-year observations. Over this period, the number of schools increased at a roughly constant rate from 61,252 to 95,413. In a typical year, the average school includes 488 students. We obtain enrollment data from the Common Core of Data maintained by the National Center for Education Statistics at the US Department of Education. For each public school in the country, we observe the numbers of White, Black, Hispanic, Asian and Native American students enrolled in each year, and we use the term minority to refer to any Black or Hispanic student (including White Hispanics) and the term White to refer to any other student.[11]

We begin by documenting changes in the racial composition of schools at the national level. In Figure 1, we present empirical distributions (PDFs) of the minority share of enrollment in all US schools in 1988 and 2014, from which we draw two important conclusions. First, each distribution is bi-modal, so the cross-sectional variation in the racial composition of schools is consistent with the Schelling model of segregation in which discriminatory, homophilic responses by parents lead to the proliferation of predominantly White and predominantly minority schools. Second, the distribution in 2014 is shifted to the right relative to 1988 (in fact it stochastically dominates it). This longitudinal variation in the racial composition of schools is unlikely to be generated by discriminatory responses, which would lead to increases in the density at *both* extremes. Instead, it is more suggestive of a demographic shift towards a more highly minority student body.

[10] We use 2000 to refer to the 2000-01 academic year and follow this convention throughout the paper. We restrict our sample to the 50 states and the District of Columbia and ignore schools in US territories. Enrollment data from a small number of states in some early years of the sample are missing. We provide detailed documentation of our sample in Appendix A.

[11] These definitions of White and minority follow from the US Government Accountability Office study GAO-16-345. If we instead define minorities as all non-White students or omit all Asian and Native-American students from our sample, our findings are essentially unchanged.

Figure 1: Empirical Distribution of Minority Share of US Schools, 1988 and 2014



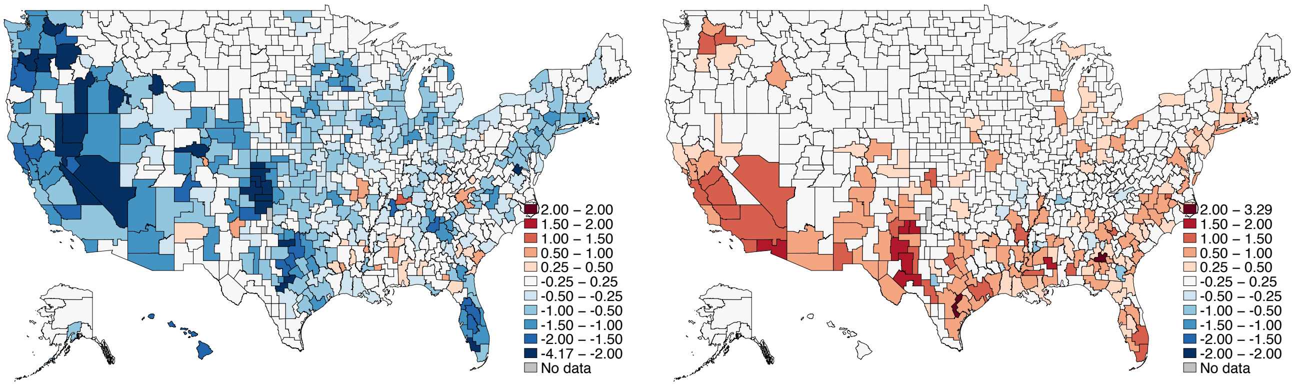
The national trend in Figure 1 is supported by regional patterns in school segregation. In Figure 2, we present the change in the proportion of schools that have over 75%[12] White and minority enrollments disaggregated to the commuting zone level (as defined in the 2000 Census).[13] From Panel 2a, it is evident that the prevalence of White segregated schools has diminished throughout the country, often at annual rates of 1-4 percentage points. The national trend revealed in the left tails of Figure 1 has unfolded in both highly populated metropolitan areas and relatively less diverse rural areas. In Panel 2b, we see that minority segregated schools have become more prevalent over the sample period throughout the sunbelt (especially along the Mexican border) at an annual rate of 0.5-2 percentage points, and to a lesser extent, in urban areas of the Northeast and rust belt at an annual rate of 0.25-1 percentage points. This is consistent with the national trend revealed in the right tails of of Figure 1. 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 over time.

[12] We find highly similar patterns when we adopt any alternative threshold between 66% and 90% to define a school as segregated.

[13] This choice of aggregation is consistent with other recent work on local "socioeconomic" markets such as Chetty et al. (2014).

Figure 2: Average Annual Change in Proportion of Segregated Schools, 1988-2014

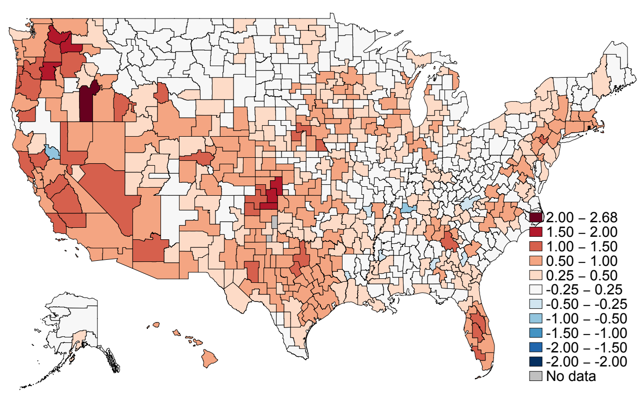
(a) Change in Proportion of Segregated White Schools (b) Change in Proportion of Segregated Minority Schools



Note: A segregated school is defined as one in which the enrollment of White (or, respectively, minority) students exceeds 75% of the total enrollment. Blue (Red) commuting zones have experienced declining (increasing) segregation during this period. Annual changes shown in percentage points.

The shift in national distributions in Figure 1 suggests we should explore whether the clear regional patterns in Figure 2 were accompanied by a similar regional demographic pattern. In Figure 3, we present the average annual change in the minority share of enrollments at the commuting zone level. Demographic changes over this period have been widespread, leading to a greater fraction of minority students in all regions of the US. The regional pattern matches Panel 2a closely, suggesting that changing demographics may play an important role in explaining the recent trends in school segregation.

Figure 3: Change in Minority Share of Students in Commuting Zone, 1988-2014



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

Broadly speaking, there are three potential sources of demographic change in aggregate public school enrollments: changes in the racial composition of private school enrollments; changes in fertility rates across races; and immigration from abroad or migration between commuting zones. In Appendix C, we present evidence that, when taken altogether, allow us to conclude that the demographic shocks observed during our sample period were largely attributable to Hispanic immigration. Briefly, national private school enrollments of minorities were stable from 1993-2003, while White enrollments decreased slightly (Figure 16); the fertility gap between minorities and Whites slightly narrowed from 1971 to 2008[14] (see Table 4); Black immigration and migration rates were small during the sample period, while Hispanic immigration and migration rates were quite large (see Figure 17); 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 number of White or Black students (see Figure 18).

Alternative Measures of Segregation

To further our understanding of national and regional trends in school segregation, we turn to a variety of alternative measures of segregation to see how they have changed since 1988. 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)), and while no single measure can fully capture all aspects of segregation – similarity in the racial composition of schools, concentration of racial groups, isolation, entropy – certain measures are well suited to capture particular aspects of segregation. Taken together, they are complementary and reveal a fuller view of how segregation has evolved.

In Figure 4, we present the average annual change in five different standard measures of segregation (details on the construction of each measure can be found in Appendix B). 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. All maps are colored such that red areas have become more segregated while blue areas have become less segregated. We present the change in the simplest measure of the concentration of minorities, the Herfindahl Index, in Panel 4a. This index measures the extent to which minorities in a commuting zone are evenly distributed across schools. We find no change in this index in the vast majority of

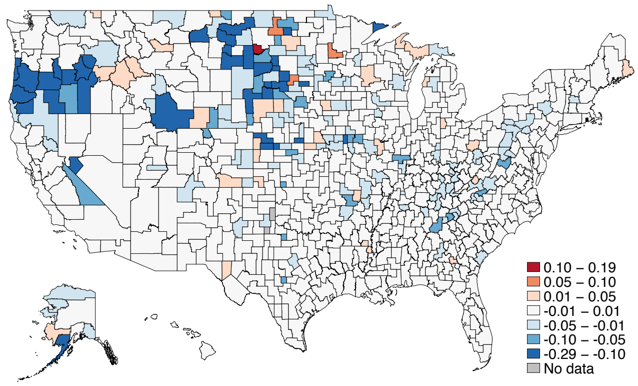
[14] Births during this period correspond to students in our sample period.

the country over the sample period. Because this measure is quite insensitive to the aggregate racial composition of the student body at the commuting zone level, this is consistent with demographics driving the changes in Figure 2. In panel 4b, we present the change in the Theil Index, which is a commonly used index of segregation (e.g. Chetty et al. (2014)) that measures the difference between the observed allocation of minority students and a hypothetical random allocation of minority students across all schools in a commuting zone; it is also fairly insensitive to changing demographic trends. As measured by the Theil Index, segregation has slightly decreased in most of the country (larger decreases are visible in more sparsely populated regions). In Panel 4c, we present the change in 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, segregation has increased slightly in the sunbelt while decreasing in other parts of the country. This pattern is consistent with a demographic shift characterized by an influx of minorities in the sunbelt, but it is inconsistent with purely discriminatory sorting. Finally, in Panels 4d and 4e, we present the changes in the Isolation Indices of White and minority students respectively. These indices measures the extent to which students of a given race interact with students of that race. Not surprisingly, White students have become less isolated in most populated regions outside the South, and all minority students have become more isolated in parts of the sunbelt and Midwest that have seen the greatest relative inflows of minority students. The trend for minority students is consistent with both demographic change and discriminatory sorting, but the trend for White students is only broadly consistent with demographic change.

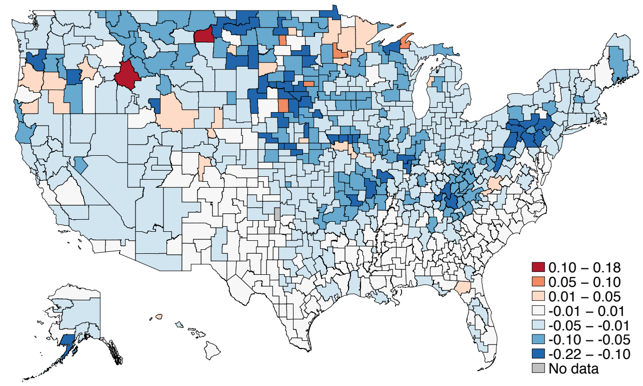
To summarize, a quarter century of enrollment data reveals broad decreases in segregation throughout the country measured in a variety of ways. Although highly segregated minority schools have become more prevalent, segregated White schools have become less prevalent at a higher rate. Hence, schools in the country tend to be less segregated in 2014 than in 1988, and all race-blind measures of segregation (Herfindahl, Theil and Dissimilarity Indices) have tended to decrease. This evidence leads us to conjecture that recent trends in segregation are predominantly driven by demographic shifts largely due to Hispanic immigration as opposed to increases in or a persistence of discriminatory preferences for peers.

Figure 4: Change in Various Measures of Segregation, 1988-2014

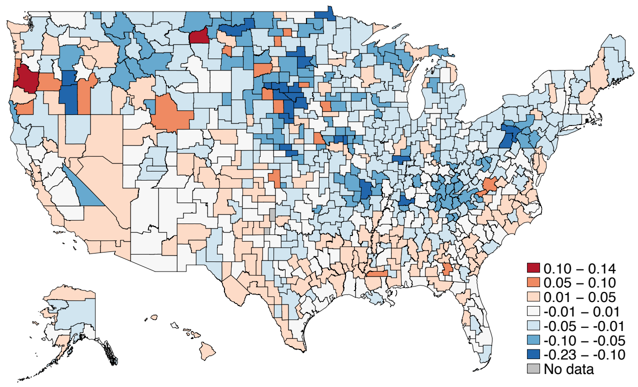
(a) Herfindahl Index



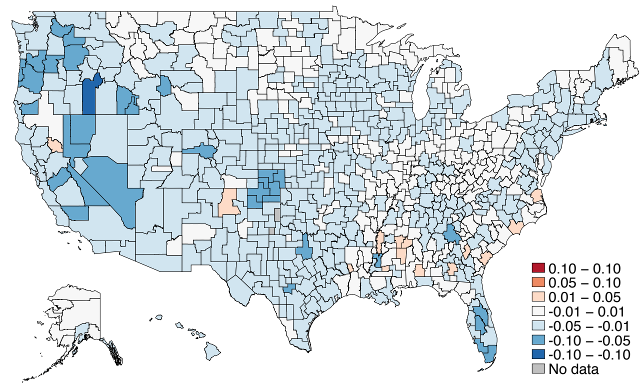
(b) Theil Index



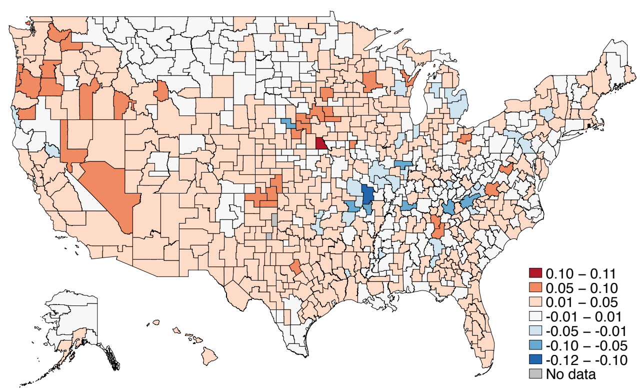
(c) Dissimilarity Index



(d) Isolation Index (Whites)



(e) Isolation Index (Minorities)



Note: Each map shows the average annual change in a particular measure of segregation. Each measure has been standardized, 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 each measure can be found in Appendix B.

3 Determinants of Segregation

3.1 A Theoretical Model of Segregation

We begin with a simple, standard model of segregation in the spirit of Schelling (1969) and Becker and Murphy (2000) whereby households observe the amenities of local schools and then choose where to enroll their children. For simplicity, we present our model and baseline results assuming that there are only two races of students, Whites and minorities. In our main analysis, we relax this assumption and allow minority students to be classified as either Black or Hispanic. Formally, let N_{rt} denote the total number of school-aged White ($r = W$) and minority ($r = M$) children living in a commuting zone with J public schools in year t. For each school j, we define n_{rjt} to be the number of race r students enrolled in year t. The school's racial composition, defined as

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

corresponds to the minority share of the school. Before the start of each school year, parents observe the amenities of all public schools in the area (including their historical racial composition) and then decide where to enroll their child. Given this set up, 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 general, school-specific function π_{rj} is the probability that a parent of a given race enrolls their child in a particular school, $\boldsymbol{s_{t-1}}$ is a vector whose jth element is s_{jt-1}, and $\boldsymbol{X_t}$ is a matrix of other school-specific amenities, whose jth element is vector $\boldsymbol{X_{jt}}$.[15] Together, equations (1) and (2) define how the race-specific enrollments (and hence the racial composition) of a school evolve from $t-1$ to t. The three arguments in equation (2), N_{rt}, $\boldsymbol{s_{t-1}}$, and $\boldsymbol{X_t}$ correspond to three distinct mechanisms behind this process.

First, variation in the racial composition of the overall enrollment of the commuting zone over time due to migration or fertility differences across races (i.e., $\boldsymbol{N_{rt}} \neq \boldsymbol{N_{rt-1}}$ where $\boldsymbol{N_{rt}} = \{N_{Wt}, N_{Mt}\}$) can cause the racial compositions of individual schools to change simply because

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

these new students must enroll somewhere. For example, a regional influx of minority households with children would increase the minority share of at least some schools. We denote this mechanism as *demographic*.

Second, parents of different races may respond systematically differently to the racial composition of a school (i.e., $\frac{\partial \pi_{Wj}}{\partial s_{kt-1}} \neq \frac{\partial \pi_{Mj}}{\partial s_{kt-1}}$). As a result, equations (1) and (2) together characterize a dynamic system (note that the arguments on the left and right hand sides of equation (2) are in different time periods). As a result, this mechanism can reinforce the effects of demographic changes through dynamic social multiplier effects, and it can also result in a positive feedback loop commonly known as "tipping". Because these dynamics will propagate even in the absence of any other changes to the schooling environment, we denote this mechanism as *endogenous*.

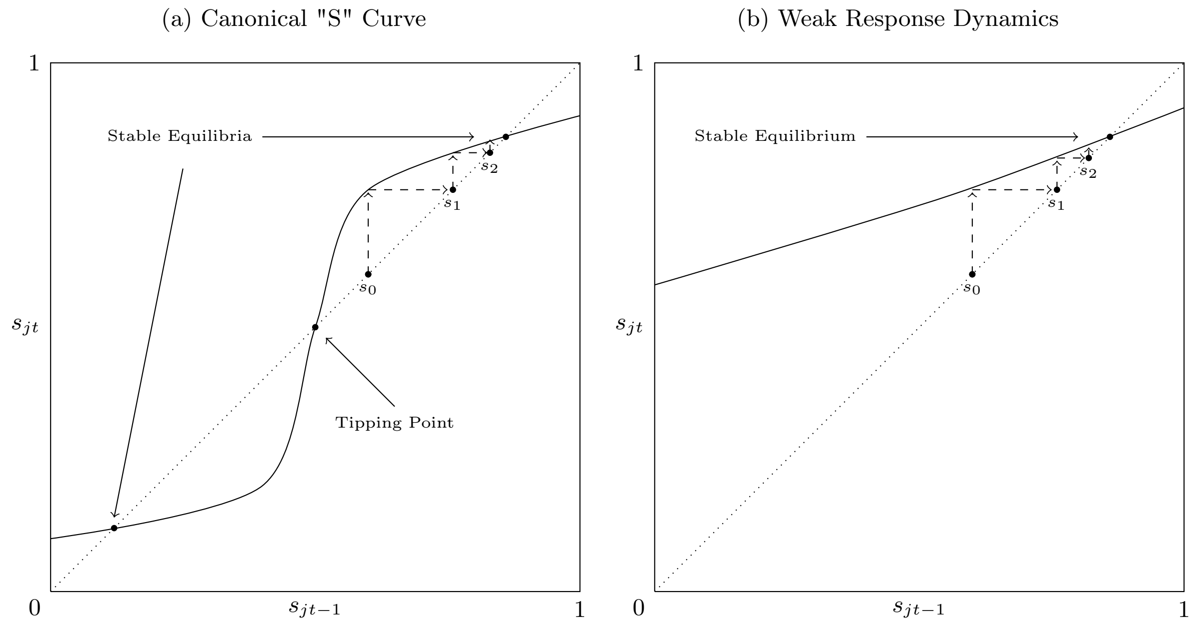
Finally, the racial composition of a school can be affected by local variation in school-specific amenities besides $\boldsymbol{s_{t-1}}$. This could happen because these amenities may be valued differently by Whites and minorities (i.e., $\frac{\partial \pi_{Wj}}{\partial x} \neq \frac{\partial \pi_{Mj}}{\partial x}$ where x is a specific amenity in $\boldsymbol{X_{kt}}$). For instance, if White parents value football more than minority parents, then increases to the football budget of a particular school would be expected to decrease the minority share of enrollment in that school. In contrast to the endogenous mechanism, changes to these amenities do not generate dynamic multiplier effects by themselves; accordingly, we denote this mechanism as *exogenous*.

We can combine equations (1) and (2) to obtain the dynamics of the racial composition of school j, which we present graphically in Figure 5.[16] In Panel 5a, we plot a *ceteris paribus* curve of s_{jt} on s_{jt-1} holding $\boldsymbol{N_{rt}}$, $\boldsymbol{s_{-jt-1}}$ and $\boldsymbol{X_t}$ fixed[17], which summarizes the endogenous evolution of s_{jt} in a canonical "S" curve. Points at which the curve intersects the 45 degree line represent equilibria; stable equilibria correspond to points where the curve crosses from above, while the equilibrium in between corresponds to a tipping point. In Panel 5b, we plot an alternative *ceteris paribus* curve of s_{jt} on s_{jt-1} assuming dynamic responses are weak (i.e., $\frac{\partial \pi_{Wj}}{\partial s_{jt-1}}$ and $\frac{\partial \pi_{Mj}}{\partial s_{jt-1}}$ are small). Weak responses cause the "S" curve to collapse and only intersect the 45 degree line at a single, stable equilibrium. Deducing the dynamics of the racial composition of j from the figure is straightforward; for a hypothetical school with a racial composition of s_0, the endogenous mechanism will result in a racial composition of s_1 one period ahead, s_2 two periods ahead, and so on. The locations of

[16]To simplify exposition, we assume discriminatory sorting, i.e., $\frac{\partial \pi_W}{\partial s_{jt-1}} < 0$ and $\frac{\partial \pi_M}{\partial s_{jt-1}} > 0$ when drawing Figure 5. We do not make this assumption in our empirical analysis but instead obtain it as a result of estimation.

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

Figure 5: Dynamics of s_{jt}



equilibria and the speeds of convergence depend upon $\boldsymbol{N_{rt}}$, $\boldsymbol{s_{-jt-1}}$ and $\boldsymbol{X_t}$ since different values of these would result in shifts and deformations of the "S" curve. This implies that these curves are school-specific (and year-specific). Following the literature (e.g., Schelling (1971); Bayer and Timmins (2005)), we utilize the canonical "S" curve for the remainder of the explanation of our model.

In order to assess the extent to which demographic shifts have contributed to recent trends in the racial compositions of schools, we consider the effect of an inflow of minorities to the commuting zone (i.e., an increase in N_{Mt}). In Panel 6a, we consider a school that was in equilibrium in $t-1$ (i.e., either at point $A^\star$ or $B^\star$). The inflow of minorities results in an upward shift of the "S" curve to the dashed curve, resulting in new equilibria. For the school at point $A^\star$, the demographic shift from $t-1$ to t generates the instantaneous effect shown as the red arrow. Other things equal, the school is no longer in equilibrium in period t and will move along a trajectory to the new equilibrium $A^{\star\star}$. The endogenous mechanism acts as a dynamic social multiplier, generating an additional social effect from t onward shown as the blue arrow. The long-run demographic effect will be equal to the instantaneous effect plus the social effect, which is the vertical distance from $A^\star$ to $A^{\star\star}$. Similar logic holds for the school at point $B^\star$. Note that the magnitudes of these effects depend not only on the demographic shift but also on the locations of the stable equilibria and the shapes of the "S" curves, both of which also depend on $\boldsymbol{s_{-jt-1}}$, $\boldsymbol{X_t}$ and the shape of π_{rj} for all r.[18]

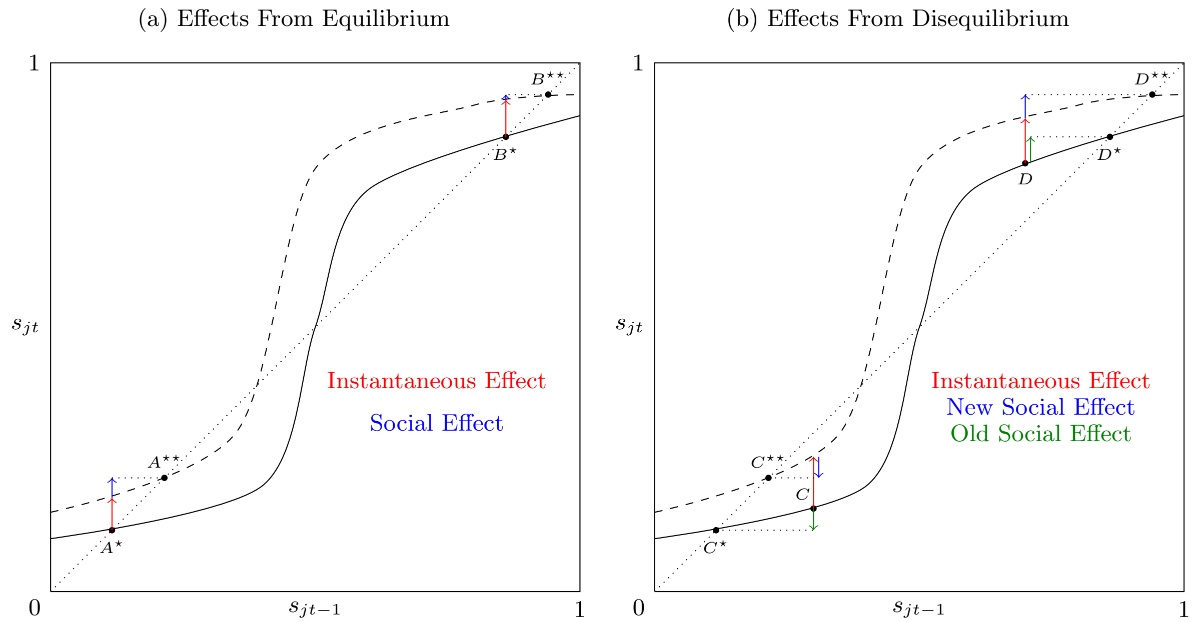
The analysis becomes more complicated when schools are out of equilibrium in $t-1$. Such schools would be subject to an endogenous social effect even in the absence of a demographic shift, hence this must be accounted for when calculating the long-run effects of changing demographics. In Panel 6b, we consider two schools with the same curve that are out of equilibrium in $t-1$. The school at point C would have moved along the solid curve to $C^{\star}$ through the "old" social effect shown as the green arrow. The inflow of minorities instead generates an instantaneous effect shown as the red arrow. Because the new equilibrium is at $C^{\star\star}$, the endogenous mechanism generates a "new" long-run social effect shown as the blue arrow. The total long-run effect, which is the vertical distance from the old equilibrium, $C^{\star}$, to the new equilibrium, $C^{\star\star}$, is thus equal to the instantaneous effect plus the net social effect. Similar logic holds for the school at point D. Note that these three arrows might not all move in the same directions. Not only are they dependent on the demographic shift, locations of stable equilibria and shapes of the "S" curves as before, they also depend on the extent to which schools are out of equilibrium in $t-1$. (We discuss the practical implications of this in greater detail with our results in Section 5.) For the special case when schools are in equilibrium in $t-1$ (as in Panel 6a), the old social effect is equal to zero.

The diagrams shown in Figures 5 and 6 present the dynamics of the racial composition of a single school, hence the equilibria as drawn represent only partial equilibria. However, equation (2) implies that enrollment demand for a single school j is potentially 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, an aggregate demographic shock that shifts the "S" curve of school j upward is likely to shift the "S" curve of a school k that is a close substitute upward as well. The associated increase in s_{kt} will make school j relatively less attractive to White parents and more attractive to minority parents in $t+1$, resulting in a small *downward* shift in the "S" curve of school j. Of course, these effects will feed back between these two schools (and any others that are substitutes) leading to potentially complex general equilibrium effects on the dynamics of other schools.[19]

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

[19] General equilibrium effects may propagate even in the absence of external shocks provided that 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

Figure 6: Demographic Effects on s_{jt}



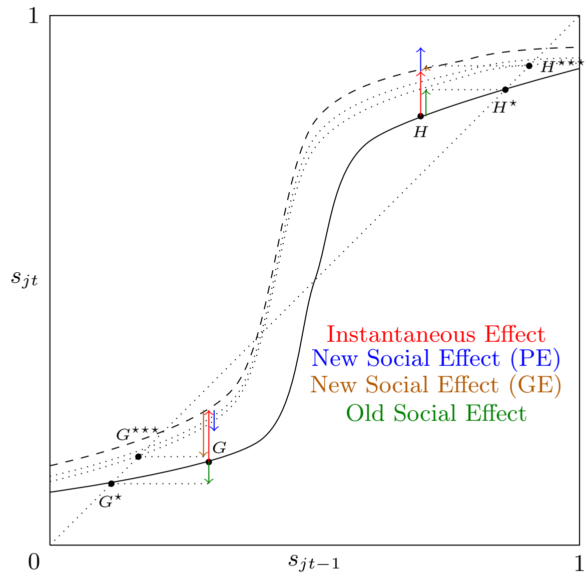
These general equilibrium effects can be represented as additional shifts of the "S" curve (shown in Figure 7) that dampen the effect of the initial shock. This results in a new GE social effect that is smaller than the new social effect from a partial equilibrium analysis.[20] In principle, general equilibrium effects could be so powerful that the stable general equilibrium (shown with three stars) could lie to the opposite side of the initial point in comparison to the original equilibrium (shown with one star). In such cases, the total long run effect of a demographic change would move in the opposite direction of the instantaneous effect. If this happened in enough schools, then an influx of minorities might actually lead to *fewer* minority segregated schools in a commuting zone. For instance, if this demographic shift made a previously 85% minority school relatively more attractive than a previously 75% minority school, then the minority share of the latter school could in principle decrease in spite of the aggregate change. It follows that the true long-run effect should be calculated with new social effects that incorporate general equilibrium considerations as

$$\text{LR Effect} = \text{Instantaneous Effect} + \text{New Social Effect} - \text{Old Social Effect} \tag{3}$$

of equilibrium, starting the feed-back loop anew.

[20]For simplicity, Figure 7 ignores the fact that the "old" social effect that accounts for general equilibrium effects will generally differ from the partial equilibrium "old" social effect (see footnote 19).

Figure 7: General Equilibrium Demographic Effects on s_{jt}



3.2 An Empirical Model of Segregation

Our simple model of segregation has a straightforward empirical analog that can be easily taken to data. Because we observe enrollments across many commuting zones, we first index all variables with c. Following a standard discrete choice framework (McFadden (1973); Berry (1994); Berry et al. (1995)),[21] we specify the demand equation as:[22]

$$\log n_{rjct} = \beta_{rc} \cdot s_{jct-1} + \gamma_{rct} + \epsilon_{rjct} \tag{4}$$

The parameter β_{rc} represents the enrollment response by parents of each race to the minority share of the school and is allowed to vary by commuting zone. The race-commuting zone-year fixed effect γ_{rct} subsumes $\log N_{rct}$ and encapsulates any demographic changes in the overall commuting zone level enrollment of each race (due to fertility, migration, shifts to private schools, etc). Finally, the residual ϵ_{rjct} subsumes $\boldsymbol{X_t}$ and s_{ktct-1} for all $k \neq j$ in the commuting zone. Hence, it includes all school j-specific amenities other than its minority share *and* all of amenities of every other

[21] As discussed in Caetano and Maheshri (2017), this demand equation can be understood in a discrete choice framework with no mathematical modification.

[22] 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_{jct-1}. We do not need to assume that $\log \pi_{rj}(\cdot)$ is additively separable in s_{kct-1} for any $k \neq j$. This allows the function $\pi_{rj}(\cdot)$ to accommodate more complex substitution patterns across schools, as the relationship between X_{jt} and s_{kt-1} is unrestricted.

school in the commuting zone to the extent that these amenities affect the enrollment choices of households who already have decided to reside in c. It follows that the first term in the right-hand-side of equation (4) corresponds to the endogenous mechanism, the second term corresponds to the demographic mechanism, and the third term corresponds to the exogenous mechanism. Because each of these three terms varies at the commuting zone level, we explicitly allow for the importance of each of the three channels to vary by location and time.[23]

With causal estimates of the social effects, $\hat{\beta}_{rc}$, we can compute the short-run and the long-run effects of observed demographic changes on the racial composition of each school in c and the overall level of segregation in c. This requires us to simulate the evolution of the racial compositions of all schools many periods into the future. For a given counterfactual number of total students of each race in the commuting zone, $\tilde{\boldsymbol{N}}_{\boldsymbol{c}}$, we can simulate the counterfactual minority share of each school and number of total students in future periods $t+\tau$, $\tau = 0, 1, 2, \ldots$ with the recursive system of equations:

$$n_{rjct}\left(\tilde{N}_{rc}, \tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau-1}}\right) = \tilde{N}_{rc} \cdot \pi_{rjct}\left(\tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau-1}}, \boldsymbol{X}_{\boldsymbol{ct}}\right) \tag{5}$$

$$\tilde{\boldsymbol{s}}_{\boldsymbol{jct+\tau}} = \frac{n_{Mjct}\left(\tilde{N}_{Mc}, \tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau-1}}\right)}{n_{Mjct}\left(\tilde{N}_{Mc}, \tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau-1}}\right) + n_{Wjct}\left(\tilde{N}_{Wc}, \tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau-1}}\right)} \tag{6}$$

with the initial condition $\tilde{\boldsymbol{s}}_{\boldsymbol{ct-1}} = \boldsymbol{s}_{\boldsymbol{ct-1}}$.[24]

In order to estimate the effects of demographic changes, we perform this simulation under two counterfactuals. In the first counterfactual, we assume $\tilde{\boldsymbol{N}}_{\boldsymbol{c}} = \boldsymbol{N}_{\boldsymbol{ct-1}}$, and in the second counterfactual, we assume $\tilde{\boldsymbol{N}}_{\boldsymbol{c}} = \boldsymbol{N}_{\boldsymbol{ct}}$. These respectively correspond to a baseline that assumes no demographic change from $t-1$ to t, and to a counterfactual that assumes that the commuting zone level demographics only evolved from $t-1$ to t as observed in the data. In both counterfactuals, we set $\tilde{\boldsymbol{s}}_{\boldsymbol{ct-1}}$ equal to the observed minority shares of all schools in period $t-1$, $\boldsymbol{s}_{\boldsymbol{ct-1}}$. This allows us to compute the short- and long-run effects of this demographic change in school j accounting for

[23]As a robustness check, we also allow β_{rc} to vary by type of school (e.g., K-5, 6-8, 9-12, etc).

[24]Following equation (4), note that $\pi_{rjct}\left(\tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau-1}}, \boldsymbol{X}_{\boldsymbol{ct}}\right) = \frac{\tilde{n}_{rjct}\left(\tilde{N}_{rc}, \tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau}}\right)}{\sum_{k\in c}\tilde{n}_{rkct}\left(\tilde{N}_{rc}, \tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau}}\right)}$ where $\tilde{n}_{rjct}\left(\tilde{N}_{rc}, \tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau}}\right) = \exp\left(\log n_{rjct}\left(\tilde{N}_{rc}, \tilde{\boldsymbol{s}}_{\boldsymbol{ct+\tau-1}}\right) + \hat{\beta}_{rc}\left(\tilde{s}_{jct+\tau} - \tilde{s}_{jct+\tau-1}\right)\right)$ for $\tau = 1, 2, \ldots$, and $\pi_{rjct}\left(\tilde{\boldsymbol{s}}_{\boldsymbol{ct-1}}, \boldsymbol{X}_{\boldsymbol{ct}}\right) = \frac{n_{rjct}}{\sum_{k\in c} n_{rkct}}$ for $\tau = 0$.

all general equilibrium effects on the co-evolution of school enrollments as

$$\text{SR Effect} = s_{jct}\left(\boldsymbol{N_{ct}}, \boldsymbol{s_{ct-1}}\right) - s_{jct}\left(\boldsymbol{N_{ct-1}}, \boldsymbol{s_{ct-1}}\right) \tag{7}$$

$$\text{LR Effect} = \lim_{\tau\to\infty} s_{jct+\tau}\left(\boldsymbol{N_{ct}}, \boldsymbol{\tilde{s}_{ct+\tau-1}}\right) - s_{jct+\tau}\left(\boldsymbol{N_{ct-1}}, \boldsymbol{\tilde{s}_{ct+\tau-1}}\right) \tag{8}$$

4 Estimating Enrollment Responses

Empirically implementing our model requires causal estimates of β_{rc} from equation (4), the social effect that generates the endogenous mechanism behind segregation. Before delving into our identification strategy, it is worth discussing the appropriate interpretation of β_{rc}. As a parameter of a demand response, it represents how individuals' enrollment *choices* at a given school are affected by its past racial compositions of schools. This should not be conflated with individuals' *preferences* for the past racial composition of a school or any simple transformation thereof. While it is true that β_{rc} is influenced by parents' preferences for the racial composition of schools, it is also comprised of all other environmental considerations that affect the ability of parents to exercise those preferences such as moving costs and the availability of local schools with the desired levels of amenities. Hence, the finding of a small value of β_{rc} should not be interpreted as evidence of weak racial discriminatory preferences. Instead, it should be interpreted as weak discriminatory demand responses that may be due to either weak discriminatory preferences or weak ability of parents to exercise their strong discriminatory preferences.[25]

Identifying social effects is well known to be a difficult problem (Manski (1993)). A key endogeneity concern in equation (4) is that school amenities that affected the enrollment decisions in $t-1$ (i.e., that were correlated to s_{jct-1}) tend to persist; thus, they may still be present in t, which would upwardly bias an OLS estimate of β_{rc}. We circumvent this and other endogeneity concerns with the identification strategy proposed by Caetano and Maheshri (2017). First, we enrich equation (4) to allow school demand to vary by grade:

$$\log n_{rgjct} = \beta_{rgc} \cdot s_{jct-1} + \gamma_{rgct} + \epsilon_{rgjct}, \tag{9}$$

where n_{rgjct} is the number of race r students enrolled in grade g in school j in commuting zone c

[25] As noted, our analysis also does not differentiate between whether these estimates reflect taste-based or statistical discrimination.

in year t. The parameter β_{rgc} now represents the enrollment response of each race to the minority share of the school, and is allowed to vary additionally by grade.[26] The race-grade-commuting zone-year fixed effect γ_{rgct} encapsulates a demographic effect at that level.[27] Finally, the error term ϵ_{rgjct} incorporates the remainder of the determinants of the school demand.

4.1 Identification of β_{rgc}

To identify causal estimates of β_{rgc}, we need to exploit variation in s_{jct-1} that is orthogonal to other determinants of school demand in t. Such variation is difficult to observe directly because many school amenities are serially correlated and hence persist from $t-1$ to t. Moreover, any identification strategy that we use must apply to all commuting zones in the country for a sufficiently long period of time. Given these considerable restrictions we exploit an identification strategy that leverages the complex panel structure of our data with no additional data requirements.

Our approach relies on the fact that students enrolled in the second highest grade of a school in year $t-2$ no longer attend the school in t. Hence, the racial composition of this cohort of students (the IV cohort) affects s_{jct-1} but does not directly affect $\log n_{rgjct}$ for any g. Of course, some school amenities that influenced the IV cohort's enrollment decision in $t-2$ will likely persist and influence the enrollment decisions of future cohorts of students in t, hence invalidating our IV. We circumvent this issue by controlling for the enrollments of *subsequent* cohorts of students in $t-1$. In doing so, we control for school amenities that persisted from $t-2$ to $t-1$. Thus, our identification assumption is that all school amenities persisting from $t-2$ to t will also have persisted from $t-2$ to $t-1$ (i.e., they cannot lay dormant in $t-1$ and then suddenly reappear in t).[28]

More formally, define $s_{gjct} = \frac{n_{gMjct}}{n_{gMjct}+n_{gWjct}}$ as the minority share of students enrolled in grade g in school j in commuting zone c in year t. Let $\underline{g}_j$ and $\overline{g}_j$ be the lowest and highest grades of instruction, respectively, that are offered at school j. We add to equation (9) the control term $C_{rgjct-1}$:

[26] In practice, we also allow β_{rgc} to vary over time, as we estimate it separately over a 2005-2009 subsample and a 2010-2014 subsample. To simplify notation, we omit the t subscript.

[27] In practice, as a robustness check we also include fixed effects at finer geographic areas than commuting zones such as school districts. The finest fixed effect that we consider is at the race-grade-ZIP code-year-grade range level, which should further control for a rich set of potential local confounders.

[28] In Caetano and Maheshri (2017), we provided several robustness checks designed to falsify this identifying assumption, and we have implemented them all here as well (see Figures XX below). We found no evidence against this identifying assumption.

$$\log n_{rgjct} = \gamma_{rgct} + \beta_{rgc} s_{jct-1} + \underbrace{\sum_{i=\underline{g}_j}^{\bar{g}_j - 1} \left(\alpha^i_{rgcW} \log n_{Wijct-1} + \alpha^i_{rgcM} \log n_{Mijct-1} \right)}_{C_{rgjct-1}} + u_{rgjct}, \tag{10}$$

and use $s^{\bar{g}_j-1}_{jct-2}$ as an IV for s_{jct-1}. Our IV estimator is consistent under the following identifying assumption:

Assumption 1. *Identifying Assumption. Cov* $\left[s^{\bar{g}_j-1}_{jt-2}, u_{rgjct} | C_{rgjct-1}, \gamma_{rgct} \right] = 0.$[29]

That is, if we control for the enrollments of all students in all grades except for the last grade in year $t-1$ ($C_{rgjct-1}$), then the racial composition of the IV cohort, as observed in $t-2$, is a valid IV for the overall racial composition of the school in $t-1$.[30]

For more intuition, we explain our strategy using a 9-12 high school as an example in the diagram below. Our IV is s^{11}_{jct-2}, the minority share of the second highest grade in $t-2$. For our IV to be valid, we control for the $t-1$ enrollments of Whites and minorities in all grades except for the highest grade (i.e., grades 9, 10 and 11). Because we cannot control for the $t-1$ enrollments of Whites and minorities in the highest grade (since no variation in s_{jct-1} would remain), we use the IV cohort's enrollments in $t-2$ to ensure we are not identified off of persistent amenities specific to the highest grade.

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

This logic is valid for any school that offers instruction for at least two grades, irrespective of its grade range. For any school that offers more than two grades of instruction, we also construct additional IVs from the minority shares of the third highest grade in $t-3$, or the fourth highest grade in $t-4$, etc., which allows us to perform over-identification tests (Hansen (1982)).

[29]This assumption contains an abuse of notation in order to simplify the exposition. We condition on the variables in $\left\{ \log n^{gr}_{jt-1}; g = \underline{g}_j, \ldots, \bar{g}_j - 1, r = W, M \right\}$, not on C^{gr}_{jt-1} as written above. In practice, we find that a linear projection of these variables and a more flexible specification of these variables generate the same results.

[30]An IV that follows this property is often called a "Conditional IV". See Angrist and Pischke (2009), pp. 175.

Relevance: What is the Identifying Variation?

In the context of equation (9), we want to exploit changes in school amenities that compelled students in the IV cohort to sort towards (or away from) that school in the past (thus changing s_{jct-1}), provided that these changes were transitory and did not affect enrollment decisions in t. To do so, we isolate variation in school amenities that affect the enrollment of the IV cohort in $t-2$ without affecting any of the enrollments of subsequent cohorts in $t-1$. Although students in the IV cohort will have aged out by period t, they do contribute to s_{jct-1}. As a result, they plausibly affect the enrollment decisions of subsequent cohorts of students in t purely through the mechanism of interest.[31]

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

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

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

Validity: Threats to Identification

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

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

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

Conversely, any school unobservable that is unique to grade $\bar{g}_j$ in $t-1$ will fail to satisfy property 3 if students in some grade $g < \bar{g}_j$ in $t-1$ *anticipate* the amenity will be present in t. This anticipation is likely because the amenity must be present in t (property 1), and must have been considered by students of different races in grade $\bar{g}_j - 1$ in $t-2$ (property 2). For instance, in the case of the example of the football coach, property 3 would hold only if the coach was at the school in $t-2$, then left that school in $t-1$, and then later it was announced that they would be reinstated. Moreover, this announcement would have had to occur *after* enrollment decisions were made in $t-1$ (otherwise the control cohorts would have anticipated the return of the coach).[32]

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

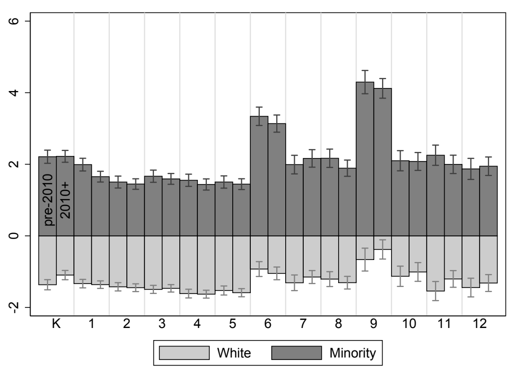
5 Results

5.1 White and Minority Segregation

5.1.1 Estimates of β_{rgc}

In order to allow for spatial heterogeneity in β_{rgc}, we subdivide commuting zones into four groups depending on whether their total enrollment as of 2002 ($N_{Mc2002} + N_{Wc2002}$) and the racial composition of that total enrollment was above or below the median for the entire US. In order to allow for β_{rgc} to vary over time, we also estimate it separately from 2005-2009 and from 2010-2014. For each of the two races and 13 grades, this yields eight distinct effects that capture heterogeneity in enrollment responses between urban and rural areas, heterogeneity in enrollment responses between highly minority regions and highly White regions, and heterogeneity in responses over time. Given the large number (208) of parameters of interest, we aggregate these effects along two dimensions in order present results in a more easily digestible, graphical format.

Figure 8: Average Estimates of β by Race and Grade, 2005-2014



Note: Each bar corresponds to the average of $\hat{\beta}_{rgc}$ weighted across all commuting zones by total enrollment of students of each race. The first bar for each grade is estimated on a 2005-2009 subsample, and the second bar for each grade is estimated on a 2010-2014 subsample. We use two groups of IVs to obtain these estimates: $s^{\bar{g}-1}_{jct-2}$ and $s^{\bar{g}-2}_{jct-3}$. The F-test for whether the coefficients of these IVs are equal to zero in the first stage regression is $F = 11,425.89$ ($p = 0.00$). The Hansen (1982) over-identification test statistic is $F = 25.13$ ($p = 0.34$), so we cannot reject the exclusion restriction (Assumption 1). The total number of school-race-grade-year observations is 1,966,476 for 2005-2009 and 2,093,372 for 2010-2014.

We first focus on the heterogeneity in parents' responses by sample period, race, and grade

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

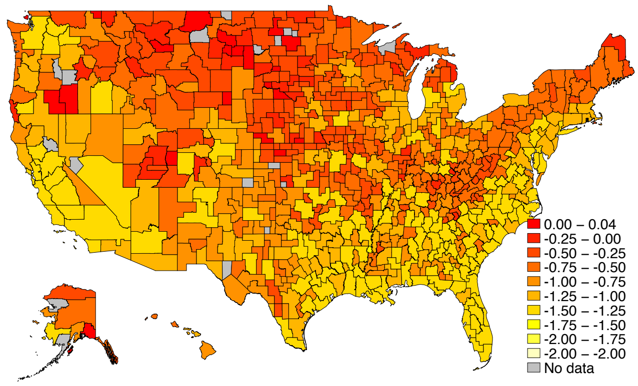
of enrollment. For each sample period, we construct race- and grade-specific estimates of β by taking averages of β_{rgc} across all commuting zones, weighted by commuting zone level enrollments of each race and grade, which we present graphically in Figure 8. There is very little change in β_{rgc} over the sample period. White (minority) parents have negative (positive) enrollment responses to more heavily minority schools, which implies the existence of the endogenous channel. In magnitude, White parents react a little less than minority parents, except in grades 6 and 9, when this difference is more pronounced. This does not necessarily imply that White parents have less discriminatory preferences than minority parents; it might only reflect the fact that minority parents can more easily translate their discriminatory preferences into choices for a variety of reasons, e.g., they may have lower moving costs or the attendance areas with higher minority share may be less expensive. Finally, parents' responses are of roughly similar magnitude across grades, though they are largest in sixth- and ninth-grade for minorities, which makes sense given that some of the most salient enrollment decisions occur when students advance from K-5, K-8 and 6-8 schools into 6-8 and 9-12 schools, all of which are the most common grade ranges for public schools in the country.[33]

Next, we focus on geographic heterogeneity in parents' responses by constructing race- and commuting zone-specific estimates of β, this time averaging β_{rgc} across all grades, weighted by enrollments of each race and grade. We map these responses in Figure 9. White parents in the sparsely populated and predominantly White areas react slightly less negatively to more heavily minority schools than the rest of the country, but there is relatively little variation in responses across more populated regions. Minority parents' responses follow an analogous geographic pattern, with stronger (positive) responses to more heavily minority schools is less populated and predominantly White areas, though there is relatively more variation.

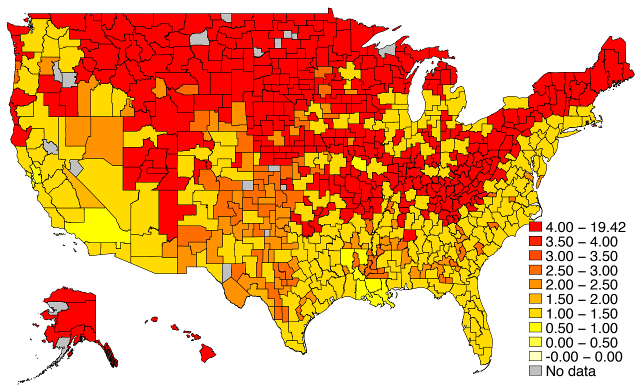
[33]See Figure 19 in the appendix for the distribution of schools by grade range in the country

Figure 9: Average Estimates of β by Race and Commuting Zone, 2005-2014

(a) White Responses to Increases in s_{jt-1}



(b) Minority Responses to Increases in s_{jt-1}



Note: Each map shows commuting zone level averages of $\hat{\beta}_{rgc}$ weighted across all grades by total local enrollments of students in each grade.

Robustness Checks

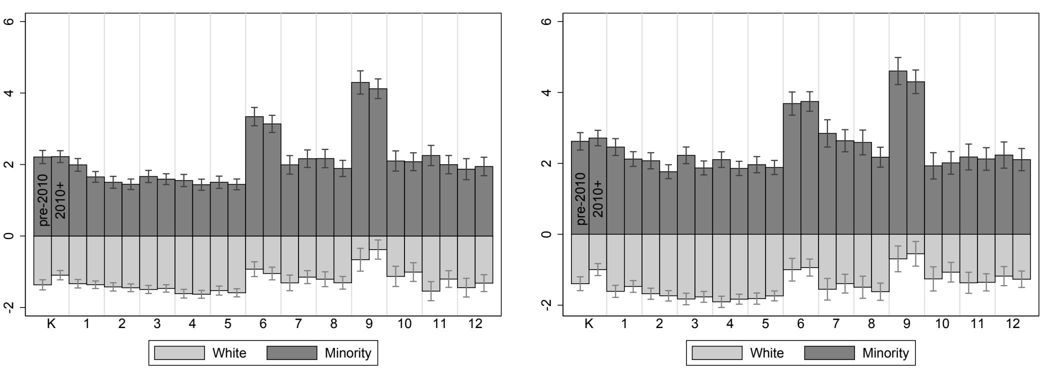
We conduct several robustness checks to support our identification strategy. First, we consider the possibility that our main estimates may partially incorporate the parental responses to the neighborhood racial composition, rather than simply the parental responses to the school racial composition. We then also consider some issues that may arise with our implementation.

One potential concern is that our estimates might be conflating the demand responses for the racial composition of the school and the neighborhood amenities. Our identification strategy was developed with this concern in mind. As long as the students in the IV cohort do not leave the neighborhood immediately after they have aged out of the school, we will be holding the neighborhood racial composition fixed. There are reasons to believe this is a plausible assumption. First, students may not be the only children in the household. For most households, it may make more sense to leave the neighborhood only after the youngest child in the household ages out of the school. Second, there are potential frictions that may prevent a household to leave the neighborhood right away. For instance, Caetano and Macartney (2016) show with a regression discontinuity design that it takes some years for households to leave the neighborhood due to school amenity concerns when their youngest child ages out of the school.[34] To further allay such concerns, in Figure 10 we present estimates of β_{rgc} from equation (10) specified with different fixed effects. Panel (a) shows results with race-grade-school district-year fixed effects and Panel (b) shows results with race-grade-ZIP code-year fixed effects. Because the estimates for each grade and race are very similar to the baseline estimates in Figure 8 that are estimated with geographically broader race-grade-commuting zone-year fixed effects, this potential issue does not seem to be particularly important in our specification.

Figure 10: Average Estimates of β by Race and Grade, 2005-2014: Different Fixed Effects

(a) School District level FEs

(b) Zip Code level FEs



Note: Each bar corresponds to the average of $\hat{\beta}_{rgc}$ weighted across all commuting zones by total enrollment of students of each race. The first bar for each grade is estimated on a 2005-2009 subsample, and the second bar for each grade is estimated on a 2010-2014 subsample. Each panel represents a different specification of fixed-effects (FEs) γ_{rgat} for different representations of the geographic area a.

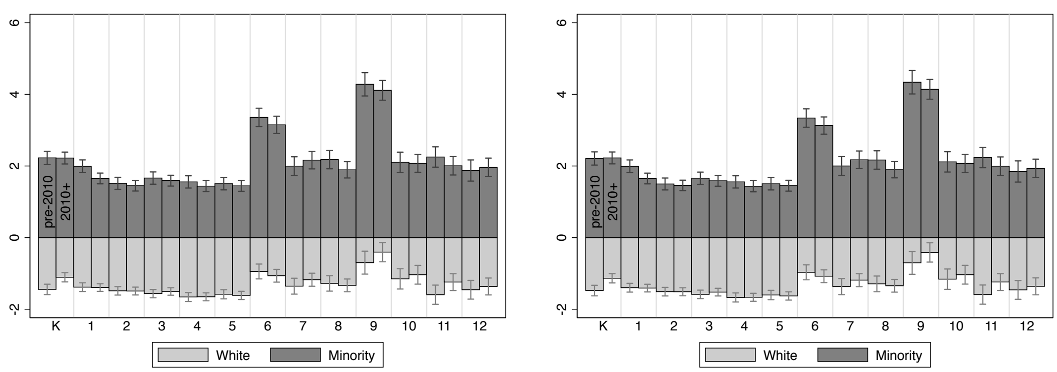
Another potential issue with our approach is that even if the logic of our IV is sound, we might be incapable of controlling for all persistent amenities simply by including $C_{rgjct-1}$ in the regression.

[34]We are not aware of any paper in the literature claiming to fully disentangle school and neighborhood amenities in the context of school segregation. The approaches developed in Caetano (2016) and in Caetano and Macartney (2016) are capable of disentangling these two sets of determinants in the context of residential sorting, but they do not analyze school segregation.

We allay this concern with two additional robustness checks. For the estimates in Panel 11a, we use only $s^{\bar{g}-2}_{jct-3}$ as an IV, which allows us to control for enrollments in year $t-2$ by including $C_{rgjct-2}$ in the regression as well.[35] This weakens our original identifying assumption, as any endogenous confounder would now need to affect decisions in $t-3$, lay dormant over the next two years (i.e., not be absorbed by either $C_{rgjct-1}$ or $C_{rgjct-2}$) and then suddenly and unexpectedly reappear in t. For an appropriate comparison, in Panel 11b we again use only $s^{\bar{g}-2}_{jct-3}$ as an IV, but this time we only include $C_{rgjct-1}$, as in the baseline case. All of the parameter estimates barely differ from the baseline ones, which suggests that $C_{rgjct-1}$ is sufficient to to control for persistent, unobserved amenities. We also performed similar tests with $s^{\bar{g}-3}_{jct-4}$ as an IV, allowing us to control for $C_{rgjct-1}$, $C_{rgjct-2}$ and $C_{rgjct-3}$, and obtained similar results.

Figure 11: Average Estimates of β by Race and Grade, 2005-2014: Additional Controls for Persistent Amenities

(a) Only $s^{\bar{g}_j-2}_{jct-3}$ as IV plus Controls in $t-2$ (b) Only $s^{\bar{g}_j-2}_{jct-3}$ as IV



Note: Each bar corresponds to the average of $\hat{\beta}_{rgc}$ weighted across all commuting zones by total enrollment of students of each race. The first bar for each grade is estimated on a 2005-2009 subsample, and the second bar for each grade is estimated on a 2010-2014 subsample. Panel 11a controls for everything in the baseline case plus $C_{rgjct-2}$. Panel 11b controls only for $C_{rgjct-1}$ as in the baseline case.

Finally, for completeness we also report in Figure 20 in the appendix the analogous estimates for a naive OLS specification of equation (9). The estimates are substantially larger in magnitude, which is consistent with the intuition of a positive OLS bias.

[35] $C_{rgjct-2}$ includes all log-enrollments of all races except the last two grades, i.e $C_{rgjct-2} = \sum_{i=\underline{g}_j}^{\bar{g}_j-2} \left(\alpha^i_{rgcW} \log n_{Wijct-2} + \alpha^i_{rgcM} \log n_{Mijct-2}\right)$.

5.1.2 Demographic Effects on Segregation

Computing the short- and long-run effects of demographic shifts on segregation with grade-specific estimates of $\hat{\beta}_{rgc}$ requires a simple modification to equation (11):

$$s^i_{jct}\left(\tilde{\boldsymbol{s}}^{\boldsymbol{i-1}}_{\boldsymbol{c}}, \tilde{\boldsymbol{N}}^{\boldsymbol{i}}_{\boldsymbol{gc}}\right) = \frac{\sum_g n_{Mgjct}\left(\tilde{\boldsymbol{s}}^{\boldsymbol{i-1}}_{\boldsymbol{c}}, \tilde{\boldsymbol{N}}^{\boldsymbol{i}}_{\boldsymbol{gc}}\right)}{\sum_g n_{Wgjct}\left(\tilde{\boldsymbol{s}}^{\boldsymbol{i-1}}_{\boldsymbol{c}}, \tilde{\boldsymbol{N}}^{\boldsymbol{i}}_{\boldsymbol{gc}}\right) + n_{Mgjct}\left(\tilde{\boldsymbol{s}}^{\boldsymbol{i-1}}_{\boldsymbol{c}}, \tilde{\boldsymbol{N}}^{\boldsymbol{i}}_{\boldsymbol{gc}}\right)}, \tag{11}$$

where $\tilde{\boldsymbol{N}}_{\boldsymbol{gc}}$ consists of $\tilde{N}_{rgc}$ for all r and g. The remainder of the simulation follows straightforwardly.

We summarize our findings for the entire US in Table 1. The fraction of White-segregated schools in commuting zones is observed to decline annually by 0.78 percentage points on average, while the fraction of Minority-segregated schools is observed to increase annually by 0.46 percentage points. This observed decline is due to demographic, endogenous and exogenous mechanisms. The average short-run (1 year) effect of a demographic shock in a commuting zone decreases the prevalence of White-segregated schools by 0.67 percentage points and increases the prevalence of minority-segregated schools by 0.28 percentage points. In the long-run, the propagation of additional social effects generate a total reduction in the prevalence of White-segregated schools by 0.73 percentage points and increase in the prevalence of minority-segregated schools by 0.33 percentage points .

Importantly, we find that general equilibrium effects are large and economically significant in terms of modulating segregation dynamics. A naive partial equilibrium analysis would have erroneously attributed over twice as large a decrease in the prevalence of White-segregated schools and over three times as large an increase in the prevalence of minority-segregated schools in the long-run due to annual demographic shocks.[36] This follows from the fact that when aggregate inflows of minorities propagate to a school that originally had a heavily White enrollments, the increase in minority share is not as large of a deterrent to prospective White parents since their alternatives were probably also exposed to these inflows. Analogously, a naive partial equilibrium analysis would have erroneously uncovered much larger increases in the prevalence of minority schools due to annual demographic shocks. The aggregate inflows of minorities that turn marginally minority

[36]In order to benchmark our findings, we compute long run partial equilibrium effects by restricting $n^r_{jct+\tau}$ to be a function only of $\tilde{s}_{jct+\tau-1}$ in equation (5) for school j instead of the entire vector of $\tilde{\boldsymbol{s}}_{\boldsymbol{jct+\tau-1}}$ for all schools in the commuting zone.

schools (e.g., $s_j = 74\%$) into segregated schools simultaneously make inframarginal minority schools (e.g., $s_j = 70\%$) less competitive for minority student enrollments, thereby dampening the effects of demographic shocks.

Table 1: Simulated Annual Demographic Effects on Prevalence of Segregated Schools, 2005-2014

	Observed Change	Short-Run Effect	Long-Run Effect	Long-Run Effect (Partial Equilibrium
White Segregated	-0.79	-0.67	-0.73	-1.62
Minority Segregated	+0.46	+0.28	+0.33	+1.09

Notes: Effects are expressed in percentage points. Partial equilibrium long-run effects do not account for general equilibrium effects across schools.

5.2 White, Black and Hispanic Segregation

If parents respond differently to inflows of Hispanic students versus Black students, then the short- and long-run effects of demographic shocks could be very different, particularly given that they are largely attributable to Hispanic immigration. In order to explore this possibility, we generalize our model by allowing r to take on three values: W, B and H. The racial composition of school j in year t is now represented by the vector s^B_{jt}, s^H_{jt} which corresponds to the fractions of Black and Hispanic students enrolled in the school respectively. The remainder of the theoretical model is unchanged, though the diagrams shown must be replaced by higher dimensional objects that map from (s^B_{jt-1}, s^H_{jt-1}) to (s^B_{jt}, s^H_{jt}). Our empirical implementation and identification strategy for enrollment responses are also unchanged, though $\boldsymbol{\beta_{rgc}}$ now represents the vector $\beta^B_{rgc}, \beta^H_{rgc}$ of race r responses to Black and Hispanic peers respectively.

5.2.1 Estimates of $\boldsymbol{\beta_{rgc}}$

We present our estimates of these responses in Figure 12 below. We allow for the same geographic and temporal heterogeneity as in the baseline case with two races.[37] The IVs that we use are constructed in analogous fashion to how we constructed IVs in the two-race case. Specifically, our main IVs are $s^{B,\bar{g}_j-1}_{jct-2}$ and $s^{H,\bar{g}_j-1}_{jct-2}$, which correspond to the Black and Hispanic shares of the next to last grade of the school in $t-2$ respectively.[38] White parents respond somewhat negatively to both

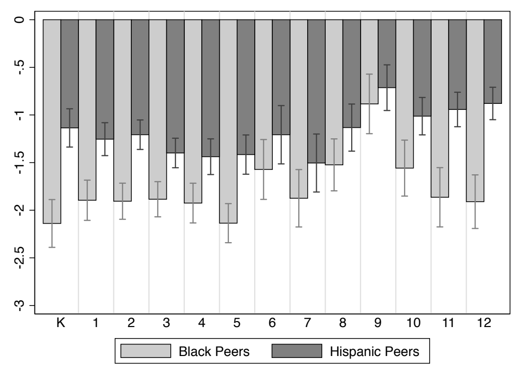
[37] We also considered alternative geographic groupings (e.g., using the Hispanic share of enrollments at the commuting zone level instead of the minority share of enrollments), and obtained similar results.

[38] Analogously, we control for the log-enrollment of all three races for all grades except the last one in $t-1$, i.e., $C_{rgjct-1} = \sum_{i=\underline{g}_j}^{\bar{g}_j-1} \left(\alpha^i_{rgcW} \log n_{Wijct-1} + \alpha^i_{rgcB} \log n_{Bijct-1} + \alpha^i_{rgcH} \log n_{Hijct-1}\right)$.

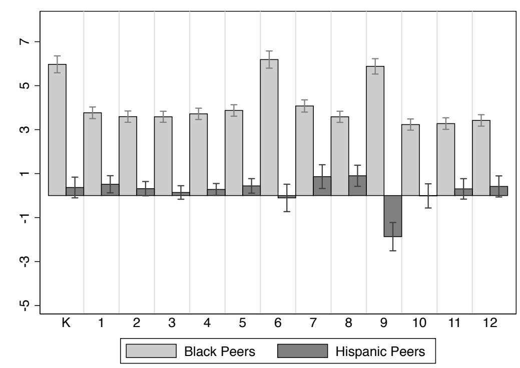
Black and Hispanic peers, though their response is roughly twice as strong for Blacks peers. Black parents respond very strongly and positively to Black peers, and have much smaller but mostly positive responses to Hispanic peers. Finally, Hispanic parents respond very strongly to Hispanic peers, but have slightly negative or no response to Black peers, especially in high school.

Figure 12: Average Estimates of β by Race (White/Black/Hispanic) and Grade

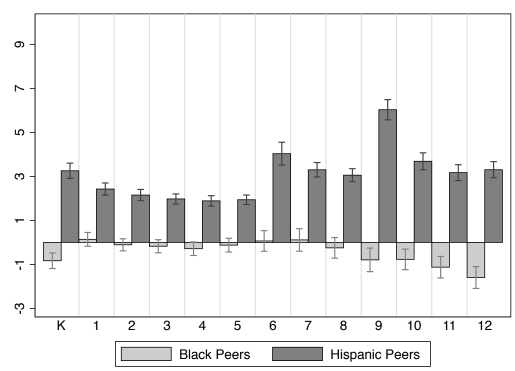
(a) White Parents' Responses



(b) Black Parents' Responses



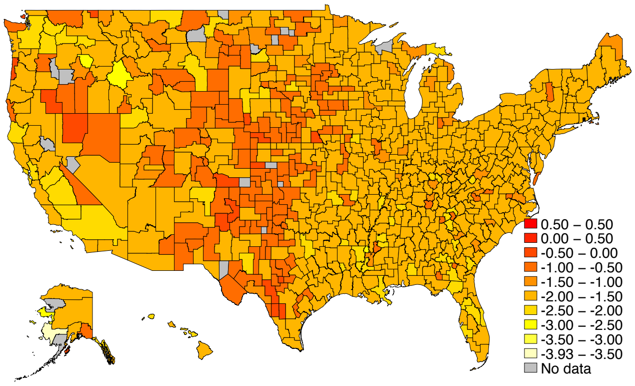
(c) Hispanic Parents' Responses



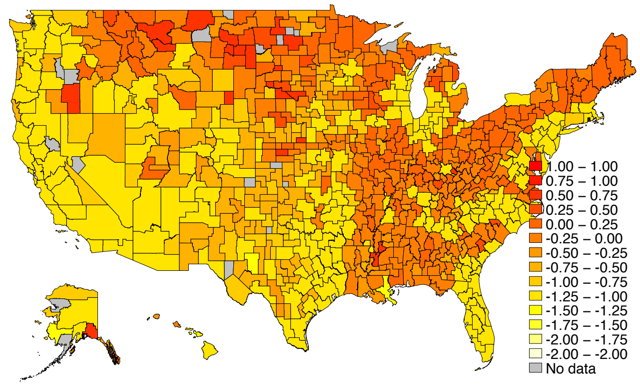
Note: Each bar corresponds to the average of $\hat{\boldsymbol{\beta}}_{\boldsymbol{rgc}}$ weighted across all commuting zones by total enrollment of students of each race. Parameters shown are estimated on the 2005-2009 subsample and are indistinguishable from parameters estimated on the 2010-2014 subsample. We use two groups of IVs to obtain these estimates: $s^{\bar{g}-1}_{jct-2}$ and $s^{\bar{g}-2}_{jct-3}$. The F-test for whether the coefficients of these IVs are equal to zero in the first stage regression is $F = 8,786.12$ ($p = 0.00$). The Hansen (1982) over-identification test statistic is $F = 17.25$ ($p = 0.48$), so we cannot reject the exclusion restriction (Assumption 1). The total number of school-race-grade-year observations is 2,949,714 for 2005-2009 and 3,140,058 for 2010-2014.

Figure 13: Average Estimates of β by Race (White/Black/Hispanic) and Commuting Zone, 2005-2014

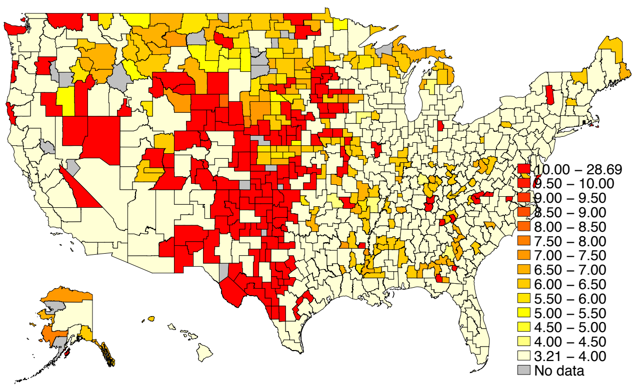
(a) White Responses to Increases in s^B_{jt-1}



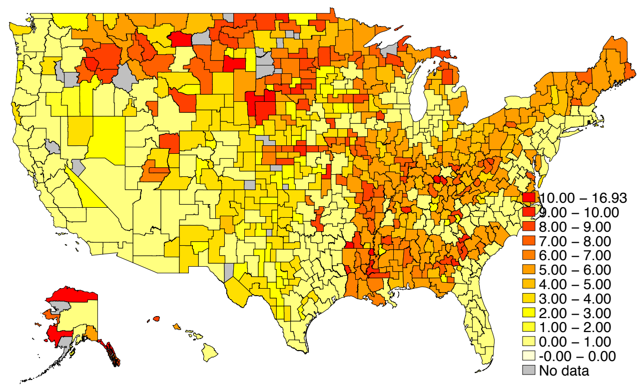
(b) White Responses to Increases in s^H_{jt-1}



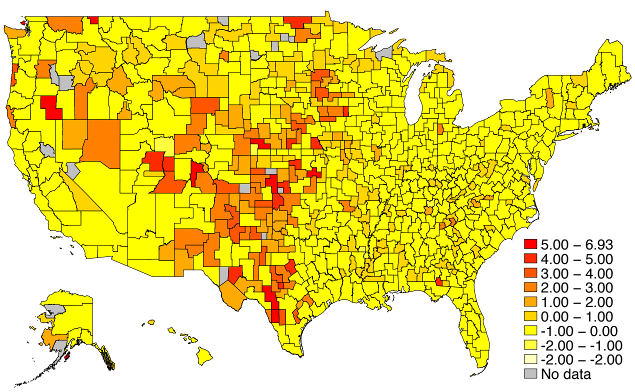
(c) Black Responses to Increases in s^B_{jt-1}



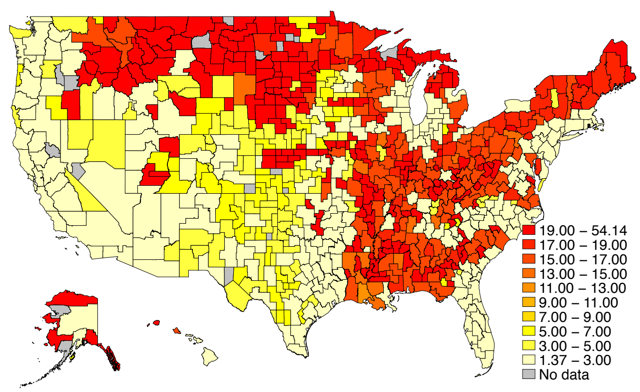
(d) Black Responses to Increases in s^H_{jt-1}



(e) Hispanic Responses to Increases in s^B_{jt-1}



(f) Hispanic Responses to Increases in s^H_{jt-1}



Note: Each map shows commuting zone level averages of $\hat{\beta}_{rgc}$ weighted across all grades by total local enrollments of students in each grade.

Figure 13 shows maps of the estimates by commuting zones. The geographic patterns of results are intuitive. Each race responds positively to increases in the share of their own race, and these responses are particularly stronger in areas where they are a minority. Each race responds negatively to increases in the share of other races, except in areas where there are fewer individuals of those other races. One exception to this pattern is the response of Black parents to Hispanic peers, which tends to be positive throughout the country. But even in this case the same relative pattern remains: Black parents respond more positively to Hispanic peers in areas with fewer Hispanic students.

A full set of robustness checks paralleling the two-race analysis are provided in Appendix D. Overall, our estimates in this more flexible specification are consistent with the estimates shown in Figure 8 that classified Black and Hispanic students together as minorities.

Remark 1. Our findings of strong within-race and small across-race responses for Black and Hispanic parents provides suggestive evidence in favor of the validity of our instrumental variables. The identifying variation does not seem to reflect some unobserved characteristic that is correlated to both Black and Hispanic enrollments, e.g., income. This suggests that we are identifying parents' responses to the *race* of their children's peers as opposed to some other characteristic of schools. Indeed, the analogous estimates for naive OLS specification of equation (9) (Figure 21 in the appendix) show both Blacks and Hispanics to respond positively to increases in Black and Hispanic shares.

5.2.2 Demographic Effects on Segregation

In Table 2, we summarize the average effects of an annual demographic shock on the prevalence of segregated White and minority schools when allowing for discriminatory responses to differ for Black and Hispanic peers. These should be understood as generalizations of the results shown in Table 1. Even when allowing for richer racial responses, we find very similar effects as before, with one exception. The naive partial equilibrium effects in Table 2 are substantially larger in magnitude than those shown in Table 1. Because commuting zone level demographic shocks tend to reflect primarily Hispanic inflows, it is not surprising that our three-race analysis implies a stronger long-run demographic effect in partial equilibrium than our two-race analysis, which conflates Blacks and Hispanics. However, it is notable that the long-run GE effects on segregation are essentially unchanged. This is consistent with the notion that schools that are close substitutes are similarly exposed to Hispanic inflows, which would change the relative attractiveness of the two schools less than would be detected in a partial equilibrium analysis.

Table 2: Simulated Annual Demographic Effects on Prevalence of Segregated Schools with Three Races, 2005-2014

	Observed Change	Short-Run Effect	Long-Run Effect	Long-Run Effect (Partial Equilibrium)
White Segregated	-0.79	-0.71	-0.71	-2.56
Minority Segregated	+0.46	+0.27	+0.40	+2.35

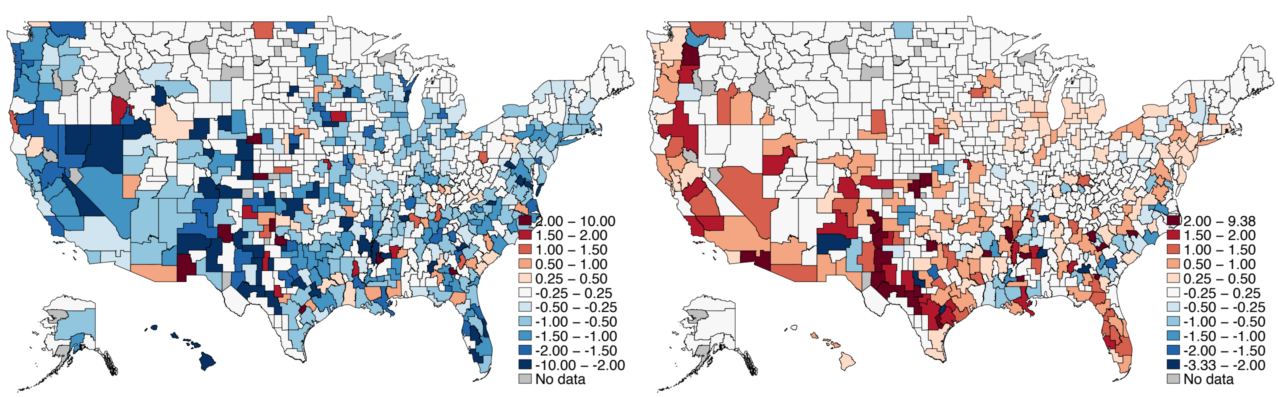
Notes: Effects are expressed in percentage points. Partial equilibrium long-run effects do not account for general equilibrium effects across schools.

In order to explore geographic patterns in these effects, we present the long-run effects of demographic shocks on the prevalence of segregated White schools and segregated Minority schools separately for each commuting zone. Because our data allows us to estimate the β_{rgc} only from 2005 onward, these annualized averages are computed over that sample period.[39]

In Panel 14a, we present the long-run effects of demographic changes on the prevalence of segregated White schools. An average one-year demographic shock will eventually desegregate 1-2% of White schools in the majority of the country. These same shocks will eventually add 0.25-1% segregated minority schools throughout the sunbelt and West coast (Panel 14b).

Figure 14: Average Annual Effects of Demographic Change, 2005-2014

(a) Long-Run Effect on White-Segregated Schools (b) Long-Run Effect on Minority-Segregated Schools



Note: A White- (minority)-segregated school is defined as one in which the enrollment of White (minority) students exceeds 75% of the total enrollment. Blue (Red) commuting zones have experienced declining (increasing) segregation during this period. Annual changes shown in percentage points.

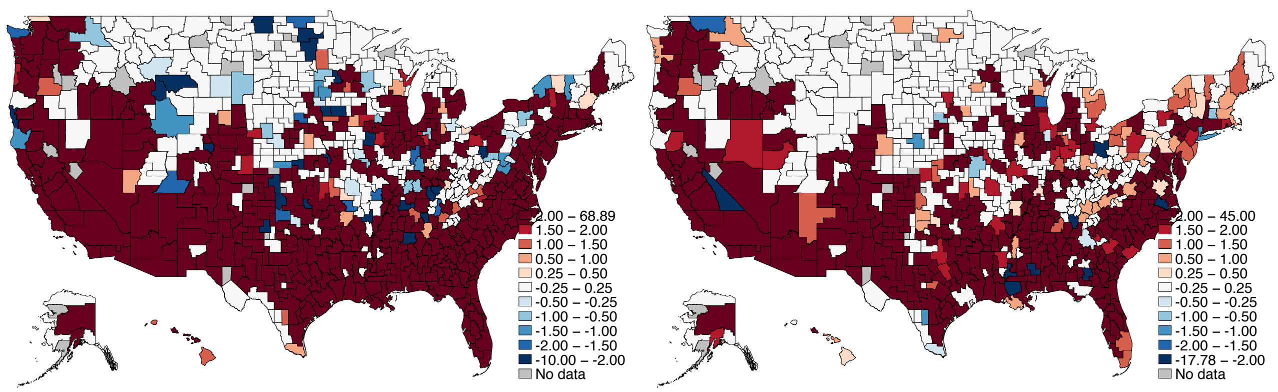
Finally, we conduct a counterfactual policy simulation in which we consider what would have

[39]For most states, enrollment data at the grade level is only available starting in 2002, and our IV approach requires data from $t-3$ and $t-2$.

endogenously happened to the prevalence of segregated schools due purely to discriminatory forces in the absence of demographic shocks. This corresponds to the "old" social effect shown as a green arrow in Figure 7, which we present in Figure 15. If the aggregate racial compositions of student bodies were fixed, segregation would substantially increase over time throughout most of the country. Given the stark disconnect between these maps and the observed trends in segregation over this period, we conclude that systematic inflows of minorities, primarily Hispanics, have kept endogenous discriminatory forces at bay. We believe this to be an important additional consideration when conducting any cost-benefit analysis of a restriction on immigration.

Figure 15: Average Annual Effects in the Absence of Demographic Change, 2005-2014

(a) Change in Prevalence of White-Segregated Schools (b) Change in Prevalence of Minority Segregated Schools



Note: A White- (minority)-segregated school is defined as one in which the enrollment of White (minority) students exceeds 75% of the total enrollment. Blue (Red) commuting zones have experienced declining (increasing) segregation during this period. The "old" social effect corresponds to what would occur in a counterfactual world without demographic shocks. Annual changes shown in percentage points.

6 Conclusion

A growing body of research has found adverse short-run and long-run effects of school segregation, particularly for minority students. It is understandable then to be concerned about the increase in the proportion of predominantly minority public schools in the United States. However, policymakers seeking to address segregation would be wise to understand the mechanisms underlying this trend. Those who insist that low minority-share schools are the only acceptable outcome will be disappointed for purely arithmetic reasons; in 2014, the four most populous commuting zones had majority "minority" enrollments.[40]

Models of segregation predict that when holding all else constant, even mild discriminatory responses will endogenously lead to increases in racial segregation over time. Our findings reveal that all else is not constant. Aggregate demographic shocks primarily due to Hispanic immigration have been an important force in reducing the segregation of White students and increasing the segregation of minority students. These continuing shocks will keep pushing more and more schools out of equilibrium, leading to a mismatch between their actual racial compositions and the racial composition compatible in general equilibrium with the amenities that they provide. Policymakers may be able to exploit this mismatch by targeting investments wisely. These investments could take the form of changes in regular amenities that may be differently attractive to different races, or they may take the form of changes in a school's racial composition through relocation policies (e.g., school busing). If schools are out of equilibrium (e.g., a school that is reasonably attractive to parents of both races has a predominantly White enrollment for historical reasons), then such investments will be even more effective at reducing segregation by taking advantage of dynamic social multiplier effects. Thus, there may be substantial scope for highly localized policies and place-based investments to mitigate increases in segregation. To that end, we view our findings as complementary to the large literature on Tiebout (1956) sorting and school choice.[41]

However, our analysis also suggests that there is limited scope for policy interventions to have lasting effects on school segregation. Even with mild discriminatory responses, the effects of one-shot policy interventions are likely to be dwarfed eventually by the endogenous process of segregation due to discrimination. Moreover, general equilibrium considerations would moderate the long-run effects of recurrent interventions at a higher level (e.g., city- or state-wide policies).

More broadly, 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. As more precise data on individuals' settlement and enrollment patterns be-

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

[41]See, for example, Epple and Sieg (1999), Bayer et al. (2004), Urquiola (2005), Bayer et al. (2007), Billings et al. (2013) and Caetano and Macartney (2016).

come available, we believe this will become a promising avenue for further inquiry.

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A Data Appendix

Our data comes from the Common Core of Data maintained by the National Center for Education Statistics at the US Department of Education. Common Core data is available from 1987 to 2014, but we drop the 1987-88 school year because of incomplete data coverage. Data from some states is missing, mostly in the early years of the sample and in 1998-1999 school year, but this represents a very small proportion of our sample. In Table 3 below, we present the state-years that are missing, and hence omitted from our analysis. Because of these data issues, we report all summaries of the data as annualized averages.

Table 3: Missing Data

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

We have recalculated all results presented omitting all states with data missing in any years and omitting all commuting zones that contain schools from any state with missing data. Our findings are qualitatively unchanged. Note that only Nevada and Tennessee have any data missing from 2002-2015, which corresponds to the sample period of our estimation (and simulation) subsample.

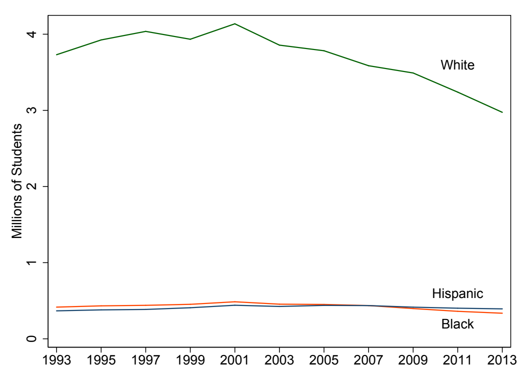
B Measures of Segregation

Consider a commuting zone with J schools, each of which enrolls n_j^W white students and n_j^M minority students. Let $n_j = n_j^W + n_j^M$ and $s_j = \frac{n_j^M}{n_j}$. Similarly, define N^W, N^M and N, as the total numbers of white, minority and all students in the commuting zone respectively, and let $S = \frac{N^M}{N}$. From these primitives, we define the following measures (see Massey and Denton (1988)):

1. The Herfindahl index $H = \sum_{j=1}^{J} s_j^2$ captures the extent to which minority students are concentrated in schools.
2. The Theil index $A = \frac{1}{J}\sum_{j=1}^{J} \frac{s_j}{\bar{s}} \log \frac{s_j}{\bar{s}}$ where $\bar{s}$ is the simple mean of s varies from 0 to $\log J$ and measures the amount of entropy in the distribution of minority students across schools. Increasing values correspond to greater segregation.
3. The Dissimilarity index $D = \frac{1}{2}\sum_{j=1}^{J} \left| \frac{n_j^W}{N^W} - \frac{n_j^M}{N^M} \right|$ varies from 0 to 1 and represents the proportion of minority students in the commuting zone that would have to switch schools to achieve an even distribution of minorities across schools.
4. The Isolation index $I_r = \sum_{j=1}^{J} \frac{n_j^r}{N^r} \frac{n_j^r}{N}$ captures the extent to which students of race r are exposed to other students of that race in schools.

C Determinants of Demographic Change: Figures

Figure 16: Private School Enrollments by Race, 1993-2013



Note: Private school enrollment data are obtained from *Private School Universe Surveys,* 1993-1994 through 2013-2014 maintained by the National Center for Education Statistics.

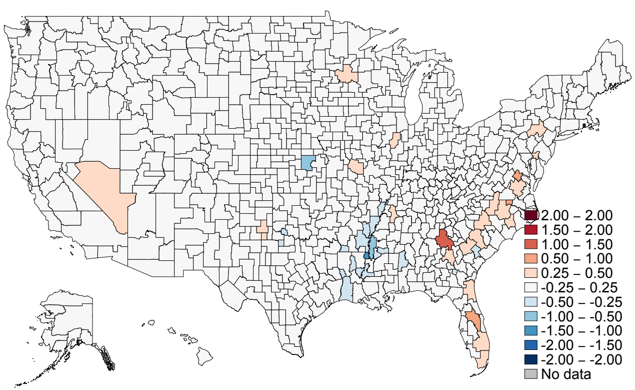
Table 4: Fertility Rates by Race, Selected Years

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

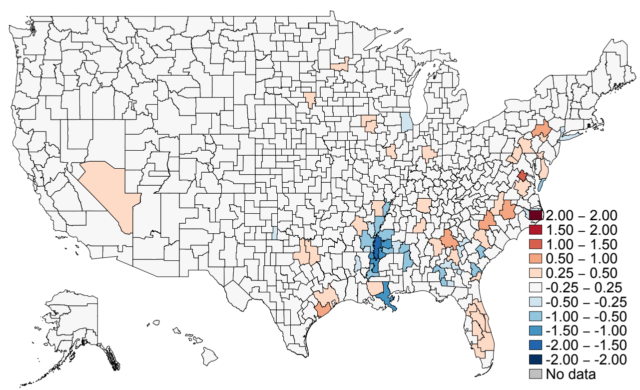
Notes: Fertility rates are defined as total births per 1,000 women aged 15-44. Details on Hispanic status of mothers not available until 1989. [1]: Includes both Hispanic and non-Hispanic White/Black mothers. Sources: *Vital Statistics of the United States*, 2003, Volume 1: Natality, and *National Vital Statistics Reports*, Vol. 56, No. 6, December 5, 2007

Figure 17: Average Annual Change in Black/Hispanic Share of School-AgePopulation due to Immigration and Migration

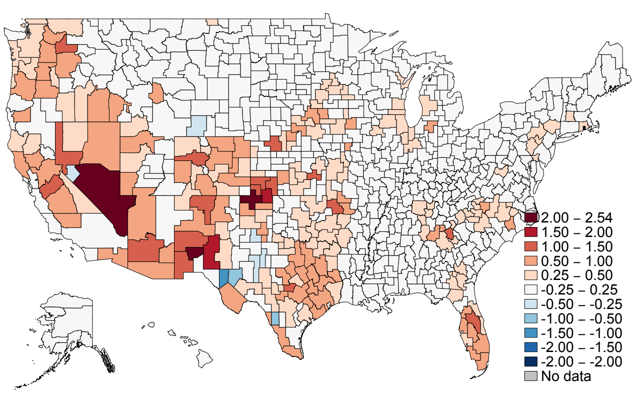
(a) Change in Black Share, 1990s



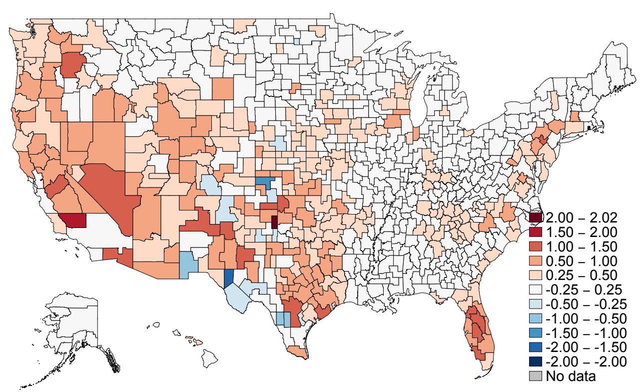
(b) Change in Black Share, 2000s



(c) Change in Hispanic Share, 1990s

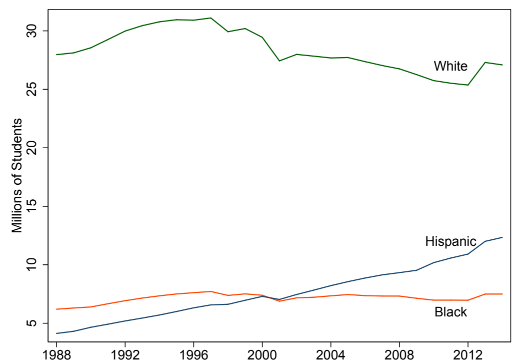


(d) Change in Hispanic Share, 2000s



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).

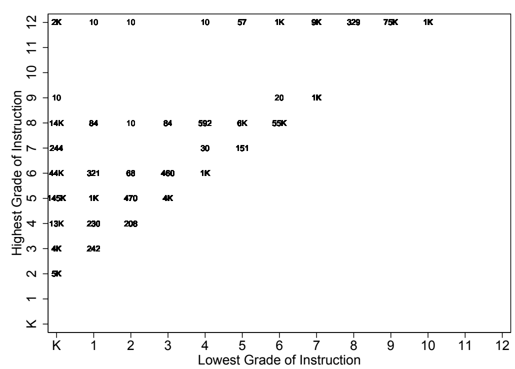
Figure 18: National Public School Enrollments by Race, 1993-2013



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

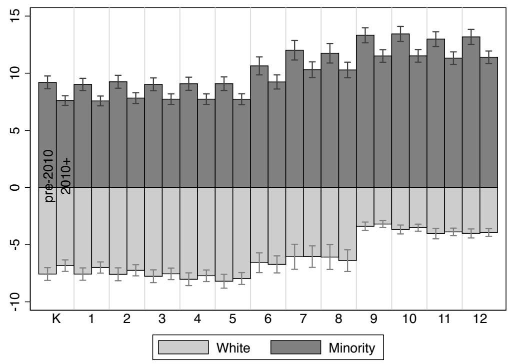
D Additional Figures

Figure 19: 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.

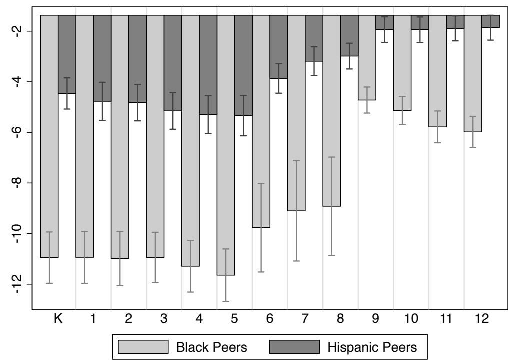
Figure 20: Average Estimates of β by Race and Grade - OLS



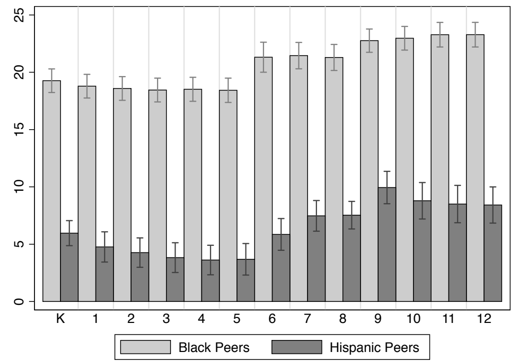
Note: Each bar corresponds to the average of $\hat{\beta}_{rgc}$ weighted across all commuting zones by total enrollment of students of each race. The first bar for each grade is estimated on a 2005-2009 subsample, and the second bar for each grade is estimated on a 2010-2014 subsample. The estimates correspond to a simple OLS regression of equation (9).

Figure 21: Average Estimates of β by Race (White/Black/Hispanic) and Grade - OLS

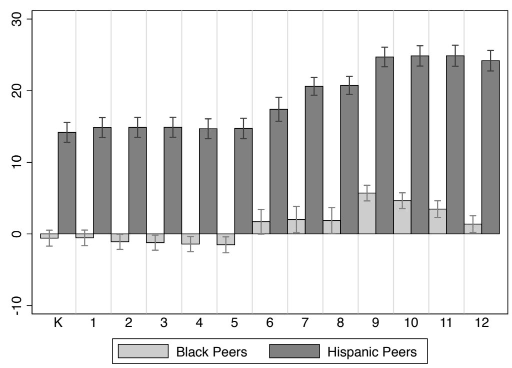
(a) White Parents' Responses



(b) Black Parents' Responses



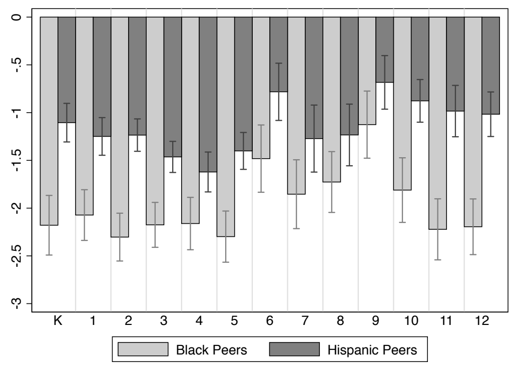
(c) Hispanic Parents' Responses



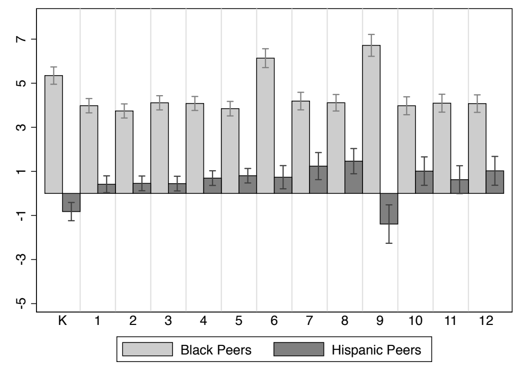
Note: Each bar corresponds to the average of $\hat{\boldsymbol{\beta}}_{\boldsymbol{rgc}}$ weighted across all commuting zones by total enrollment of students of each race. Parameters shown are estimated on the 2005-2009 subsample. The estimates correspond to a simple OLS regression of equation (9).

Figure 22: Average Estimates of β by Race (White/Black/Hispanic) and Grade: School District FEs

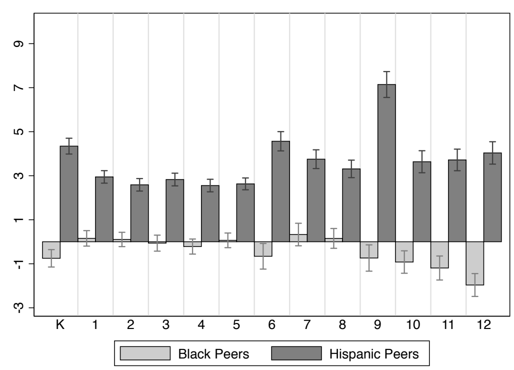
(a) White Parents' Responses



(b) Black Parents' Responses



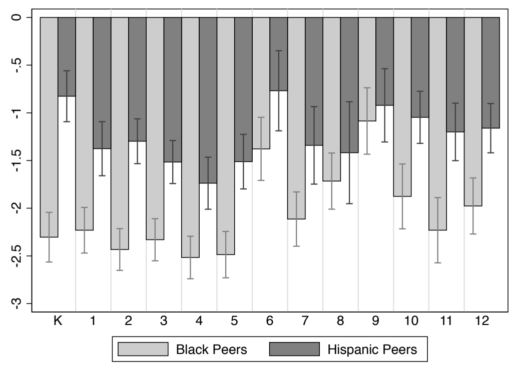
(c) Hispanic Parents' Responses



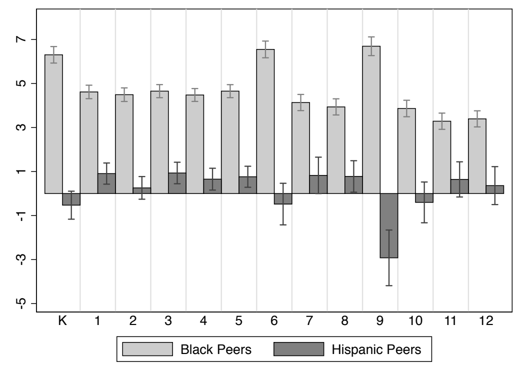
Note: Each bar corresponds to the average of $\hat{\boldsymbol{\beta}}_{\boldsymbol{rgc}}$ weighted across all commuting zones by total enrollment of students of each race. Parameters shown are estimated on the 2005-2009 subsample and are indistinguishable from parameters estimated on the 2010-2014 subsample. All panels use the specification of fixed-effects (FEs) γ_{rgat} where the geographic area a is a school district.

Figure 23: Average Estimates of β by Race (White/Black/Hispanic) and Grade: Zip Code FEs

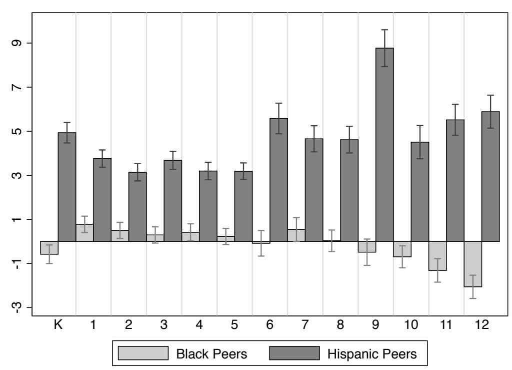
(a) White Parents' Responses



(b) Black Parents' Responses



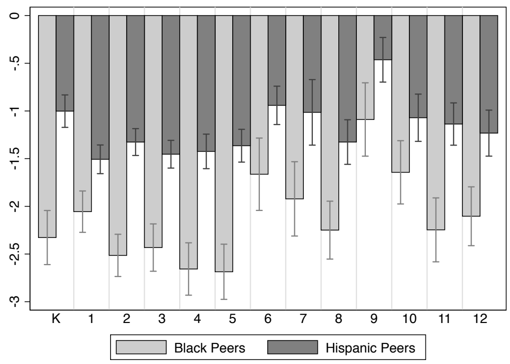
(c) Hispanic Parents' Responses



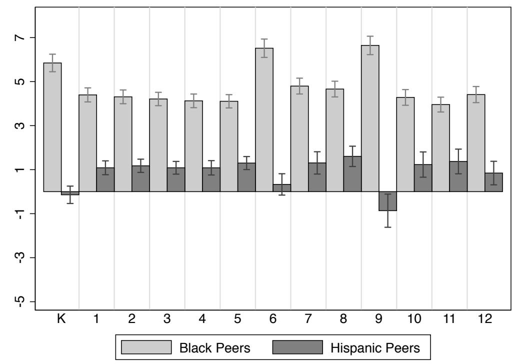
Note: Each bar corresponds to the average of $\hat{\boldsymbol{\beta}}_{\boldsymbol{rgc}}$ weighted across all commuting zones by total enrollment of students of each race. Parameters shown are estimated on the 2005-2009 subsample and are indistinguishable from parameters estimated on the 2010-2014 subsample. All panels use the specification of fixed-effects (FEs) γ_{rgat} where the geographic area a is a Zip code.

Figure 24: Average Estimates of β by Race (White/Black/Hispanic) and Grade: Additional Controls for Persistent Amenities

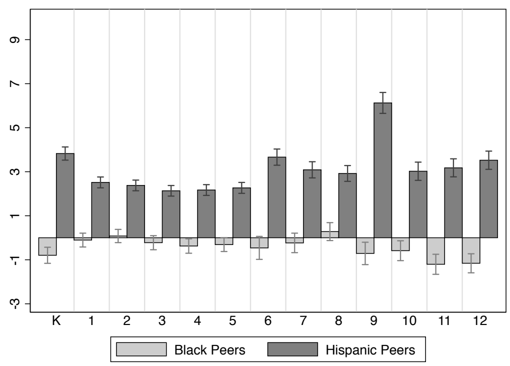
(a) White Parents' Responses



(b) Black Parents' Responses



(c) Hispanic Parents' Responses



Note: Each bar corresponds to the average of $\hat{\boldsymbol{\beta}}_{\boldsymbol{rgc}}$ weighted across all commuting zones by total enrollment of students of each race. Parameters shown are estimated on the 2005-2009 subsample and are indistinguishable from parameters estimated on the 2010-2014 subsample. Only $s_{jct-3}^{\bar{g}_j-2}$ is used as IV, and the baseline specification of control is augmented to include $C_{rgjct-2}$.