Explaining Recent Trends in US School Segregation

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From 2002 to 2018, the fraction of minority-segregated public schools in the United States roughly doubled, but the fraction of White-segregated schools decreased at an even faster rate. Endogenous segregation fueled by parents choosing schools on the basis of their racial compositions can in principle dwarf all other determinants of segregation over time because of social multiplier effects. However, we find that demographic change from Hispanic immigration has been the biggest driver of these trends. These findings are particularly pronounced in urban areas, which experienced the largest changes in segregation and are where policy makers are most concerned about the pernicious effects of segregation.

I. Introduction

School segregation has occupied a prominent role in the public sphere since the landmark *Brown v. Board of Education* (1954) ruling and the Elementary and Secondary Education Act (1966), which identified the reduction of segregation as a primary goal of federal education policy. Indeed, policy makers seeking to reduce racial gaps in student achievement, graduation rates, and

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long-run outcomes in the labor market have good reason to target school segregation: exposure to a higher concentration of minority students has been repeatedly found to reduce minority achievement,[1] and segregated schools have been linked to long-run adverse effects on the occupational aspirations, expectations, and attainment of minority students.[2] In this paper, we analyze the universe of public school enrollments in the United States from 2002 to 2018 to document how local school segregation has evolved and understand its determinants.

Three mechanisms shape the racial compositions of schools and in turn the overall level of school segregation. First, parents may sort toward (or away from) specific schools because of their racial compositions. This mechanism generates the endogenous feedback loop described in the seminal Schelling (1969) model of segregation. If parents prefer that their children attend schools with more peers of the same race, then initial inflows of minorities into a school may lead to more (fewer) minority (White) students enrolling in that school next year, which in turn will trigger subsequent net inflows of minorities in the future. This ultimately leads to a highly segregated school system (Becker and Murphy 2000). Second, the racial compositions of schools may change in response to an aggregate demographic change in the local school market. For instance, an influx of minorities to a city may mechanically impact the racial compositions of schools, as these minority students must enroll somewhere in the city. Finally, parents of different races may seek different schools for other residual reasons, such as other school and neighborhood characteristics.

As pointed out by Manski (1993), distinguishing between endogenous effects and effects arising from other sources is potentially invaluable to policy makers because the feedback loop that arises from the endogenous mechanism generates dynamic treatment effects of one-shot policies that may far exceed their short-run effects. In our setup, we allow for external shocks (due to either the demographic or the residual mechanism) to reverberate into the future because of the feedback loop generated by the endogenous mechanism. In previous work, empirical researchers have explored aspects of each of these mechanisms in isolation. For example, Boustan (2010) has analyzed White flight, or the decision of Whites to leave areas that have experienced an increase in minority share, which falls under the endogenous mechanism. Cascio and Lewis (2012) demonstrate that Hispanic immigration has affected the racial compositions of schools in California, which falls under the demographic mechanism. And Lutz (2011) analyzes the effects of court-ordered dismissals of desegregation policies on school segregation,

[1] Cutler and Glaeser (1997), Guryan (2004), Card and Rothstein (2007), Hanushek, Kain, and Rivkin (2009), Fryer (2010), and Billings, Deming, and Rockoff (2013).

[2] Granovetter (1986), Wilson (1987), and Wells and Crain (1994).

which falls under the residual mechanism. However, no prior study has assessed the relative importance of these mechanisms against one another.

The interplay between these three mechanisms raises several practical obstacles to a proper decomposition of observed changes in segregation. Identifying how segregation changes endogenously requires us to identify how parents' choices are influenced by the racial compositions of schools versus other school and neighborhood features (including unobserved ones). Moreover, the endogenous mechanism implies that effects arising from all three mechanisms are dynamic. For instance, any shock to a school today may affect enrollments of White and minority students differently; in turn, the ensuing change in racial composition may trigger further enrollment responses. As this feedback loop continues, that original shock may potentially generate much larger effects on segregation in the long run. This is further complicated by the necessity to account for the consequences of multiple schools being affected by the same shocks at the same time (e.g., an aggregated demographic shock in a metropolitan area that simultaneously affects many schools). The responses to these shocks in any one school may in turn later affect other schools to varying degrees, depending on their substitutability.

In this paper, we build on previous work (e.g., Bayer, McMillan, and Rueben 2004; Bayer, Ferreira, and McMillan 2007; Wong 2013; Caetano and Maheshri 2017) to develop a novel empirical approach to decompose observed changes in segregation into these three channels for all public schools in the United States. Our approach makes three innovations over existing approaches, each of which is found to be empirically important. First, we analyze the dynamic process of segregation in a nonstationary environment. This allows us to explicitly account for aggregate demographic changes in the student body, which are found to be critical determinants of segregation. Second, we model how segregation evolves in a general equilibrium framework in which changes in enrollment at one school propagate to other nearby schools. We find that neglecting these general equilibrium concerns leads to a dramatic overstatement of the role of the demographic mechanism in explaining segregation. Third, we conduct our analysis at a much larger scale than previous work in the literature. The breadth of our analysis—the entire country over a long period of time—is critical, since the United States is a large, diverse country. While some urban centers have recently experienced major inflows of immigrants, others have not. In addition, different states, cities, and rural areas may differ in racial attitudes and have had unique past experiences with segregation.

To briefly preview our results, from 2003 to 2018 the endogenous mechanism has been the least important and the demographic mechanism has been the most important. However, the relative roles of each mechanism vary across the country. The demographic mechanism explains most of the trends in the larger, more urban commuting zones, which have incidentally experienced the largest changes in segregation levels in recent decades.

However, in more sparsely populated commuting zones that have been less exposed to demographic change, the other two mechanisms play larger roles.

The results of our decomposition follow from several empirical fundamentals. We find that White parents tend to sort away from minority peers throughout the country, but these responses are moderate in size and of higher intensity in densely populated areas. In contrast, we find that Black and Hispanic parents strongly seek same-race peers for their children. This is particularly pronounced in areas where same-race peers are scarce, which tend to be smaller and more rural. In areas where same-race peers are plentiful, minority parents seek such peers for their children less intensely. As a result, the endogenous channel is limited in explaining segregation trends in urban areas. We also find that Black parents have a mild positive response to Hispanic peers (relative to White peers), but Hispanic parents respond similarly to peers of all other races, which highlights important heterogeneity between different minority groups that has been largely overlooked. Finally, we document that demographic shocks have been very large in urban areas and the Sun Belt but have been less so in other areas. We collect a variety of evidence that these demographic shocks are mostly due to Hispanic immigration.

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

Although we coarsely decompose the causes of school segregation into only three mechanisms, our findings are useful to inform policy. For instance, our finding that immigration has played a prominent role in keeping segregation at bay from endogenous forces suggests that restrictions on immigration may slow or even reverse the massive desegregation of predominantly White schools, which has been the most widespread and striking trend in US school segregation in recent decades. Furthermore, the impact of any policy on segregation is likely going to be very different in the short run and in the long run because of the endogenous mechanism, since its effects are gradual but accumulate over time even if no other actions are taken. This is especially true in midsize cities, where we find the endogenous mechanism to be strongest. A finer understanding of the determinants of school segregation could be possible with more precise data and context-specific research designs. For instance, in a given commuting zone, one might be able to decompose the endogenous channel further to better understand the role of choice frictions in preventing sorting,[3] or one might be able to decompose the residual channel into specific policies and local investments.[4] Doing so could aid greatly in the design of policies tailored to combat segregation in specific education markets and would complement the findings of this paper.

The remainder of the paper is organized as follows. In section II we present a conceptual framework to analyze segregation, and in section III we explain how it can be taken to data. In section IV we describe our data set and document how the levels of school segregation have evolved recently. We present our estimation results in section V and decomposition results in section VI before concluding in section VII. We include a detailed sensitivity analysis of our findings and additional supporting results in appendixes A–D (available online).

II. Conceptual Framework

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

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

$$s_{jt} = \frac{n_{\mathrm{M}jt}}{n_{\mathrm{W}jt} + n_{\mathrm{M}jt}}. \tag{1}$$

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

$$n_{rjt} = N_{rt} \cdot \pi_{rj}(\boldsymbol{s}_{t-1}, \boldsymbol{X}_t), \tag{2}$$

where the school-race-specific function π_{rj} is the probability that a parent of a given race enrolls his or her child in a particular school, $\boldsymbol{s}_{t-1}$ is a vector whose jth element is s_{jt-1}, and $\boldsymbol{X}_t$ is a matrix of other school-specific characteristics

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

[4] See, e.g., Logan et al. (2008).

whose jth element is vector $\boldsymbol{X}_{jt}$.[5] Together, equations (1) and (2) define how the racial compositions of all schools simultaneously evolve from $t-1$ to t; that is, they combine to yield a mapping from $\boldsymbol{s}_{t-1}$ to $\boldsymbol{s}_t$ that defines a J-dimensional dynamic system:

$$s_{jt} = s_{jt}(\boldsymbol{N}_t, \boldsymbol{s}_{t-1}, \boldsymbol{X}_t), \tag{3}$$

where $\boldsymbol{N}_t = (N_{\mathrm{W}t}, N_{\mathrm{M}t})$.

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

Second, parents of different races may respond differently to the racial composition of a school (i.e., $\partial\pi_{\mathrm{W}j}/\partial s_{kt-1} \neq \partial\pi_{\mathrm{M}j}/\partial s_{kt-1}$). This is a response to the racial share and whatever else may be caused by it. It includes responses to preferences to live around others of the same race, but it also includes responses to changes in expectations triggered by changes in the racial share. For instance, a change in s_{jt-1} may signal to households today that the characteristics of the school (or associated neighborhood) will change in the future, and some households may choose or avoid that school and neighborhood today because of the ensuing changes in expectations. This may lead to dynamic social multiplier effects that can generate the positive feedback loop commonly known as "tipping" (Schelling 1971), as any change in s_{jt-1} triggers further sorting, which further changes the racial share leading to yet more sorting, and so on. Because these dynamics will continue to propagate even in the absence of any other changes to the school environment, we refer to this as the endogenous mechanism, following Manski (1993).

Third, segregation may arise if parents of different races have systematically different preferences for any other school or neighborhood characteristics besides their racial compositions (i.e., $\partial\pi_{\mathrm{W}j}/\partial x_k \neq \partial\pi_{\mathrm{M}j}/\partial x_k$, where x_k is a specific characteristic in $\boldsymbol{X}_{kt}$). If, for instance, Hispanic parents valued bilingual education more than White parents on average, then all else constant, improvements in bilingual education at a particular school would be expected to increase the minority share of enrollment in that school. More generally, the effects of any school or neighborhood characteristics that are not affected by the racial shares of schools would fall under this mechanism.[6] Importantly, such changes to these characteristics do not generate a positive feedback loop by themselves. We refer to this as the residual mechanism.

[5] Hereafter, vectors and matrices are displayed in boldface type.

[6] Changes in s_{jt-1} may also signal future neighborhood changes. For instance, a reduction in the Hispanic share of a school may lead White households to expect

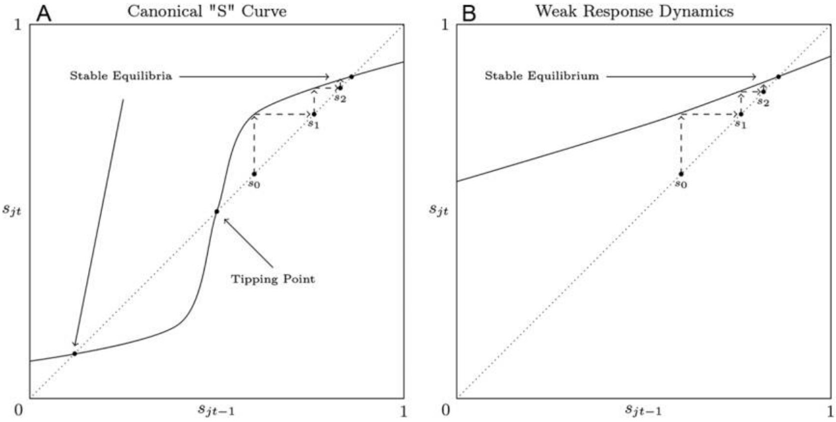

FIG. 1.—Dynamics of s_{jt}.

We illustrate the dynamics of s_{jt} that arise from the endogenous mechanism in figure 1.[7] In figure 1*A*, we plot a ceteris paribus curve of s_{jt} on s_{jt-1} holding $\boldsymbol{N}_t$, $\boldsymbol{s}_{-jt-1}$, and $\boldsymbol{X}_t$ fixed,[8] which summarizes the evolution of s_{jt} in a canonical S curve. Points at which the curve intersects the 45° line represent equilibria. In this scenario, we have multiplicity of equilibria because $\partial\pi_{\mathrm{W}j}/\partial s_{jt-1} < 0$ or $\partial\pi_{\mathrm{M}j}/\partial s_{jt-1} > 0$ and are large in magnitude. In figure 1*B*, we plot an alternative ceteris paribus curve of s_{jt} on s_{jt-1} if $\partial\pi_{\mathrm{W}j}/\partial s_{jt-1} < 0$ and $\partial\pi_{\mathrm{M}j}/\partial s_{jt-1} > 0$ are small in magnitude. In this scenario, the S curve collapses and intersects the 45° line only at a single equilibrium. Deducing the dynamics of s_{jt} is straightforward; hypothetically, if the school had a racial composition of s_0, the endogenous mechanism would result in a racial composition of s_1 one period ahead, s_2 two periods ahead, and so on. The locations of equilibria and the speeds of convergence depend on $\boldsymbol{N}_t$, $\boldsymbol{s}_{-jt-1}$, and $\boldsymbol{X}_t$, since different values of these would result in shifts and deformations of the curve. This implies that these curves are school specific (and year specific). Following the literature (e.g., Bayer and Timmins 2005; Banzhaf and Walsh 2013), we utilize the S curve for the remainder of our exposition.[9]

that this neighborhood will become more attractive to them for whatever reason (e.g., they may expect local venues to change in the near future to cater to their preferences). In this example, the effects of s_{jt-1} on demand through expected neighborhood changes are included in the endogenous mechanism. To the extent that neighborhood amenities are expected to change beyond what is implied by changes to the school's racial composition, they are loaded onto the $\boldsymbol{X}_{jt}$ vector.

[7] To simplify exposition in this section, we assume $\partial\pi_{\mathrm{W}j}/\partial s_{jt-1} < 0$ and $\partial\pi_{\mathrm{M}j}/\partial s_{jt-1} > 0$ when drawing fig. 1. We find robust empirical support for this assumption.

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

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

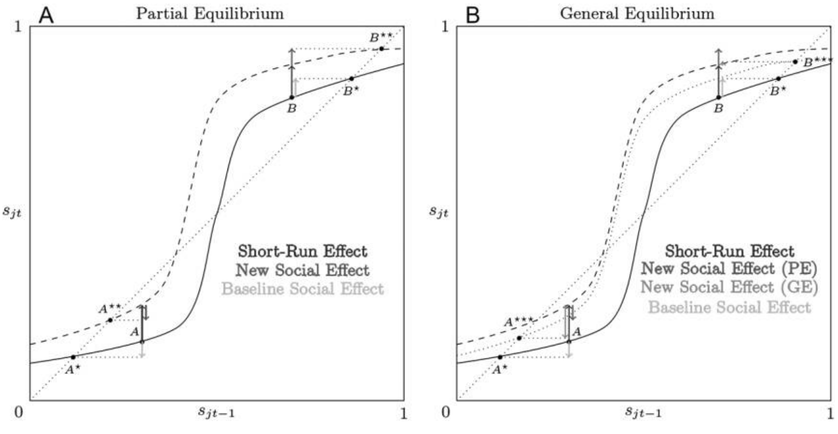

FIG. 2.—Effects of changes in demographics/other characteristics on s_{jt}. A color version of this figure is available online.

To assess how the demographic (or residual) mechanism interacts with the endogenous mechanism, we consider the effect of a hypothetical shock in figure 2. The shock as shown could be an inflow of minorities to the commuting zone (i.e., an increase in N_{Mt}) or a change in some school characteristic or policy that is preferable to minority parents relative to White parents. Figure 2*A* depicts a representative school with a racial composition at either point *A* or *B* in $t - 1$. In the absence of changes, the school at point *A* would have moved along the solid curve to A^* through the "baseline" social effect shown as the very light gray arrow (similarly, the school at point *B* would have moved to B^*). The shock generates an upward shift of the S curve to the dashed curve, which results in new equilibria: A^{**} and B^{**}. For the school at point *A*, the shock from $t - 1$ to t generates the short-run effect shown as the dark gray arrow. The endogenous mechanism then acts as a dynamic social multiplier, generating an additional social effect from t onward, shown as the light gray arrow. The long-run demographic (or residual) effect will be equal to the short-run effect plus the new social effect, net of the baseline social effect; this is simply the vertical distance from A^* to A^{**}. Similar logic holds for the school at point *B*. Note that the magnitudes of these effects depend not only on the size of the shock but also on the locations of the stable equilibria and the shapes of the S curves, all of which also depend on $\boldsymbol{s}_{-jt-1}$, $\boldsymbol{X}_t$, and the shape of π_{rj} for all r.[10] Moreover, the magnitudes of these effects also depend on the extent to which schools are out of equilibrium in $t - 1$. In the rare case that school j is in equilibrium in $t - 1$, the "baseline"

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

social effect would simply be zero. Still, the new social effect would be nonzero since the shift in the curve would take the school out of equilibrium.

The diagram shown in figure 2*A* only shows the dynamics of a single school, so the equilibria as drawn represent "partial" equilibria. However, equation (2) implies that enrollment demand for a single school j is a function of the prior racial compositions of all of the schools in the commuting zones ($\mathbf{s}_{t-1}$) depending on substitution patterns across schools. For example, a demographic shock that shifts the S curve of school j upward is likely to shift the S curve of a school j' that is a close substitute upward as well. All else constant, the associated increase in $s_{j't}$ will make school j relatively less attractive to minority parents and more attractive to White parents in $t + 1$ (because a close substitute, j', became disproportionately more attractive to minorities), resulting in a small downward shift in the S curve of school j. These effects will feed back between these two schools and any others that are substitutes leading to potentially complex general equilibrium effects on the dynamics of other schools.[11] We represent these general equilibrium effects as additional shifts of the S curve (shown in fig. 2*B*) that dampen the effect of the initial shock.[12] This results in a new general equilibrium social effect that is smaller than the new social effect from a partial equilibrium perspective.[13]

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

III. Empirical Approach

We now develop an empirical approach that allows us to take our conceptual framework to data. Our goal is to study how the racial compositions of schools change over time with the understanding that observed changes may be attributable to movements along the S curve toward equilibrium (i.e., the endogenous mechanism), demographic shocks, or any other shift in the S curve that may or may not change the locations of equilibria. We do so by

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

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

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

constructing S curves for every school that vary explicitly in $\boldsymbol{s}$ and $\boldsymbol{N}$ and that vary implicitly in $\boldsymbol{X}$ in order to characterize the dynamic system of segregation. This requires us to identify how π_{rj} varies with $\boldsymbol{s}_{t-1}$. Enrollment responses to s_{jt-1} pin down the shape of j's S curve—that is, how movements along the S curve occur—while enrollment responses to $\boldsymbol{s}_{-jt-1}$ pin down the general equilibrium effects. These responses can be obtained from a standard discrete choice framework (McFadden 1973; Berry 1994).[14] Here, we present a simpler and mathematically equivalent reduced-form estimation approach (see Caetano and Maheshri 2017). For exposition, we describe our approach for a single commuting zone; in practice, we implement it simultaneously for all commuting zones.

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

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

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

With causal estimates of $\hat{\beta}_r$, we can simulate the evolution of the racial compositions of all schools into the future under different counterfactuals. Equations (1) and (2) have empirical analogs that describe how any counterfactual state vector $\tilde{\boldsymbol{s}}_{jt-1}$ will evolve (given some counterfactual trajectory of

[14] The outside option in our analysis corresponds to enrolling a child in any nonpublic school. Thus, trends in the proportion of students of each race into and out of the outside option should be understood as part of the demographic channel. As we discuss in remark 3, nearly all demographic changes during our sample period can be attributed to immigration.

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

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

the aggregate commuting zone enrollments, $\tilde{\boldsymbol{N}}_t$). To simulate this trajectory from t_0, we use the equations of motion

$$s_j\left(\tilde{\boldsymbol{N}}_t, \tilde{s}_{jt-1}, \boldsymbol{X}_{t_0}\right) = \frac{\hat{n}_{\mathrm{M}j}\left(\tilde{N}_{\mathrm{M}t}, \tilde{\mathbf{s}}_{t-1}, \boldsymbol{X}_{t_0}\right)}{\hat{n}_{\mathrm{M}j}\left(\tilde{N}_{\mathrm{M}t}, \tilde{\mathbf{s}}_{t-1}, \boldsymbol{X}_{t_0}\right) + \hat{n}_{\mathrm{W}j}\left(\tilde{N}_{\mathrm{W}t}, \tilde{\mathbf{s}}_{t-1}, \boldsymbol{X}_{t_0}\right)} \quad \forall\ j \tag{5}$$

along with the estimated demand functions

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

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

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

and the initial condition $\tilde{\mathbf{s}}_{t_0-1} = \mathbf{s}_{t_0-1}$ (i.e., the counterfactual value for year $t_0 - 1$ is set to the observed value).[17]

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

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

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

$$\Delta^{D}_{jt_0 \to t} = \hat{s}_j(\boldsymbol{N}_t, \mathbf{s}_{t-1}, \boldsymbol{X}_{t_0}) - \hat{s}_j(\boldsymbol{N}_{t_0}, \mathbf{s}_{t-1}, \boldsymbol{X}_{t_0}), \tag{9}$$

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

$$\begin{aligned} \Delta^{R}_{jt_0 \to t} &= s_{jt} - \hat{s}_j(\boldsymbol{N}_t, \mathbf{s}_{t-1}, \boldsymbol{X}_{t_0}) \\ &= s_j(\boldsymbol{N}_t, \mathbf{s}_{t-1}, \boldsymbol{X}_t) - \hat{s}_j(\boldsymbol{N}_t, \mathbf{s}_{t-1}, \boldsymbol{X}_{t_0}), \end{aligned} \tag{10}$$

since $s_{jt}(\boldsymbol{N}_t, \mathbf{s}_{t-1}, \boldsymbol{X}_t)$ differs from $\hat{s}_{jt}(\boldsymbol{N}_t, \mathbf{s}_{t-1}, \boldsymbol{X}_{t_0})$ only in terms of other school and neighborhood characteristics, which are subsumed in the residual. Note that $\Delta^{d}_{jt_0 \to t} + \Delta^{D}_{jt_0 \to t} + \Delta^{R}_{jt_0 \to t} = s_{jt} - s_{jt_0}$, so this represents a full decomposition of the observed change in racial composition.

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

A. Identification of β

Identifying endogenous effects such as β_r is known to be a difficult problem (Manski 1993). School characteristics that lead parents to chose a particular school in $t - 1$ tend to persist into the current period t. If White and minority parents have different preferences for such characteristics, then the ordinary least squares estimate of β_r will be biased upward (in magnitude). As such, we employ the instrumental variable (IV) strategy proposed in Caetano and Maheshri (2017).

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

Of course, comprehensive data on transitory shocks to school characteristics for all schools in the entire country is not available. We circumvent this obstacle with an approach that relies solely on enrollment data. We isolate exogenous variation in s_{jt-1} by focusing on the component of s_{jt-2} that is orthogonal to n_{rjt-1}. The cohort structure of schooling presents a natural source of such variation: students enrolled in the second-highest grade of school j in $t - 2$ no longer enroll in that school in t, since they have aged out. Hence, the racial composition of this cohort (hereafter, the "IV cohort") influences s_{jt-1} without directly affecting n_{rjt}. To isolate the transitory component, we control for the enrollments of subsequent cohorts of students (hereafter, the "control cohorts") in $t - 1$. The variation in the IV from $t - 2$ that is orthogonal to the enrollments of the control cohorts in $t - 1$ is the component that is likely irrelevant to choices in t.

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

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

where n_{rgjct} refers to the number of race r students enrolled in grade g in school j in commuting zone c in year t. The parameter β_{rg} represents the enrollment response of each race to the minority share of the school, and it is now allowed to vary by grade.[18] The race–grade–commuting zone–year fixed effects, γ_{rgct}, encapsulate the demographic effect (disaggregated by grade).[19] Finally, the error term, ϵ_{rgjct}, incorporates the remainder of the determinants of the school demand.

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

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

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

Third, we use

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

as an IV for s_{jct-1} in equation (13). Our IV estimator of β_{rg} is consistent under the following identifying assumption.[20]

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

In words, our identification assumption states that unobserved school characteristics that affected parents' enrollment decisions in the past ($s_{jt-2}^{\bar{g}_j-1}$) but do not affect enrollment decisions in $t-1$ ($C_{rgjct-1}$) cannot suddenly reappear and affect enrollment decisions in t.[21] To help explain how we implement this IV strategy, consider a 9–12 high school as an example in the diagram below. Cohorts age diagonally in this diagram—for example, the IV cohort is in grade 11 in $t-2$, grade 12 in $t-1$, and out of school in t. Our IV is s_{jct-2}^{11}, and to absorb persistent (confounding) school characteristics we control for the $t-1$ enrollments of Whites and minorities in all

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

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

[20] This assumption contains an abuse of notation, for simplicity. We actually condition on the variables in $\{\log n_{rgjt-1}; g = \underline{g}_j, \ldots, \bar{g}_j - 1, r = \mathrm{W}, \mathrm{M}\}$, not on $C_{rgjct-1}$ as written above.

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

grades except for the highest grade. For schools that offer more than two grades of instruction, we can construct additional instruments from the IV cohort observed in earlier grades, such as s^{10}_{jct-3} and s^{9}_{jct-4}, which permits overidentification tests (Hansen 1982).[22]

	9th	*10th*	*11th*	*12th*
t	Dep. Var.	Dep. Var.	Dep. Var.	Dep. Var.
$t-1$	Control	Control	Control	
$t-2$			IV	
$t-3$		IV		
$t-4$	IV			

B. Relevance: What Is the Identifying Variation?

We identify β by using all changes in school characteristics that (1) compelled students in the IV cohort to sort toward that school in the past (thus changing s_{jct-1}) and (2) did not affect enrollment decisions in t. Because we cannot observe—or even enumerate—all of these shocks, our strategy relies on the fact that their effects are observed in enrollment data. We provide a concrete example of a shock here for intuition. Consider a popular and well-known ESL (English as a second language) teacher in a 9–12 high school who retired just before year $t-3$. On average, ESL instruction is plausibly valued more by Hispanic parents than by other parents, so this teacher would have affected the racial composition of ninth graders in $t-4$ (who are members of the IV cohort) without directly affecting the enrollments of any subsequent cohorts of students. Despite retiring, the teacher would still have influenced the minority share in $t-1$, since some members of the IV cohort remain in the same school simply as a result of inertia. However, the IV cohort aged out of the school by t, so the only way the teacher could affect the enrollment decisions of students in t would be through parents' enrollment response to the minority share in $t-1$. This is precisely the effect that we seek to identify.

Of course, this is just a single example that is not meant to be representative. However, we conjecture that in practice, a wide variety of circumstances could lead to some students remaining enrolled in a school despite the fact that the initial attraction is no longer present. Indeed, any forecast error on the part of households who sorted in the past—perhaps they expected school and neighborhood amenities to trend in a certain way, which went unrealized in actuality—will generate identifying variation for us. Importantly, we can test our conjecture directly: if parents' information sets did

[22] Our IV strategy differs from the well-known IV strategy in Hoxby (2000), which also uses variation in adjacent cohort enrollments. Ours is primarily distinguished by the use of variation only from the oldest cohort and the inclusion of control variables to block grade-specific amenities.

not change from $t - 2$ to $t - 1$ (or if they did change but no children remained in the school as a result of inertia), then we would not have a first stage. Because we use only enrollment data to isolate this plausibly exogenous variation, our approach is agnostic to the nature of the specific transitory shock in the past that led students to the school. Thus, we do not need to obtain data on specific shocks. Parents' expectations of the future trajectories of schools may differ from one another, as they are formed through conversations with other parents, real estate agents, online reviews, and so on. Whatever these expectations are, they lead to the choices that we observe in the data. This crucially allows us to perform our analysis nationally and over a relatively long sample period. Moreover, it increases the power of our IV by aggregating all such transitory shocks, including those that are unobservable or even inconceivable to us as researchers.

Remark 1.—The term β_{rg} represents how individuals' enrollment choices are affected by the prior racial compositions of schools. This should not be conflated with individuals' preferences for the past racial composition of a school or any simple transformation thereof. While it is true that β_{rg} is influenced by parents' preferences for the racial composition of schools, it is also composed of all other environmental considerations that affect the ability of parents to exercise those preferences, such as moving costs, the availability of local schools with desired amenities, and even supply-side restrictions that might steer households of different races toward certain neighborhoods (Christensen and Timmins 2019). Hence, the finding of a small value of β_{rg} should not be interpreted as evidence of weak racial preferences of race r parents. Instead, it should be interpreted only as weak demand responses, which is compatible with strong racial preferences and a weak ability to exercise those preferences.

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

IV. Data

We obtain enrollment data from the Common Core of Data maintained by the National Center for Education Statistics at the US Department of Education; the database covers the entire population of American public school students from 1988 to 2018.[23] We restrict our sample to the 50 states and the District of Columbia and ignore schools in US territories. From 1988 to 2001, enrollment data were available only at the school-race level of disaggregation; in 2002, enrollment data were made available at the school-grade-race level of disaggregation. As such, our estimation uses the 2002–18 subsample of our data, and our simulation analysis uses only the 2003–18 subsample of our data. Nevertheless, for greater context we present background data from the entire sample in this section only. Enrollment data from a small number of states in some early years of the sample are missing, but this is a minor issue in the post-2002 subsample that we use for our analysis.[24] Our sample includes all public charter schools and magnet schools. For each school, we observe the numbers of White, Black, Hispanic, Asian, and Native American students enrolled in each grade in each year, and we use the term "minority" to refer to any Black or Hispanic student (including White Hispanics) and the term "White" to refer to any other student.[25]

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

The national trend has unfolded differently across the country. In figure 4, we present locally weighted least squares regressions of the prevalence of segregated schools in all US commuting zones in 1988 and 2018 against the total

[23] We use 2000 to refer to the 2000–1 academic year and follow this convention throughout the paper.

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

[25] These definitions of White and minority follow from US Government Accountability Office study GAO-16-345. If we instead classify Native Americans as minorities, define minorities as all non-White students, or omit all Asian and Native American students from our sample entirely, our findings are essentially unchanged. Starting in 2015, students were separately classified as being of two races, although the specific races were not reported. Because of this ambiguity, we omitted them from our analysis entirely. However, when we replicate our entire analysis using the 2002–14 subsample, our findings are again essentially unchanged.

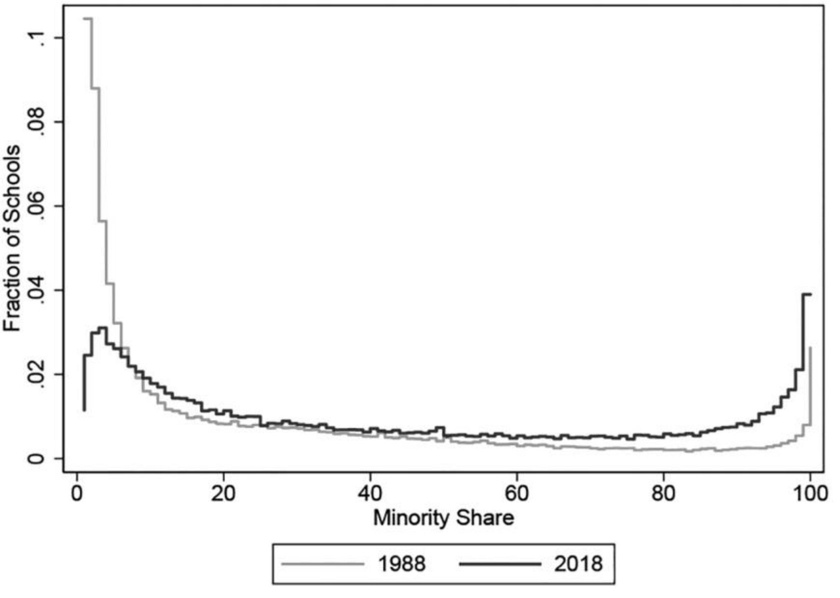

FIG. 3.—Empirical distribution of minority share of US schools, 1988 and 2018. A color version of this figure is available online.

student populations of each commuting zone.[26] A histogram of the log(population) of commuting zones and representative cities for the largest bins of commuting zones is provided for context. Over this period, the desegregation of predominantly White schools has occurred everywhere, from sparsely populated rural areas to large urban areas, where it is more pronounced. However, increasing minority segregation has been mostly concentrated in large, urban commuting zones.

Regional patterns of school segregation can be found in figure 2 in appendix B. The prevalence of White-segregated schools has diminished throughout the country, often at annual rates of 1–4 percentage points, in both highly populated metropolitan areas and relatively less diverse rural areas. Meanwhile, minority-segregated schools have become more prevalent over the sample period throughout the Sun Belt, especially along the southern border, at an annual rate of 0.5–2 percentage points and in urban areas of the Northeast and Rust Belt at an annual rate of 0.25–1 percentage points. The larger magnitudes and broader geographic scope of the desegregation of

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

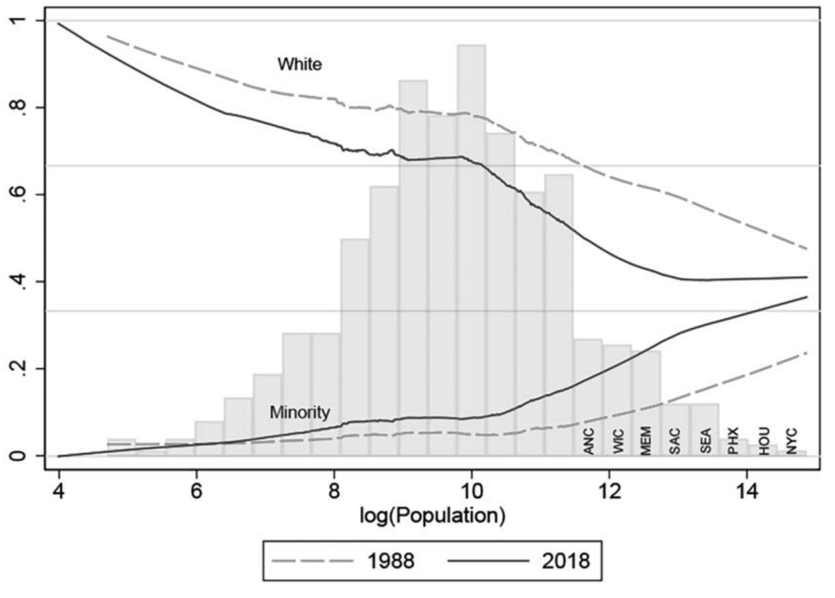

FIG. 4.—Prevalence of segregated schools in a commuting zone by student population, 1988 and 2018. We present locally weighted least squares regressions of the fractions of segregated schools in commuting zones in 1988 and 2018 against the total student populations (in logs) of each commuting zone (bandwidth = 0.5). We define White-segregated schools as more than 75% White and minority-segregated schools as more than 75% minority. The category "White" includes non-Hispanic Whites, Asians, and Native Americans (see n. 25). ANC = Anchorage, Alaska; HOU = Houston, Texas; MEM = Memphis, Tennessee; NYC = New York, New York; PHX = Phoenix, Arizona; SAC = Sacramento, California; SEA = Seattle, Washington; WIC = Wichita, Kansas. A color version of this figure is available online.

White schools relative to the segregation of minority schools has resulted in a public school system that is becoming less segregated overall.[27]

For additional context, demographic changes in the aggregate student body can be found in figure 6 in appendix B, as measured by the average annual change in the minority share of enrollments at the commuting zone level from 1988 to 2018. Thus, in this map we eliminate all sorting across schools within commuting zones, so observed changes in (aggregate) racial composition are attributable only to the demographic mechanism. Demographic change over this period has been widespread, leading to a greater fraction

[27] These findings are consistent with Rivkin (2016), who presents national evidence of recent desegregation in US public schools, and Clotfelter, Vigdor, and Ladd (2006), who document that segregation levels in southern schools have remained roughly constant from 1994 to 2004.

of minority students in all regions of the United States except for sparsely populated areas. The association between the spatial distribution of demographic trends and segregation trends is striking and motivates the need to determine the extent to which this relationship is causal.

Remark 3.—There are four potential sources of demographic change in aggregate public school enrollments: changes in the racial composition of school enrollments outside the public school system (i.e., private school or homeschooling), changes in fertility rates across races, migration between commuting zones, and immigration. In appendix B, we present a variety of evidence that leads us to conclude that the demographic change observed during our sample period was largely due to Hispanic immigration. We summarize that evidence here. National private school enrollments of minorities were stable from 1993 to 2018, while White enrollments decreased slightly (fig. 4 in app. B);[28] the fertility gap between minorities and Whites slightly narrowed from 1971 to 2018 (table 2 in app. B); Black immigration and migration rates were small during the sample period, while Hispanic immigration and migration rates were quite large and widespread (fig. 5 in app. B); and there was a large observed increase in the absolute number of Hispanic students over the sample period that was not accompanied by a similar change in the numbers of White or Black students (fig. 6 in app. B).

V. Estimation Results

For our empirical analysis, we generalize from the two-race model in section II and allow White, Black, and Hispanic parents to respond differently to their children's peers of each of these three races. We also allow for spatial heterogeneity in their responses by subdividing commuting zones into four groups by the size of their public school population.[29] Thus, equation (12) transforms into the estimation equation

$$\log n_{rgjct} = \gamma_{rgct} + \boldsymbol{\beta}_{rgc}{}' \mathbf{s}_{jct-1} + C_{rgjct-1} + u_{rgjct}, \tag{14}$$

where $\boldsymbol{\beta}_{rgc}$ is now a 2×1 column vector that contains race r parents' responses to the shares of Black and Hispanic students in grade g and

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

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

commuting zone c, respectively.[30] Given three races, 13 grades, four groups of commuting zones, and two responses (to the Black and Hispanic shares of the school), $\boldsymbol{\beta}_{rgc}$ contains 312 distinct parameters that capture heterogeneity in enrollment responses between parents of different races, grades, and sizes of commuting zones. With such a large number of parameters, we report our results by averaging estimates along different dimensions to highlight relevant heterogeneity in a digestible format.[31]

In figure 5, we present estimates of parents' responses to the racial composition of their children's school. In figure 5*A*, we see that White parents with children of all grades respond negatively to both Black and Hispanic peers. This response is larger to Black peers, although this difference is not always statistically significant.[32] In figure 5*B*, we see that Black parents respond very strongly and positively to Black peers; they exhibit a much weaker positive response to Hispanic peers relative to White peers. Analogously, in figure 5*C* we see that Hispanic parents respond positively to Hispanic peers in all grades, although these responses are smaller in magnitude than those of Black parents. Hispanic parents exhibit little response to Black peers in all grades.

These responses are stronger in kindergarten, grade 6, and grade 9, which commonly mark transitions into elementary, middle, and high school, respectively. This is consistent with the notion that the estimates comprise both preferences for peers and constraints on switching schools (remark 1).[33]

In figures 13–15 in appendix D, we aggregate these responses across grades and disaggregate them by commuting zone to highlight spatial variation, which is primarily driven by heterogeneity in the sizes of commuting zones.[34] We find that White parents respond negatively to an increase in

[30] The control term $C_{rgjct-1}$ is now equal to $\Sigma_{i=\underline{g}_j}^{\bar{g}_j-1}(\alpha_{rigc\mathrm{W}} \log n_{\mathrm{W}ijct-1} + \alpha_{rigc\mathrm{B}} \log n_{\mathrm{B}ijct-1} + \alpha_{rigc\mathrm{H}} \log n_{\mathrm{H}ijct-1})$. We use as IVs the 2×1 vector $\boldsymbol{s}_{jct-2}^{\bar{g}_j-1}$ defined for the Black and Hispanic shares of enrollments in an analogous manner to eq. (13).

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

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

[33] See fig. 1 in app. A for the distribution of schools by grade range in the country.

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

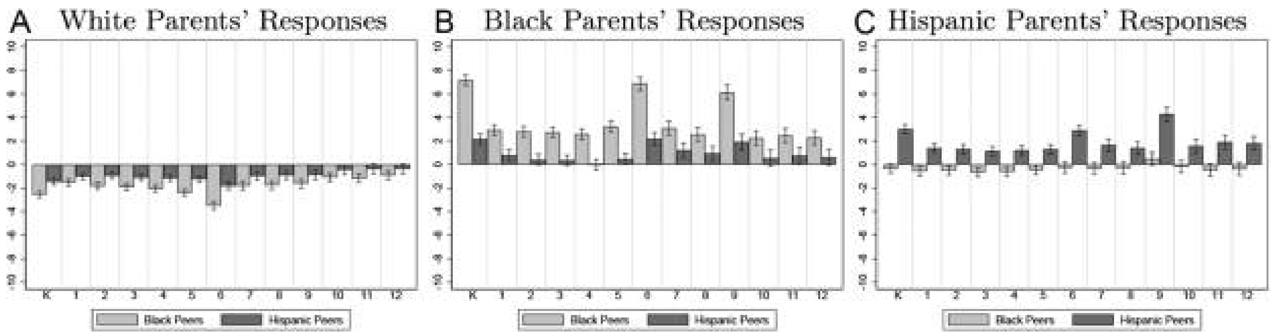

FIG. 5.—Estimates of parents' responses to peers by grade, 2005–18. Estimates obtained from equation (14) are aggregated across commuting zones. The 95% confidence intervals shown are constructed with standard errors that are clustered at the race–grade–year–commuting zone level. The p-values from F-tests of whether the IVs ($s^{\bar{g}_j-1}_{jt-2}$ and $s^{\bar{g}_j-2}_{jt-3}$) are significant in the first-stage regressions are always less than 1%. There are 7,578,789 school-race-grade-year observations in the sample.

Black peers in more populous commuting zones, which tend to have sizable Black student populations. However, White parents have very small negative responses to Black peers in less populous areas. White parents have extremely small negative responses to Hispanic peers everywhere but slightly larger negative responses in more populous areas. Black parents respond most positively to Black peers in parts of the country where Black peers are most scarce. These responses exceed Black parents' responses in large urban areas by a factor of four on average. Similarly, Hispanic parents have weaker positive responses to Hispanic peers in areas with large Hispanic populations and stronger positive responses in the interior of the country, which has a smaller Hispanic population.

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

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

VI. Simulation Results

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

For each counterfactual time series of racial compositions, we calculate how the prevalence of school segregation would have evolved. In figure 6, we present the proportions of White- and minority-segregated schools that were observed in the data and the proportions of segregated schools that would have existed under the two counterfactuals over a 16-year period. Three results are immediate. First, endogenous sorting, in the absence of any other changes to the school environment, would have increased the proportion of White- and minority-segregated schools by roughly 8 and 2 percentage points, respectively. Second, demographic shocks more than offset the endogenous effects for White-segregated schools, but it exacerbated

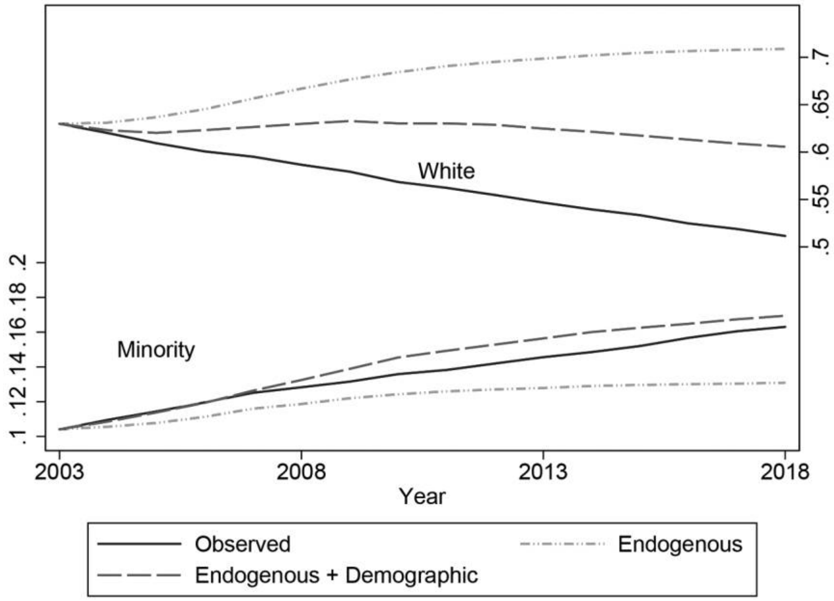

FIG. 6.—Decomposing observed changes in the prevalence of segregated schools, 2003–18. A White-segregated (minority-segregated) school has more than 75% White (minority) enrollment. The decomposition is implemented for all schools that operate in every year from 2003 to 2018 and averaged annually across the United States. The solid , dot-dashed , and dashed paths correspond to segregation levels computed with $\tilde{s}^{D}_{jt}$, $\tilde{s}^{DE}_{jt}$, and s_{jt}, respectively. The total vertical change in the dot-dashed path corresponds to the change in segregation through the endogenous channel, the vertical difference between the dashed path and the dot-dashed path corresponds to the change in segregation through the demographic channel, and the vertical difference between the solid path and the green path corresponds to the change in segregation through the residual channel. A color version of this figure is available online.

the proliferation of minority-segregated schools by roughly three times as much as the endogenous effect. Third, the residual mechanism (the vertical distance between the solid line and the dashed line) always reduces segregation. We conjecture that this is because school and neighborhood characteristics may have adjusted to accommodate new inflows of Hispanics. As Hispanics become more prevalent in the country, residual sorting might then lead to greater mixing of races in many commuting zones.

Because the largest changes in the school segregation have occurred in the largest commuting zones (see fig. 4), we present these counterfactual trajectories against commuting zone population in fig. 7. The endogenous mechanism (solid gray line) has essentially no effect in very small commuting zones and is weak in very large commuting zones, but in midsize commuting

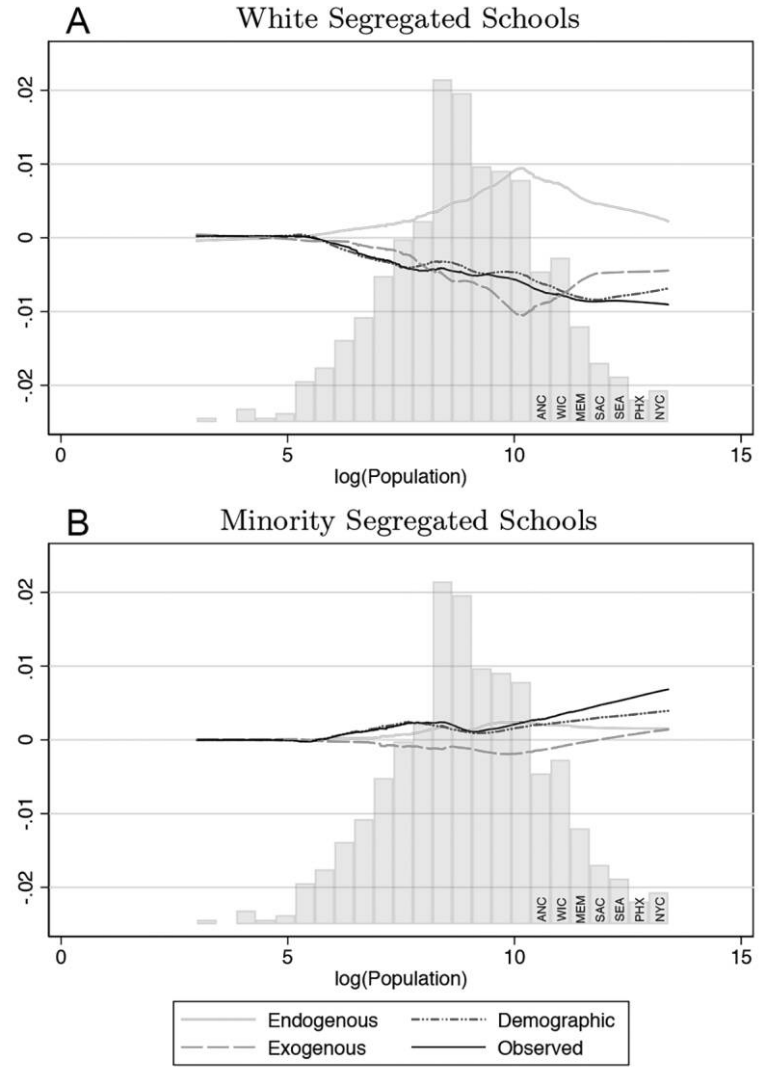

FIG. 7.—Decomposing observed changes in the prevalence of segregated schools, 2003–18. We present locally weighted least squares regressions of each trajectory against the total student populations of each commuting zone in logs (bandwidth = 0.3). We overlay a histogram of commuting zones by population along with example cities for the largest bins. A White-segregated (minority-segregated) school has more than 75% White (minority) enrollment. The decomposition is implemented for all schools that operate in every year from 2003 to 2018. The solid gray, dot-dashed , and dashed paths correspond to segregation levels computed with $\tilde{s}^{\mathrm{E}}_{jt}$, $\tilde{s}^{\mathrm{D}}_{jt}$, and s^{X}_{jt}, respectively. The total vertical change in the dot-dashed path corresponds to the change in segregation through the endogenous channel, the vertical difference between the dashed path and the dot-dashed path corresponds to the change in segregation through the demographic channel, and the vertical difference between the solid gray path and the dashed path corresponds to the change in segregation through the residual channel. ANC = Anchorage, Alaska; MEM = Memphis, Tennessee; NYC = New York, New York; PHX = Phoenix, Arizona; SAC = Sacramento, California; SEA = Seattle, Washington; WIC = Wichita, Kansas. A color version of this figure is available online.

zones it can be quite large. As expected, this mechanism always contributes to increasing segregation. The demographic mechanism (dot-dashed line) tends to be strong everywhere except for the smallest commuting zones, and it is even stronger in the largest commuting zones. This is consistent with the fact that demographic change has been widespread except in the most sparsely populated regions of the country, and it has been particularly notable in large urban areas. In all types of commuting zones, the demographic mechanism has led to desegregation of White schools and segregation of minority schools. Finally, the residual mechanism (dashed line) is weak in the smallest and largest commuting zones but is stronger in midsize commuting zones. It always contributes to desegregation of both White and minority schools with the exception of the largest cities, in which it has led to an increase in minority-segregated schools. Indeed, this may help explain why the largest cities have experienced a greater increase in minority-segregated schools than slightly smaller cities, as the residual mechanism's contribution to segregation is increasing in population in the right of figure 7*B*.[35]

To summarize, all three mechanisms have played roles in explaining the evolution of school segregation from 2003 to 2018, and their relative importance varies systematically. While the endogenous and residual mechanisms are of similar and large importance for midsize cities, the demographic mechanism is substantially more important for larger cities, where the endogenous mechanism is weak. In the absence of exogenous changes to schooling markets, endogenous sorting would have increased all forms of school segregation nearly everywhere, as parents desire to enroll their children in schools with peers of the same race. Residual sorting has helped to desegregate White schools and dampen the segregation of minority schools almost everywhere except in the largest cities, where it has had the opposite effect. Finally, to the extent that we view school segregation as an urban concern, it is critical to recognize that changing demographics have played an immense role in shaping segregation.

VII. 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, policy makers 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

[35] We replicate our decomposition for alternative measures of segregation in fig. 16 in app. D.

arithmetic reasons; in 2018, the four most populous commuting zones had majority "minority" enrollments.[36]

Models of segregation predict that when holding all else constant, even mild endogenous responses will lead to substantial increases in racial segregation over time. Our findings reveal that all else is not constant. Continuing aggregate demographic shocks, primarily due to Hispanic immigration, have kept segregation at bay over the past quarter century. They have been a key force in desegregating White schools and segregating minority schools, especially in areas that experienced the greatest change in segregation: large, urban commuting zones. Exogenous changes to the schooling environment (and the sorting of students that resulted from those changes) have reduced the prevalence of both White- and minority-segregated schools in most areas, although there is substantial heterogeneity in these effects across commuting zones. This may reflect the fact that local urban and educational policies to combat segregation have varied considerably throughout the country during this period—for example, the ending of many desegregation policies in the South that returned control of schools to local authorities and led to an increase in segregation (Lutz 2011) and the proliferation of school choice (Hoxby 2007). In any case, we conjecture that some of this reduction in segregation may have been an indirect response to changing demographics if, for example, neighborhood amenities adjusted to cater to new Hispanic residents into previously predominantly White attendance areas. If true, then demographic change is an even stronger force for desegregation than what we find in this paper.

Our findings suggest that an understanding of sorting at the local level could be enriched by a greater understanding of sorting at regional levels. Synthesizing a model of migration with a model of segregation might reveal complementarities between broad regional policies regarding immigration or relocation incentives with narrow place-based policies at the school or neighborhood levels. Because the settlement decisions of new immigrants are in part determined by the racial and ethnic composition of potential peers (Munshi 2003), deeper connections between the endogenous and demographic mechanisms may be illuminated, although this lies well beyond the scope of this paper. As more precise data on individuals' settlement and enrollment patterns become available, we believe this will become a promising avenue for further inquiry. The recent residential migration of minorities to suburbs in the past two decades may also signal new trends in school segregation that merit closer analysis to complement studies of White flight from 1960 to 1990 (e.g., Welch and Light 1987; Boustan 2010; Baum-Snow and Lutz 2011).

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

Ultimately, segregation itself should be analyzed in a broader context. While researchers have, with good reason, focused on the negative effects of segregation in predominantly minority schools, exposure to diversity has been found to positively impact White students in other contexts along a variety of outcomes related to educational attainment, cognitive growth, and civic-mindedness.[37] As a result, the ongoing desegregation of White schools may generate widespread prosocial impacts that, while difficult to quantify, shape society in profound ways.

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

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