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What determines school segregation? The crucial role of neighborhood factors ☆

Gregorio Caetano [a], Hugh Macartney [b,*]

[a] University of Georgia, United States
[b] Duke University and NBER, United States

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ABSTRACT

We develop a novel strategy to identify the relative importance of school and neighborhood factors in determining school segregation. Using detailed student enrollment and residential location data, our research design compares differences in student composition between adjacent Census blocks served by different schools to analogous differences between those schools. Our findings indicate that neighborhood factors explain around 62% of racial segregation and 44% of economic segregation across all schools, playing an even more pronounced role in urban areas, where school segregation has been especially acute. These findings suggest that the involvement of urban planners is essential when attempting to confront inequality of opportunity through education.

1. Introduction

Widespread and rising socioeconomic inequality continues to be a pressing concern in the United States and abroad. School segregation has received particular attention as a way to address disparities in opportunity, with ample evidence that school segregation widens the socioeconomic gap in achievement, attainment, college attendance, incarceration, health, and earnings (Guryan, 2004; Hanushek et al., 2009; Johnson, 2011; Billings et al., 2014).

Nearly three decades ago, following one of the most ambitious attempts of the twentieth century to reduce inequality in the United States, the era of court-ordered desegregation came to a close. Not surprisingly, school segregation rose substantially as a result (Clotfelter et al., 2008; Lutz, 2011). This reversal in policy was based, in no small part, on the belief that school choice reforms (e.g., allowing for magnet and charter schools) and compensatory redistribution of school resources could achieve a similar end without curtailing parental schooling decisions.

In recent years, school choice reforms have seen increased adoption in the United States, though students continue to attend their assigned neighborhood school in the vast majority of cases. At the same time, federal programs (such as Title I), as well as many state and local initiatives, have helped reduce the gap in spending across schools (Cascio and Reber, 2013). Yet school segregation has remained stubbornly pervasive, even in urban areas (Orfield et al., 2014), where school choice reforms have been disproportionately embraced.

One seldom explored reason why education policies have been ineffective at reducing school segregation is its potential first-order dependence on non-school factors, given their likely importance for residential sorting under the traditional school choice paradigm. Intuitively, a household's decision about where to reside depends on both school and neighborhood amenities, the latter of which being less influenced by education policy, or not at all. Examples of neighborhood amenities include the quality of parks, prevalence of walkable streets, age and style of dwellings, and

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* Corresponding author.
E-mail address: hugh.macartney@duke.edu (H. Macartney).

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availability of nearby desirable venues (Jacobs, 1961; Glaeser et al., 2001). Such features tend to vary particularly intensely across neighborhoods within high density cities.

The potential for non-school (neighborhood) factors to affect school segregation is best understood by way of example. Consider the case in which two otherwise similar schools differ according to some pre-existing natural neighborhood amenity. For instance, suppose the attendance area of one school contains a picturesque lake, while the other does not. Further, let affluent families care more about residing near the lake than non-affluent families. As a result, the socioeconomic composition of the schools would differ entirely because of neighborhood factors, as the school near the lake would attract more affluent students.

The initial difference due to the lake may then beget additional differences. For instance, the influx of affluent households could lead to further sorting of affluent households if they prefer to reside near similar households. It could also lead to gentrification, in which more desirable venues (e.g., restaurants, retail shops), higher quality buildings, and walkable streets arise to cater to demand. Such amenities might spur even more sorting, which could result in additional desirable amenities, and so on. Many other positive feedback loops like these could arise, which would result in increased segregation. Some may in turn lead to an interaction between neighborhood and school factors: for example, the school near the lake might respond to the influx of affluent households by altering its features to appeal to its student body, giving rise to school differences that drive further sorting and set yet more positive feedback loops in motion (in this case, attributable to school factors).

In this article, we identify the relative importance of school and neighborhood factors in determining socioeconomic segregation patterns across schools. Our research design builds on the key insight from Black (1999) that houses located sufficiently close to each other but served by different schools should share neighborhood features. Thus, with the exception of differential school factors, households should be indifferent between residing within adjacent blocks on opposite sides of the boundary separating the schools. We adapt this idea to address our research question by comparing the socioeconomic composition between two adjacent Census blocks assigned to different attendance areas. Any systematic difference in the composition between those blocks must arise as a result of a disparity in the local provision of school features that are valued heterogeneously along socioeconomic lines. We draw upon this logic to estimate the degree to which the difference in composition between two schools sharing a boundary (which depends on both school and neighborhood factors) predicts the difference in composition between the two associated adjacent blocks at the boundary (which depends only on school factors).

Our approach sidesteps important endogeneity concerns raised in the literature. For instance, a major issue noted by Bayer et al. (2007) in the context of the boundary approach is that endogenous residential sorting due to original differences in school amenities at the boundary may lead to further local differences in house prices. While, in the standard context, this observation implies that one needs to control for these differences in local amenities, the issue does not apply to our analysis. Indeed, under our approach, any discontinuous change in student socioeconomic composition across the boundary is by definition attributable to school factors.

Critically, such factors represent not only original differences in school features, but also any differences that arise from household sorting in response to differences in those features. These include changes via positive feedback loops that are initiated by school factors (analogous to the discussion above). Returning to our example, school differences that cause more affluent neighbors to sort into the attendance area with the lake could cause a differential investment in housing across the boundary if affluent families take better care of their houses. In turn, if more affluent families disproportionately value residing near houses that are well cared for, then additional sorting would ensue, leading to further segregation. Under our approach, all such effects would contribute to the school (rather than neighborhood) component of school segregation.

Another strength of our approach is that it does not require the researcher to observe all relevant school and neighborhood characteristics. Since it only uses information about the socioeconomic composition of boundary blocks and schools, the approach is agnostic about whether features are observed or unobserved, picking up both sources of variation. This is particularly valuable as school features may be disproportionately observed by researchers, relative to neighborhood features.

We implement our research design using rich data on the socioeconomic status of North Carolina students, the schools that they attend, and the blocks in which they reside. We report results by student race and economic advantage across all school attendance area boundaries in the state. We also stratify the results according to whether the schools of interest are located in an urban area, and according to the grade level of the schools.

Our analysis reveals that neighborhood features explain about 62% of school racial segregation and 44% of school economic segregation. These percentages are larger in urban areas (72% and 65%, respectively) than in non-urban areas (57% and 23%, respectively). As mentioned, we hypothesize this occurs because the density of neighborhood features to choose from is greater (relative to school features) in urban areas. Indeed, it is easy to enumerate many non-school features that may differ from one block to the next in urban areas, such as restaurants, coffee shops, museums, retail stores, green spaces, public spaces, street width, through traffic, lot size, parking, public transit, and proximity to a zoned area (Turner et al., 2014). In contrast, these features are perceived to be more similar from one block to the next in non-urban areas, as non-urban residents tend to use cars as their primary mode of transportation.

We also find that neighborhood features tend to play a larger role in later grades than in earlier grades. We speculate this is due to the fact that households with students in high school have a smaller number of options to choose from regarding school features (given larger attendance areas) but face the same set of options in terms of neighborhood features.

In addition, the evidence indicates that the way in which school and neighborhood factors affect school segregation is positively correlated: attendance areas with neighborhood factors that tend to attract affluent students also include school factors that tend to attract affluent students. Thus, feedback loops originally arising from neighborhood factors are reinforced by those arising from school factors, and vice versa, resulting in greater segregation than without this interaction. Our results suggest that the positive correlation between school and neighborhood factors accounts for about half of the school segregation that occurs by race and income, in both urban and non-urban areas.

Our findings suggest that, in the absence of top-down reassignment policies that constrain individual choice, education policymakers are considerably more limited in their ability to affect school segregation than previously thought. A nontrivial portion of school segregation is subject to neighborhood factors, particularly in urban settings. Consequently, any attempt to lower segregation across schools will be more successful with the engagement of urban planners, irrespective of the existing education policy landscape. This is particularly true in the face of technological and environmental upheaval (Glaeser, 2011), which may grant planners more latitude in their future urban design ambitions.

The remainder of this article is organized as follows: The next section sets out our empirical framework, Section 3 describes the data used in our analysis, and Section 4 presents our results. Section 5 explores and rules out several potential validity concerns associated with our research design, and Section 6 addresses considerations regarding the sources of variation we exploit. Section 7 then interprets our results through the lens of a dynamic model, and Section 8 concludes.

2. Empirical framework

In this section, we first set out a model of the demand for school and neighborhood amenities. We then exploit it to identify the relative importance of school and neighborhood factors in explaining the degree of segregation across schools.

2.1. A model of school and neighborhood choice

Our framework is based upon a model of households jointly choosing their school and neighborhood. The term "neighborhood" refers to a Census block, which we shorten to "block" for convenience. Each block k is uniquely associated with one attendance area (and thus to one school) s, where we use $\mathcal{K}_s$ to denote the set of blocks associated with s. This implies that each household chooses the block in which it will reside, with the understanding that it is selecting both the school and neighborhood amenities to which it will be exposed.

Specifically, each household h of type $\tau \in \{A, B\}$ (e.g., white and non-white, or advantaged and disadvantaged) observes the vector of school-related amenities $\mathbb{S} = [\mathbb{S}_1, \ldots, \mathbb{S}_K]'$ and the vector of neighborhood-related amenities $\mathbb{N} = [\mathbb{N}_1, \ldots, \mathbb{N}_{\mathbb{K}}]'$, where k indexes the K neighborhoods in their choice set (each of which is assigned to a school indexed by s).[1] Each household selects the option that maximizes its utility:

$$u_k^{h,\tau} = \underbrace{\phi_S^\tau \mathbb{S}_k + \phi_N^\tau \mathbb{N}_k}_{\delta_k^\tau} + \zeta_k^{h,\tau}, \tag{1}$$

where δ_k^τ corresponds to the mean utility of households of type τ for neighborhood k, and $\zeta_k^{h,\tau}$ is an idiosyncratic error term that captures household-specific deviations from that mean. The mean utility depends on the preference parameter scalars ϕ_S^τ and ϕ_N^τ, each of which depends on the household's type τ.

As is standard in discrete choice frameworks, we assume that $\zeta_k^{h,\tau}$ is independently and identically drawn from the extreme value distribution. This yields the familiar expression for the proportion of students residing in neighborhood k who are of type A:

$$\pi_k = \frac{n_k^A}{n_k^A + n_k^B},$$

where $n_k^\tau = n^\tau \cdot \frac{exp(\delta_k^\tau)}{\sum_{\tilde{k}} exp\left(\delta_{\tilde{k}}^\tau\right)}$ and n^τ is the total number of type-τ students across all blocks.

Under the normalization $\sum_{\tilde{k}} \exp(\delta_{\tilde{k}}^\tau) = n^\tau$, we have:

$$\begin{aligned} \pi_k &= \frac{\exp(\delta_k^A)}{\exp(\delta_k^A) + \exp(\delta_k^B)} \\ &= \frac{\exp(\phi_S^A \mathbb{S}_k + \phi_N^A \mathbb{N}_k)}{\exp(\phi_S^A \mathbb{S}_k + \phi_N^A \mathbb{N}_k) + \exp(\phi_S^B \mathbb{S}_k + \phi_N^B \mathbb{N}_k)}. \end{aligned} \tag{2}$$

Similarly, the proportion of students attending school s who are of type A is:

$$\begin{aligned} \pi_s &= \frac{n_s^A}{n_s^A + n_s^B} \\ &= \frac{\sum_{k \in \mathcal{K}_s} \exp(\delta_k^A)}{\sum_{k \in \mathcal{K}_s} \left[\exp(\delta_k^A) + \exp(\delta_k^B)\right]} \\ &= \frac{\sum_{k \in \mathcal{K}_s} \left[\exp(\phi_S^A \mathbb{S}_k + \phi_N^A \mathbb{N}_k)\right]}{\sum_{k \in \mathcal{K}_s} \left[\exp(\phi_S^A \mathbb{S}_k + \phi_N^A \mathbb{N}_k) + \exp(\phi_S^B \mathbb{S}_k + \phi_N^B \mathbb{N}_k)\right]}. \end{aligned} \tag{3}$$

2.2. Defining the estimand

Our goal is to identify the relative importance of school factors in explaining school segregation. Before doing so, it is important to define what we mean by "school factors," "neighborhood factors," and "school segregation" in the context of our framework. Notice that Eq. (2) implies

$$\ln\left(\frac{\pi_k}{1-\pi_k}\right) = \delta_k^A - \delta_k^B = \left(\phi_S^A - \phi_S^B\right)\mathbb{S}_k + \left(\phi_N^A - \phi_N^B\right)\mathbb{N}_k.$$

The difference in this measure across any two blocks k and k' is then

$$\ln\left(\frac{\pi_k}{1-\pi_k}\right) - \ln\left(\frac{\pi_{k'}}{1-\pi_{k'}}\right) = \ln\left[\frac{\pi_k(1-\pi_{k'})}{\pi_{k'}(1-\pi_k)}\right] = \Delta S_{k,k'} + \Delta N_{k,k'}, \tag{4}$$

where $\Delta S_{k,k'} := S_k - S_{k'} = \left(\phi_S^A - \phi_S^B\right)(\mathbb{S}_k - \mathbb{S}_{k'})$ and $\Delta N_{k,k'} := N_k - N_{k'} = \left(\phi_N^A - \phi_N^B\right)(\mathbb{N}_k - \mathbb{N}_{k'})$.[2] The term $\Delta S_{k,k'}$ represents the component of the gap between π_k and $\pi_{k'}$ that is due to "school factors," which jointly arises from a difference in school amenities $(\mathbb{S}_k - \mathbb{S}_{k'})$ and an across-group difference in the preferences over those amenities $(\phi_S^A - \phi_S^B)$. Analogously, the term $\Delta N_{k,k'}$ represents the component of the gap between π_k and $\pi_{k'}$ that is due to "neighborhood factors," which depends on the difference in neighborhood amenities $(\mathbb{N}_k - \mathbb{N}_{k'})$ and the across-group difference in preferences over those amenities $(\phi_N^A - \phi_N^B)$.

The distinction between $\mathbb{S}$ and $\mathbb{N}$ is at the heart of our identification strategy, which will be made explicit in the next subsection. The key difference between them is that school-related amenities are uniform across blocks served by the same school, while neighborhood-related amenities need not be. The first part of this statement is made precise by the following assumption:

Assumption 1. $\mathbb{S}_k = \mathbb{S}_s \ \forall \ k \in \mathcal{K}_s$.

The rationale behind this identifying assumption is that all school-aged children are entitled to attend the public school to which their residence is assigned, and in the case of North Carolina the vast majority of them do so.[3] Consequently, the school amenity is uniform across blocks served by the same school, since the benefits of school amenities can be identically realized irrespective of where within the attendance area a student resides.[4] In contrast, the consumption of neighborhood amenities is more optional, often

[1] For expositional simplicity, we assume that blocks can be different in the values of only one school amenity and only one neighborhood amenity. In practice, blocks differ from each other because of many school and neighborhood amenities, so that $\mathbb{S}$ and $\mathbb{N}$ should be understood as indices of all corresponding amenities. Moreover, some amenities inherently conflate school and neighborhood amenities, such as the block average house price. In that case, the component of the price that capitalizes school amenities is included in the index $\mathbb{S}$, and the component that capitalizes neighborhood amenities is included in the index $\mathbb{N}$.

[2] These expressions arise from the following definitions: $S_k := \left(\phi_S^A - \phi_S^B\right)\mathbb{S}_k$ and $N_k := \left(\phi_N^A - \phi_N^B\right)\mathbb{N}_k$.

[3] The exceptions to this rule are students who attend private, charter or magnet schools, or those who receive home schooling. As discussed in Section 3, charter and magnet schools account for a very small fraction of public school enrollment in our setting; and, in addition, the degree of home schooling is negligible. In our framework, private schools contribute to neighborhood factors, but only insofar as the distance between the student's residence and the private school is salient.

[4] Some other public goods are likely to ensure that students residing in different areas of the attendance zone have equitable access to the school. For instance, free school busing is a form of public good that is enjoyed more by those residing further from the school, partially compensating for their longer commute to the school.

depending on their distance from a student's residence. For example, on average, those residing near a park will likely enjoy it more frequently than those residing far from it.

It is worth noting that Assumption 1 is actually stronger than necessary for identification to hold.[5] A key situation in which Assumption 1, or even its weaker variant, would fail is if households were heterogeneous in their preferences with respect to the distance between their residence and the school their child attends. In Section 5.2, we show that this is not a first-order concern in our context.

For the school-level comparison analogous to Eq. (4), we apply Assumption 1 to Eq. (3), obtaining

$$\ln\left(\frac{\pi_s}{1-\pi_s}\right) = \left(\phi_S^A - \phi_S^B\right)\mathbb{S}_s + \ln\left(\sum_{k\in\mathcal{K}_s}\exp\left(\phi_N^A\mathbb{N}_k\right)\right) - \ln\left(\sum_{k\in\mathcal{K}_s}\exp\left(\phi_N^B\mathbb{N}_k\right)\right).$$

Defining $N_s := \ln\left(\sum_{k\in\mathcal{K}_s}\exp\left(\phi_N^A\mathbb{N}_k\right)\right) - \ln\left(\sum_{k\in\mathcal{K}_s}\exp(\phi_N^B\mathbb{N}_k)\right)$ and $\Delta N_{s,s'} := N_s - N_{s'}$, we can compare the two schools s and s' (corresponding to block k and k', respectively):

$$\ln\left(\frac{\pi_s}{1-\pi_s}\right) - \ln\left(\frac{\pi_{s'}}{1-\pi_{s'}}\right) = \ln\left[\frac{\pi_s(1-\pi_{s'})}{\pi_{s'}(1-\pi_s)}\right] = \Delta S_{s,s'} + \Delta N_{s,s'}. \quad (5)$$

Note that $var\left(\ln\left[\frac{\pi_s(1-\pi_{s'})}{\pi_{s'}(1-\pi_s)}\right]\right) = var(\Delta S_{s,s'} + \Delta N_{s,s'})$ is equal to zero if $\pi_s = \pi_{s'}$ for any two schools s and s', and it tends to grow as the gap in composition between school pairs increases. In terms of the model notation, within-pair differences only arise if two conditions are satisfied along at least one dimension (i.e., S, N). For the school dimension, the conditions are: (i) types differ in preferences over school amenities ($\phi_S^A \neq \phi_S^B$); and (ii) schools differ in the level of school amenities ($\mathbb{S}_s \neq \mathbb{S}_{s'}$). For the neighborhood dimension, the conditions are: (i') types differ in preferences over neighborhood amenities ($\phi_N^A \neq \phi_N^B$); and (ii') schools differ in their neighborhood amenity ($\sum_{k\in\mathcal{K}_s}\exp(\phi_N^\tau\mathbb{N}_k) \neq \sum_{k\in\mathcal{K}_{s'}}\exp(\phi_N^\tau\mathbb{N}_k)$ for $\tau\in\{A,B\}$).

Our goal is to identify the relative role of $\Delta S_{s,s'}$ and $\Delta N_{s,s'}$ in explaining total variance

$$var(\Delta S_{s,s'} + \Delta N_{s,s'}) = var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2\cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'}). \quad (6)$$

We define the relative role of $\Delta S_{s,s'}$ as

$$\Omega_S := \frac{var(\Delta S_{s,s'}) + cov(\Delta S_{s,s'}, \Delta N_{s,s'})}{var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2\cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'})}, \quad (7)$$

and the relative role of $\Delta N_{s,s'}$ as $\Omega_N := 1 - \Omega_S$.

Given the definition above, the covariance term $cov(\Delta S_{s,s'}, \Delta N_{s,s'})$ may play an important role in explaining school segregation. It will be positive if school amenities that attract a disproportionate number of students of a given type are located near neighborhood amenities that attract a disproportionate number of students of that same type. As discussed in Remark 1, that is the case in the context of this article, implying that Ω_S is bounded between 0 and 1, and allowing us to interpret it as a proportion.

Note that the definition of Ω_S attributes half of the covariance term to school factors, and the other half to neighborhood factors. This is an arbitrary attribution. In Section 7, we offer a theoretically sound method of attributing the covariance term, based on our estimate of Ω_S. Prior to that discussion, however, we must explain our strategy for identifying and estimating Ω_S, which we turn to next.

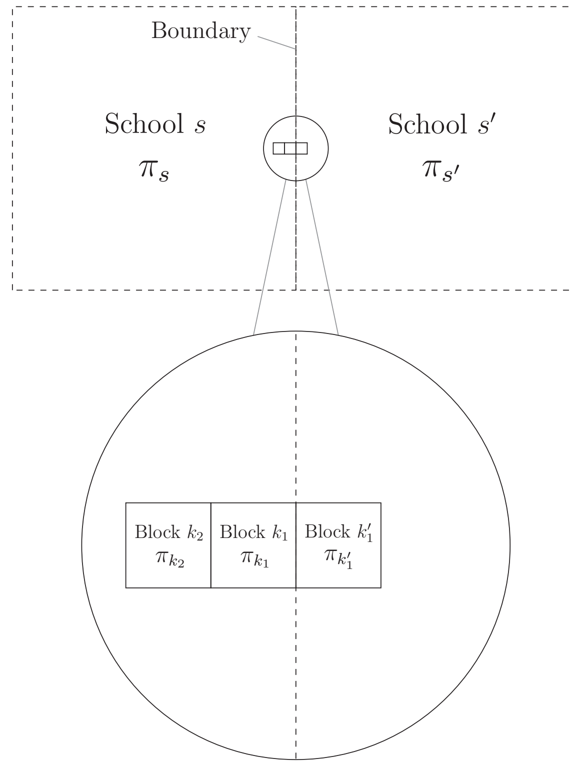


Fig. 1. Visualizing Sources of Variation. *Notes*: This Figure illustrates a specific boundary of the many we observe in the data. The key variables of interest are the proportions (π) of students who are white or economically advantaged for blocks k_2, k_1 and k_1', along with the analogous proportions for the associated schools s and s'. Blocks k_1 and k_1' are adjacent to each other but located in different attendance areas. Blocks k_2 and k_1 are adjacent to each other and located in the same attendance area s.

2.3. Identification strategy

To identify the role of school and neighborhood factors in explaining school segregation, we exploit block-level variation at the boundary between two school attendance areas. It is helpful to visualize our approach using Fig. 1. Consider two blocks, k_1 and k_1', which are adjacent to each other but served by different schools, s and s', respectively. Our research design involves comparing how the proportion of students of a given type varies across the boundary at the block level (from π_{k_1} to $\pi_{k_1'}$) to how it varies at the attendance area level (from π_s to $\pi_{s'}$).[6]

A simple cross-boundary comparison of proportions is able to recover the relative importance of each factor. In particular, consider the following regression equation:

$$\ln\left[\frac{\pi_{k_1}\left(1-\pi_{k_1'}\right)}{\pi_{k_1'}\left(1-\pi_{k_1}\right)}\right] = \alpha^{log} + \beta^{log}\cdot\ln\left[\frac{\pi_s(1-\pi_{s'})}{\pi_{s'}(1-\pi_s)}\right] + \text{error}^{log}. \quad (8)$$

Substituting the expressions from Eqs. (4) and (5), and applying Assumption 1 so that $\Delta S_{k_1,k_1'} = \Delta S_{s,s'}$, the regression can be equivalently expressed as

$$\Delta S_{s,s'} + \Delta N_{k_1,k_1'} = \alpha^{log} + \beta^{log}\cdot[\Delta S_{s,s'} + \Delta N_{s,s'}] + \text{error}^{log}. \quad (9)$$

[5] Identification still holds if Assumption 1 is weakened to the following: $\mathbb{S}_{k_1} = \mathbb{S}_s + \text{error}_{k_1}$, where error_{k_1} is uncorrelated with π_s (across all schools), and k_1 is a boundary block, defined in the next subsection. In words, the discontinuity we find at the boundary is representative of the overall change in school amenities. We use the more straightforward Assumption 1 for notational simplicity.

[6] Block k_2 depicted in Fig. 1 is used later to correct for a potential source of bias in our approach.

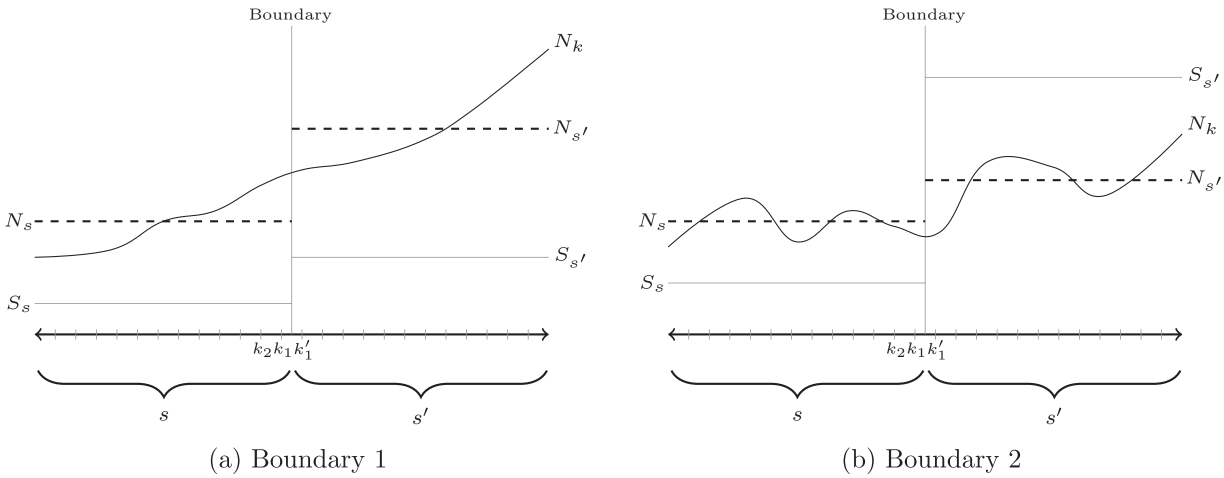


Fig. 2. Understanding Assumptions 2 and 2′. *Notes*: This figure shows, for two different boundaries (each depicted in one of the panels), how school and neighborhood factors vary across blocks. In the middle of each panel, we depict the boundary separating attendance areas s and s'. The horizontal axis represents the blocks in both attendance areas, and the vertical axis represents the school and neighborhood factors, S and N. The dashed lines represent the weighted average of N_k across all blocks within the attendance area, denoted as N_s and $N_{s'}$ depending on the attendance area. We highlight three blocks closest to the boundary: k_2, k_1 and k_1', as also described in Fig. 1.

The ordinary least squares (OLS) slope parameter in Eq. (9) is

$$\beta^{log} = plim\left(\hat{\beta}^{log}\right) = \frac{cov\left(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta S_{s,s'} + \Delta N_{k_1,k_1'}\right)}{var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2 \cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'})}. \quad (10)$$

Thus, $\hat{\beta}^{log}$ is a consistent estimator of Ω_S under the following identifying assumption:

Assumption 2. $cov\left(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta N_{k_1,k_1'}\right) = 0.$

In words, the (highly local) difference in neighborhood factors between two adjacent blocks, $\Delta N_{k_1,k_1'}$, is uncorrelated with the school-level difference in composition, $\ln\left[\frac{\pi_s(1-\pi_{s'})}{\pi_{s'}(1-\pi_s)}\right] := \Delta S_{s,s'} + \Delta N_{s,s'}$.

Applying Assumption 2 to Eq. (10), we have:

$$\begin{aligned} \beta^{log} &= \frac{cov\left(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta S_{s,s'}\right)}{var\left(\Delta S_{s,s'}\right) + var\left(\Delta N_{s,s'}\right) + 2 \cdot cov\left(\Delta S_{s,s'}, \Delta N_{s,s'}\right)} \\ &= \frac{var\left(\Delta S_{s,s'}\right) + cov\left(\Delta S_{s,s'}, \Delta N_{s,s'}\right)}{var\left(\Delta S_{s,s'}\right) + var\left(\Delta N_{s,s'}\right) + 2 \cdot cov\left(\Delta S_{s,s'}, \Delta N_{s,s'}\right)} \\ &= \Omega_S. \end{aligned} \quad (11)$$

Intuitively, as one moves across the boundary from k_1 in attendance area s to k_1' in attendance area s', only school factors can systematically change the values of both $\ln\left[\frac{\pi_{k_1}\left(1-\pi_{k_1'}\right)}{\pi_{k_1'}\left(1-\pi_{k_1}\right)}\right]$ and $\ln\left[\frac{\pi_s(1-\pi_{s'})}{\pi_{s'}(1-\pi_s)}\right]$. Thus, under Assumption 2, the slope coefficient from the regression in Eq. (10) represents the degree to which segregation across schools is explained by school factors.

2.3.1. Relaxing Assumption 2

While Assumption 2 may seem similar to the one often invoked in the boundary fixed effects literature (see Black, 1999, for instance), that is not the case. To see why, consider two blocks k_1 and k_1' with initial differences in school amenities. Because of this initial difference, people may sort, leading to further differences between the blocks (e.g., different neighbors, different investments in housing). Under the boundary fixed effects approach, one is concerned with identifying the effect on house prices of the initial difference in school features separately from further sorting-based differences. In contrast, under our approach, it is unnecessary to separately identify these two sources, as they are both attributable to school factors. More formally, anything that affects the gap between π_{k_1} and $\pi_{k_1'}$ because of the difference in school amenities is attributed to $\Delta S_{s,s'}$, and not to $\Delta N_{k_1,k_1'}$. This rules out concerns related to post-determined differences at the boundary, but one may still be concerned about pre-determined differences driving our results, such as major roads or rivers coinciding with a boundary. Below, we relax the assumption to accommodate some of these concerns, and Section 5.1 rules out remaining issues in detail.

To better understand Assumption 2, consider the example depicted in Fig. 2. For simplicity, we interpret the figure in terms of race, but the intuition is analogous for income. Each panel depicts a boundary along with its two associated attendance areas.[7] In the middle of each panel, we depict the boundary, with attendance area s to its left and attendance area s' to its right. In keeping with Assumption 1, school factors (represented by horizontal solid lines S_s and $S_{s'}$) do not vary within attendance area. Neighborhood factors vary by block (as illustrated by the curve denoted as N_k in each panel), and they can vary in unrestricted ways depending on the specific amenities distributed across the blocks in the two attendance areas as well as white and non-white preferences for those amenities.[8] We also depict N_s and $N_{s'}$ as dashed lines in each panel, representing the weighted average of all N_k within each attendance area.

For simplicity, assume that our sample consists of only the two boundaries depicted in Fig. 2. From the figure, note that $\Delta N_{k_1,k_1'} = N_{k_1} - N_{k_1'}$ is negative in Panel (a) and positive in Panel (b) (this is inferred by inspecting the slope of the N_k curve at the boundary in each case), which implies that $cov\left(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta N_{k_1,k_1'}\right) = 0$. Departing from this simple example, it is clear that this assumption might fail to hold in practice: indeed, the slope at the boundaries must be just so in order for the covariance to equal zero. In general, $cov\left(\Delta N_{s,s'}, \Delta N_{k_1,k_1'}\right)$ is likely to be positive (as is the case for

[7] Unless stated otherwise, we use "boundary" as shorthand to denote a geographical dividing line between two schools that is associated with a specific block pair (k_1, k_1'). Indeed, in the data, we observe many different boundaries for the same pair of attendance school areas (s, s').

[8] Distance from the amenity may play an important role for these heterogeneous preferences too. For instance, the N_k curve in Panel (a) is consistent with a situation in which there exists only one salient neighborhood amenity (e.g., a park) located in the far right of attendance area s', and whites prefer residing close to it more than non-whites do, though at slightly varying degrees depending on the distance.

Panel (a)), and $cov\left(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta N_{k_1,k_1'}\right)$ will also be positive if $cov(\Delta S_{s,s'}, \Delta N_{s,s'}) > 0$.[9]

To relax Assumption 2, we appeal to an alternative block-level comparison, which is also highlighted in Fig. 2. Consider block k_2, which is adjacent to block k_1 and is served by the same school s, and the analogous measure of the difference in proportion between these two blocks: $\ln\left[\frac{\pi_{k_2}(1-\pi_{k_1})}{\pi_{k_1}(1-\pi_{k_2})}\right]$. This difference does not systematically depend on the school component, since both blocks are contained within the same attendance area. Thus, the OLS estimator of the slope coefficient of the analogous regression to Eq. (10) (by regressing $\ln\left[\frac{\pi_{k_2}(1-\pi_{k_1})}{\pi_{k_1}(1-\pi_{k_2})}\right]$ on $\ln\left[\frac{\pi_s(1-\pi_{s'})}{\pi_{s'}(1-\pi_s)}\right]$) is:

$$\beta^{log}_{placebo} = \frac{cov(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta N_{k_2,k_1})}{var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2 \cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'})}. \tag{12}$$

We propose the following alternative to Assumption 2:

Assumption 2′. $cov\left(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta N_{k_1,k_1'}\right) = cov(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta N_{k_2,k_1})$

A sufficient condition for this assumption to hold is for N to vary around the boundary in a linear fashion from k_2 to k_1' (i.e., in Fig. 2, the portion of the N_k curve from k_2 to k_1 must have the same slope as the portion of the N_k curve from k_1 to k_1'). Given the close proximity of blocks k_2 and k_1' (with only block k_1 separating them), we view this local approximation as plausible. One potential issue, which we consider in detail in Section 5.1, is that attendance boundaries may separate neighborhoods beyond their school allocation (e.g., due to a major road or river). In that case, the slope from k_2 to k_1 may be systematically different than the slope from k_1 to k_1', leading us to attribute to S some of the effect that is due to N. In practice, we find no evidence that this occurs in enough boundaries for that to be a concern.

Under Assumption 2′, we form the corrected estimator of Ω_S as:

$$\Omega^{log}_S := \beta^{log} - \beta^{log}_{placebo}, \tag{13}$$

where β^{log} is defined by Eq. (10) and $\beta^{log}_{placebo}$ is defined by Eq. (12). Under Assumptions 1 and 2′, $\hat{\Omega}^{log}_S$ is a consistent estimator of Ω_S.

2.4. A feasible estimator

It is important to note that estimating $\hat{\Omega}^{log}_S$ depends on being able to properly measure $\ln\left[\frac{\pi_{k_1}\left(1-\pi_{k_1'}\right)}{\pi_{k_1'}(1-\pi_{k_1})}\right]$ and $\ln\left[\frac{\pi_{k_2}(1-\pi_{k_1})}{\pi_{k_1}(1-\pi_{k_2})}\right]$. In practice, for any block k, rather than observing the population proportions π_k, we are only able to obtain sample analogues, which are measured with error ($\hat{\pi}_k = \pi_k + \epsilon_k$). While exploiting variation across highly local blocks makes Assumption 2′ more plausible, blocks are very small geographic units in which few school-age children tend to reside, making the effect of measurement error more pronounced and making it more likely that $\hat{\pi}_k = 0$ or $\hat{\pi}_k = 1$, even if $0 < \pi_k < 1$.[10] In such cases, $\ln\left(\frac{\hat{\pi}_{k_1}\left(1-\hat{\pi}_{k_1'}\right)}{\hat{\pi}_{k_1'}(1-\hat{\pi}_{k_1})}\right)$ and $\ln\left[\frac{\hat{\pi}_{k_2}(1-\hat{\pi}_{k_1})}{\hat{\pi}_{k_1}(1-\hat{\pi}_{k_2})}\right]$ would be undefined and thus the estimation of $\hat{\Omega}^{log}_S$ would be infeasible.

To address this concern, we draw upon a linear approximation that retains our interpretation of the slope parameter in the presence of measurement error. In Appendix A, and also in the Monte Carlo simulations in Appendix B, we show that the slope β from the linear-on-linear regression

$$\Delta\hat{\pi}_{k_1,k_1'} = \alpha + \beta \cdot \Delta\hat{\pi}_{s,s'} + \text{error} \tag{14}$$

(for which the quantities are defined for all observations), provides a very good approximation of the log-on-log slope β^{log} from Eq. (8). This is also true for the placebo versions from these equations: the slope estimator obtained from the regression

$$\Delta\hat{\pi}_{k_2,k_1} = \alpha_{placebo} + \beta_{placebo} \cdot \Delta\hat{\pi}_{s,s'} + \text{error}_{placebo}. \tag{15}$$

is approximately the same as the log-on-log slope $\beta^{log}_{placebo}$ from Eq. (12).[11]

Based on the concordance between the linear-on-linear and log-on-log regressions, we henceforth refer to the specifications in Eqs. (14) and (15) when discussing and estimating the effect of school factors on school segregation.

3. Data

To determine the extent to which school and neighborhood factors drive school segregation, we draw upon rich administrative data provided by the North Carolina Education Research Data Center (NCERDC), focusing on the 2011–12 school year.[12] The dataset contains detailed longitudinal information covering all third through twelfth grade students who attend North Carolina public schools, including their grade, race, an indicator for economic advantage,[13] the school they attend, and, crucially for our research design, their Census block of residence.[14] While students are classified as being white, black, Hispanic, Asian, American Indian or of mixed race, we choose to concentrate on white versus non-white students for our analysis of segregation along racial lines. We use the indicator of economic advantage to investigate segregation along economic lines.

The data also include important information about each public school, such as its grade span (i.e., the lowest and highest grade served) and location (both a latitude-longitude combination and urban-suburban–rural classification). As discussed, each student is connected to both a school and a Census block of residence. This feature of the data allows us to discern the location of school boundaries by identifying boundary blocks that are adjacent to each other but inferred (based on enrollment data) to be served

[9] Note that $cov(\Delta S_{s,s'}, \Delta N_{s,s'}) > 0$ in this example: attendance areas with school amenities that attract a disproportionate number of white students tend to also feature neighborhood amenities that attract a disproportionate number of white students, and vice versa.

[10] For instance, if the population proportion is 70% and we observe only one student in a block (as is a frequent occurrence in our data), the block proportion can only take the value 0 or 1, rather than 0.7.

[11] We conducted many simulations to understand this regularity. The similarity of the slope parameter across the log-on-log and the linear-on-linear specifications appears to hold as long as most values of $|\Delta\pi_{k_1,k_1'}|$ and $|\Delta\pi_{s,s'}|$ lie sufficiently below 1, as is the case in our context.

[12] We have also carried out the analysis using data from 2009–10 and 2010–11 school years, obtaining similar results in each case.

[13] We define a student as economically advantaged if the student's household income is above 185% of the federal poverty threshold, which is recorded in our data as not qualifying for a reduced-price lunch at school.

[14] The Census block represents a very fine level of geography, encompassing between one and a few hundred residents (with very large numbers usually due to apartment buildings in urban centers). For the 2011–12 school year, we know the Census block of residence for 93% of public school students. The match rate is fairly uniform across grade spans, with coverage ranging from 91% for elementary grades to 94% for secondary grades. We obtained data at the block level from a previously available version of the standard NCERDC repository. The data has since been updated to only include block groups, but should be available via custom request.

Table 1
Descriptive statistics.

	Elementary		Middle		Secondary	
	Boundary	School	Boundary	School	Boundary	School
Prop. white	0.59	0.53	0.57	0.54	0.59	0.55
	(0.46)	(0.28)	(0.46)	(0.27)	(0.46)	(0.26)
Prop. black	0.23	0.25	0.26	0.26	0.26	0.29
	(0.39)	(0.23)	(0.41)	(0.22)	(0.41)	(0.24)
Prop. economically advantaged	0.42	0.40	0.43	0.41	0.50	0.47
	(0.45)	(0.23)	(0.45)	(0.20)	(0.46)	(0.19)
N - Students	34,001	266,720	29,426	264,295	33,619	368,974
All schools						
N - Schools	1,093		471		518	
Avg. Students per school	244		561		712	
Avg. Blocks per school	93		205		256	
N - Boundary block pairs	12,661		9,256		9,700	
Urban schools						
N - schools	246		92		100	
Avg. Students per school	259		669		836	
Avg. Blocks per school	100		245		315	
N - Boundary block pairs	2,105		1,611		1,469	

Notes: Standard deviations in parentheses. "Elementary," "Middle" and "Secondary" refer to schools serving third through fifth grade students, sixth through eighth grade students and ninth through twelfth grade students, respectively. "Urban schools" refers to the sample of school pairs in which both schools are located in urban areas.

by different schools in the same district.[15] It also allows us to determine the share of students within each school and block that are of a particular type (e.g., white or economically advantaged).

With these data in hand, we are able to implement our research design for different student subsets of interest. Using the information about each student's grade and cross-checking against school grade spans, we classify schools serving any third through fifth grade students as elementary schools, those serving any sixth through eighth grade students as middle schools and those serving any ninth through twelfth grade students as secondary schools, presenting our results for each category. We also subdivide our results according to whether schools serve urban or non-urban areas (i.e., suburban or rural). Our final estimation sample is constructed by removing all magnet and charter schools, which do not strictly adhere to the attendance area boundary system that we exploit.[16] Thus, socioeconomic proportions at the school and block level are calculated using only traditional public school students.

Descriptive statistics for our proportions of interest (i.e., white and economically advantaged) are reported in Table 1, along with information about the relevant dimensions (i.e., local boundary level, school level, and grade level). For each school-grade level, the average proportions of white and economically advantaged students are reasonably similar across boundary blocks and across school attendance areas and there is a large degree of variation across both boundary blocks and schools (though, as one might expect, the variance is substantially higher for blocks since they are geographically smaller). Regardless of the level, the proportion of black students tends to be about half of the non-white proportion, with the remainder consisting mostly of Hispanic students. The total number of students in our sample is 266,720, 264,295 and 368,974 at the elementary, middle and high school levels, respectively, and the number of students residing next to an attendance area boundary ranges from 9 to 13 percent of the total. The number of schools serving elementary, middle and secondary grades is 1,093, 471 and 518, respectively, approximately twenty percent of which are located in an urban area.[17] On a per-school basis, the average number of students is 244, 561 and 712, while the average number of blocks is 93, 205 and 256 (each corresponding to elementary, middle and high schools, respectively). In terms of our unit of analysis, there are between 9,256 and 12,661 boundary block pairs depending on the grade level, approximately 16% of which are located in urban areas.

4. Results

In this section, we implement the approach detailed in Section 2.3 to estimate the relative role of school features in explaining school segregation, both in terms of race (white vs. non-white students) and income (economically advantaged vs. economically disadvantaged students). To provide more intuition, we present estimates of both β and $\beta_{placebo}$, which allow us to calculate the estimate of primary interest, $\hat{\Omega}_S := \hat{\beta} - \hat{\beta}_{placebo}$.

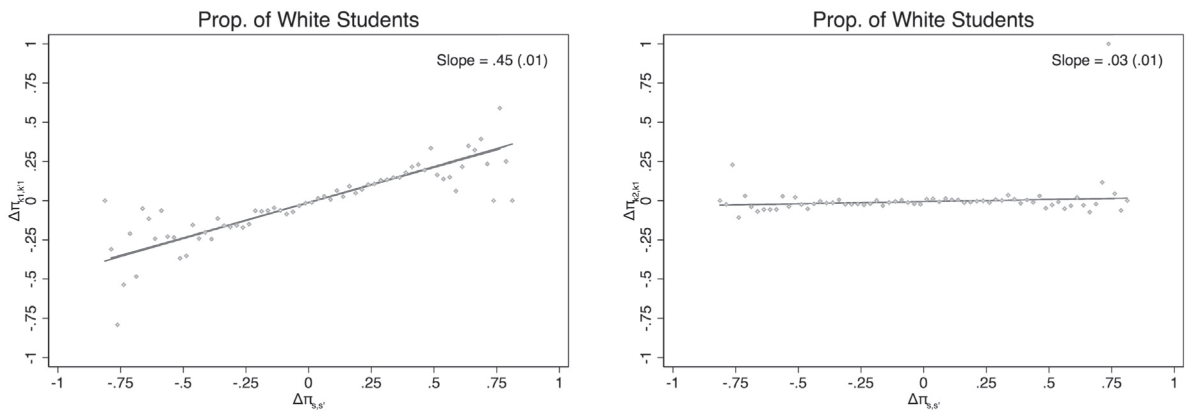
4.1. All schools

Our main results for race are presented in Panel (a) of Fig. 3. The horizontal axis measures the difference in the proportions of white students between schools s and s' ($\Delta\pi^{white}_{s,s'}$), while the vertical axis measures the difference in the proportions of white students between boundary blocks k_1 and k'_1 ($\Delta\pi^{white}_{k_1,k'_1}$). The scatter plot shows averages of $\Delta\pi^{white}_{k_1,k'_1}$ across all boundaries with similar values

[15] Geo-coded boundary information is only available for a small minority of North Carolina districts in the 2009–10 school year (and not at all for other years), via the School Attendance Boundary Information System (SABINS). Motivated by this and the fact that we do not possess exact student addresses to understand how actual boundaries divide some Census blocks, we restrict our analysis to boundary blocks for which all students residing within are served by a single school. Depending on the grade level, this covers between 67% and 71% of all boundary blocks. Interior blocks (not adjacent to a block served by a different school) are unaffected by this restriction and are fully retained in our sample. Whenever we drop a block that is served by more than one school, we retain the boundary path containing it by defining the single-school blocks adjacent to it as boundary blocks k_1 and k'_1, rather than blocks k_2 and k'_2. Footnote 23 in Section 5.1 shows that this restriction does not affect our results.

[16] In our data, magnet and charter schools account for about 5% and 3% of total public school enrollment, respectively. While charter schools in North Carolina place no geographical restrictions on applicants (other than requiring state residency), many magnet schools rely on a hybrid admission process that grants students residing within a priority/walk zone the right to enroll before any lottery applicants are considered. As we do not possess lottery information, we abstract from magnet and charter schools in our analysis. After dropping them and recognizing that North Carolina does not feature open enrollment for the period of interest, our sample contains only boundaries which are binding for schooling allocations.

[17] The urban schools in our sample are located across about twenty cities in the state, with over 80% of the schools located in (by descending share) Charlotte, Fayetteville, Greensboro, Raleigh, Durham, Winston-Salem, Burlington, and Wilmington.



(a) Blocks in Different Attendance Areas (b) Blocks in the Same Attendance Area

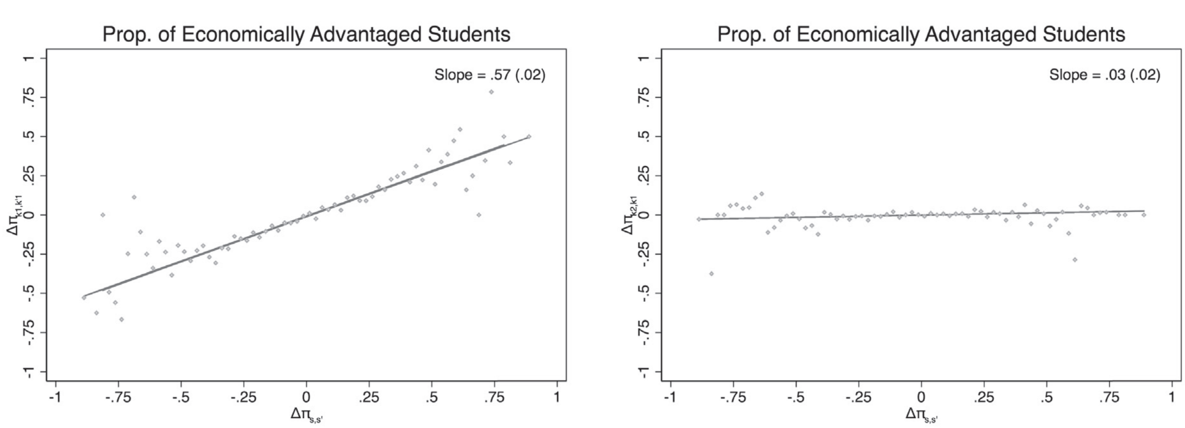
Fig. 3. The Relative Role of School Factors on School Segregation by Race. *Notes*: In the left panel, we relate each pair of adjacent blocks k_1 and k_1' in different attendance areas to their corresponding assigned school pair s and s'. The horizontal axis measures the difference in the proportion of students in school s who are white relative to the analogous proportion in school s'. The vertical axis measures the difference in the proportion of students in block k_1 who are white relative to the analogous proportion in block k_1'. The scatter plot represents averages of the variable in the vertical axis across all block pairs with similar values of the variable in the horizontal axis (in increments of 2.5 percentage points). The line represents the ordinary least squares fit of the disaggregated regression at the block-pair level. The regression slope estimate along with its standard error (in parenthesis) are also shown. The right panel shows an analogous plot, but with a different vertical axis: instead of considering blocks k_1 and k_1', it considers blocks k_2 and k_1. These results were obtained from a sample of 31,617 block pairs along with their associated schools.

of $\Delta\pi^{white}_{s,s'}$ (in increments of 2.5 percentage points). The line represents the ordinary least squares fit of the disaggregated regression at the boundary block pair level. The corresponding regression slope estimate and standard error (in parenthesis) are reported in the top right-hand portion of the panel. Panel (a) of Fig. 3 suggests that 45% of racial school segregation is due to school factors. Panel (a) of Fig. 4 reports the analogous results for income, suggesting that 57% of economic school segregation is due to school factors.

As discussed, one potential issue with the estimates from Panel (a) is that they may reflect highly local variation in neighborhood features, in addition to school features. This concerns Assumption 2, which states that no systematic change in neighborhood features across adjacent blocks should exist. If it is violated, then the results from Panel (a) would represent an upper bound of the true value (see discussion pertaining to Fig. 2). We use the "placebo" estimates from Panel (b) of the respective figures to provide a correction for the estimates in Panel (a). In particular, we construct a plot that is similar to Panel (a) but uses a different vertical axis: rather than considering the difference between adjacent blocks k_1 and k_1' (which are served by different schools), we calculate the difference between adjacent blocks k_2 and k_1 (which are served by the same school). The placebo estimates for race and income are both equal to 3%. Thus, under Assumption 2′, our estimates for the relative role of school factors in explaining racial and economic school segregation are respectively 42% ($= 45 - 3$) and 54% ($= 57 - 3$). This indicates that neighborhood factors play a key role in both racial and economic segregation across schools.

4.2. Urban status

We carry out our analysis separately for school pairs located in urban and non-urban areas, the estimates for which are reported in Table 2 alongside the overall estimates discussed above. We find that school factors matter substantially less in urban areas: they account for 35% (=37–2) of racial segregation in urban areas and 45% (=51–6) of racial segregation in non-urban areas. The analogous estimates for economic segregation are 40% (=42–2) for urban areas and 69% (=71–2) for non-urban areas. (All pairwise differences are significant at the 1% level.)



(a) Blocks in Different Attendance Areas (b) Blocks in the Same Attendance Area

Fig. 4. The Relative Role of School Factors on School Segregation by Income. *Notes*: See the notes for Fig. 3, which presents the analogous results by race.

Table 2
The relative role of school factors on school segregation.

	All Schools		Urban Schools		Non-Urban Schools	
	$\hat{\beta}_{ols}$	$\hat{\beta}_{placebo}$	$\hat{\beta}_{ols}$	$\hat{\beta}_{placebo}$	$\hat{\beta}_{ols}$	$\hat{\beta}_{placebo}$
Race	0.45***	0.03*	0.37***	0.02	0.51***	0.06***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)
Income	0.57***	0.03*	0.42***	0.02	0.71***	0.02
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Observations	31,617		5,185		21,002	

Notes: "All Schools" refers to the full sample of school pairs. "Urban Schools" refers to the sample of school pairs in which both schools are located in urban areas, and "Non-Urban Schools" refers to the sample of school pairs in which both schools are located in a non-urban area. $\hat{\beta}_{ols}$ represents the OLS estimate of β, defined in Eq. (14), and $\hat{\beta}_{placebo}$ represents the OLS estimate of $\beta_{placebo}$, defined in Eq. (15). "Observations" refers to the number of unique block pairs used in the regressions. Standard errors, shown in parentheses, are corrected for heteroskedasticity and clustered by attendance area pair, (s, s'). *** denotes significance at the 1% level; and * denotes significance at the 10% level.

Table 3
The relative role of school factors on school segregation by grade.

	Elementary Grades		Middle Grades		Secondary Grades	
	$\hat{\beta}_{ols}$	$\hat{\beta}_{placebo}$	$\hat{\beta}_{ols}$	$\hat{\beta}_{placebo}$	$\hat{\beta}_{ols}$	$\hat{\beta}_{placebo}$
Race	0.53***	0.02	0.45***	0.03	0.35***	0.03
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
Income	0.62***	0.02	0.50***	0.03	0.58***	0.03
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	12,661		9,256		9,700	

Notes: "All Schools" refers to the full sample of school pairs. "Elementary Grades," "Middle Grades," and "Secondary Grades" refers to the sample of school pairs that serve students in grades 3 through 5, 6 through 8, and 9 through 12, respectively. $\hat{\beta}_{ols}$ represents the OLS estimate of β, defined in Eq. (14), and $\hat{\beta}_{placebo}$ represents the OLS estimate of $\beta_{placebo}$, defined in Eq. (15). "Observations" refers to the number of unique block pairs used in the regressions. Standard errors, shown in parentheses, are corrected for heteroskedasticity and clustered by attendance area pair, (s, s'). *** denotes significance at the 1% level.

4.3. Grade level

We also report our results by grade level, presenting the associated results in Table 3. The columns "Elementary grades," "Middle grades," and "Secondary grades" restrict attention to students enrolled in grades 3 through 5, 6 through 8, and 9 through 12, respectively. The estimates indicate that the importance of school features in explaining racial school segregation is monotonically decreasing in the grade level, with such features accounting for 51% (=53–2), 42% (=45–3), and 32% (=35–3) of the variation in the elementary, middle, and high grades, respectively. The analogous income results are 60%, 47% and 55%. (All pairwise differences are significant at the 1% level.)

5. Addressing potential validity concerns

In this section, we assess the extent to which our results are robust to potential concerns about the validity of our estimates.

5.1. Geographical features (e.g., Major Roads, Lakes) coinciding with boundaries

As in the boundary fixed effects literature, a key validity concern is that boundaries may coincide with particular geographical features, such as rivers, lakes, or major roads. In this scenario, differences in the socioeconomic composition of those residing in block k_1 and those residing in block k'_1 would reflect not only S, but N as well. Assumption 2′ would then be violated, as the difference between k_1 and k'_1 would tend to be larger than the difference between k_2 and k_1. Importantly however, this would bias our estimates of the role of S upward, making our conclusion that N plays a key role conservative.

Regardless, Fig. 5 shows why local differences at the boundary, if they exist, are not first order in our context.[18] It plots the average proportion of elementary students in each block who are white (π_k^{white}) for blocks ranging from k_{30} to k'_{30}.[19] This average is calculated across all boundaries for each block k_l (k'_l), where l reflects the number of degrees of separation from the boundary.[20] In the plot, we

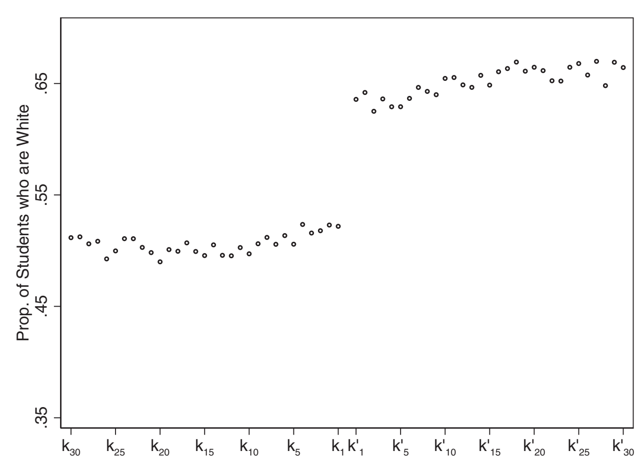


Fig. 5. Proportion of Elementary Students who are White in Each Block. *Notes*: This figure plots the average proportion of students who are white across all boundaries for each block k_l (k'_l). The index l reflects the number of degrees of separation from the boundary in their corresponding attendance area. See footnote 20 for details on how l is measured. The attendance area on the right of each pair is the one that attracts white students disproportionately.

[18] Appendix Fig. C.1 presents analogous plots for each combination of grade range, race and income.

[19] Note that Fig. 5 is the empirical analog of the theoretical Fig. 2 aggregated across all boundaries, given that only π_k is observed directly (rather than S_k or N_k).

[20] Block k_2 is indexed as "2" because it is the nearest block (in terms of the Euclidian distance) to block k_1, among all blocks located within attendance area s that are adjacent to block k_1 but not to block k'_1. For $l \geqslant 3$, block k_l is indexed as "l" because it is the nearest block to block k_{l-1}, among all blocks located within attendance area s that are adjacent to block k_{l-1} but not to block k_{l-2}. We use an analogous definition for each block in attendance area s'. We truncate the plot at 30 to avoid any potential selection issue, as some attendance areas have no more than 30 degrees of separation from the boundary. Results are unchanged if we use different notions of distance.

assign the school with the largest proportion of students who are white to the right-hand-side attendance area (s').[21]

Note a salient feature of the figure: as one approaches the boundary from the left (block k_1), the slope is similar to the slope as one approaches it from the right (block k'_1). This leads us to conclude that geographical features coinciding with a boundary do not play a first-order role in our analysis, and that Assumption 2′ (N varies linearly at the boundary) is valid. We now explain the logic of this conclusion in greater detail.

Fig. 5 looks very different from what it would look like if major roads, lakes, or rivers tended to coincide with attendance area boundaries. For instance, consider a case in which all boundaries coincide with a disamenity, which attracts a disproportionately low number of affluent families (e.g., a major road). Then one would expect affluent families on both sides of the boundary would disproportionately want to reside farther from the boundary. In terms of Fig. 5, this would imply a negative slope when approaching the boundary from the left and a positive slope when approaching it from the right (in other words, opposite signed slopes).[22] We discuss this concern in detail in Appendix B.3, in which we implement a series of Monte Carlo experiments to convey this point, and conclude that Fig. 5 rules out biases of this type that are larger than two percentage points.

Finally, there is an alternative manifestation of this concern that is not addressed by Fig. 5. Perhaps the disamenity of residing near a major road (or the amenity of residing near a lake) dissipates over a very short distance, in no more than one block. This cannot be detected by Fig. 5, as it will only affect the discontinuity at the boundary, but not the slopes around both sides of the boundary. An approach that handles this concern is one exactly like our primary one, but without considering the existence of the blocks closest to the boundary, k_1 and k'_1 (analogously to a "donut" regression discontinuity design approach – for example, see Barreca et al., 2011). Specifically, we estimate $\hat{\Omega}_S^{donut} := \hat{\beta}_2 - \hat{\beta}_{placebo}$ where $\hat{\beta}_2$ is the OLS estimate of the regression of $\Delta\pi_{k_2,k'_2}$ on $\Delta\pi_{s,s'}$. We find $\hat{\Omega}_S^{donut}$ to be very similar to $\hat{\Omega}_S$, suggesting that this potential issue is not of primary importance in our context.[23]

Note that the "donut" strategy cannot rule out the possibility of a neighborhood amenity that is discontinuous at the boundary, but does not dissipate over a short distance from the boundary (e.g., a cliff coinciding with the boundary, where a disproportionate number of affluent households prefer to reside at the top rather than the bottom of the cliff, irrespective of the distance to the boundary). If that was the case, then we would be overestimating the role school amenities play in explaining school segregation, as we would be wrongly attributing part of the discontinuity at the boundary to school amenities. However, we find it unlikely that this potential confounder would play a first-order role with respect to our findings.

Remark 1. The interpretation of Ω_S as a proportion hinges on it being bounded between 0 and 1. Note, upon inspection of Eq. (7), that this is violated only if the covariance $cov(\Delta S, \Delta N)$ is negative and larger in magnitude than only one of the variance terms. However, Fig. 5 suggests that $cov(\Delta S, \Delta N) > 0$, which guarantees $\Omega_S \in [0, 1]$. To see why, note that there is a positive discontinuity at the boundary and a positive slope on both sides of the boundary. While the discontinuity speaks to the role of ΔS, the slopes speak to the role of ΔN. Thus, we conclude that attendance areas tending to attract a disproportionate number of affluent families because of their school amenities also tend to attract a disproportionate number of affluent families because of their neighborhood amenities.

5.2. Distance between residence and school

Another potential concern is the possibility that households care about how close to the school they reside within the attendance area. For instance, parents may care about the commute cost from their home to the school. Alternatively, it may be beneficial to reside closer to the school, since they would have disproportional access to some of the school's off-hours amenities (e.g., playground).

This concern could generate bias in our main estimate only if students of one type have more intense preferences than students of the other type. For instance, consider the example in which affluent families care more about residing near the school than non-affluent families. Then Assumption 1 would be violated, since $\mathbb{S}$ would vary within the attendance area.[24]

Fortunately, Fig. 5 is capable of detecting such an issue. Given that the school's location tends to be in the interior of the attendance area (as opposed to exactly at the boundary), we would observe a higher proportion of affluent families clustering near the school on both sides. In this case, Fig. 5 would look very different from what we see: the slope as one approaches the boundary from the left would be negative, while the slope as one approaches it from the right would be positive. In particular, these slopes would be different from each other.

In Appendix B.4, we discuss this concern in greater detail, implementing a series of Monte Carlo experiments to convey this point, and concluding that Fig. 5 rules out biases of this type that are larger than one percentage point.

5.3. Multidimensional sorting

Another potential concern is that the primary dimension along which sorting occurs (e.g., race or income) is setting-dependent. For example, sorting in urban areas may happen predominantly by race, while sorting in non-urban areas may be mainly due to income. If that were the case, then the race estimate in Table 2 would more accurately reflect the role of school factors in urban areas, while the income estimate would more accurately reflect the role of school factors in non-urban areas.

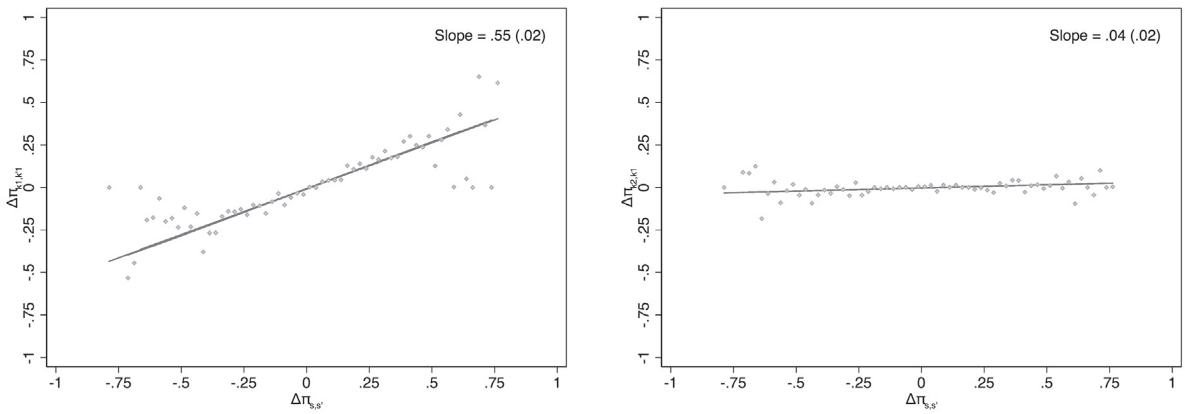
To assess this concern, we perform a robustness check by estimating versions of Eqs. (14) and (15) using two dimensions simultaneously. Specifically, in the case of Eq. (14), we calculate the extent to which $\Delta\pi_{s,s'}^{rich\ white}$ helps predict $\Delta\pi_{k_1,k'_1}^{rich\ white}$, where $\pi_s^{rich\ white}$ and $\pi_k^{rich\ white}$ respectively represent the proportion of students in school s and block k who are both economically advantaged and white, compared to all other types (non-white of any income, or economically disadvantaged and white). Eq. (15) is estimated analogously.

[21] We have not done so when implementing our approach in the previous sections, as our research design is agnostic to which side is more attractive to a given group. Indeed, our approach yields virtually the same estimates when we choose attendance area s to be the one that attracts white households disproportionately.

[22] Alternatively, consider the case of a boundary amenity, which attracts a disproportionately high number of affluent families (e.g., a picturesque lake). Using the same logic, affluent families on both sides of the boundary would tend to concentrate around the boundaries. This would imply a positive slope when approaching the boundary from the left and a negative slope when approaching it from the right (i.e., opposite signed slopes, once again).

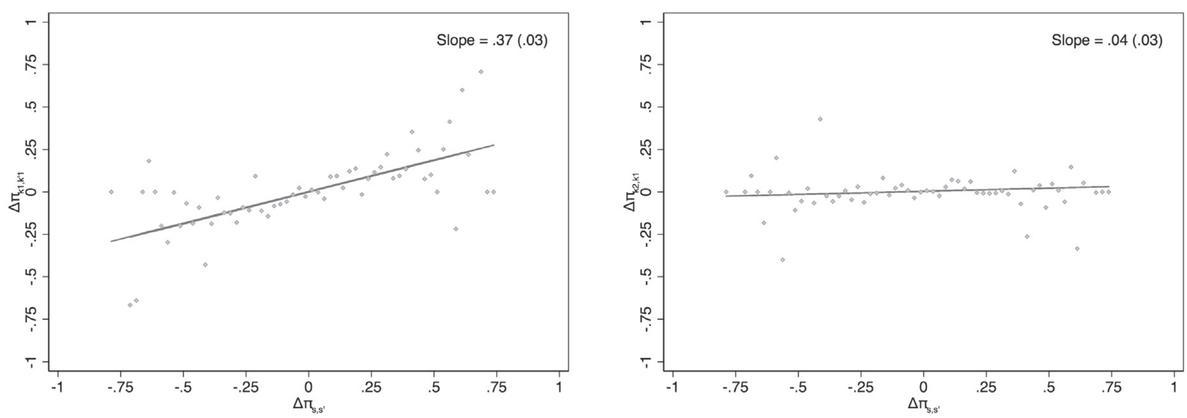
[23] The similarity between $\hat{\Omega}_S$ and $\hat{\Omega}_S^{donut}$ also suggests that restricting our sample to only boundary blocks that were not bisected by the attendance boundary does not generate any bias (as noted in footnote 15).

[24] Even the weaker version of Assumption 1 (defined in footnote 5) would be violated in this case, as the discontinuity in $\mathbb{S}_k$ at the boundary would not be representative of the discontinuity overall. However, the weaker version would not be violated if preferences over the residence-school distance were homogeneous, even if the location of the school were farther from the boundary on one side versus the other.



(a) Blocks in Different Attendance Areas (b) Blocks in the Same Attendance Area

Fig. 6. The Effect of $\Delta\pi^{rich\ white}_{s,s'}$ on $\Delta\pi^{rich\ white}_{k_1,k_1'}$ – All Schools. *Notes*: See the notes for Fig. 3, which presents the analogous results by race.



(a) Blocks in Different Attendance Areas (b) Blocks in the Same Attendance Area

Fig. 7. The Effect of $\Delta\pi^{rich\ white}_{s,s'}$ on $\Delta\pi^{rich\ white}_{k_1,k_1'}$ – Urban Schools Only. *Notes*: See the notes for Fig. 3, which presents the analogous results by race and for all schools.

The corresponding plots are shown in Fig. 6 for all schools and Fig. 7 for urban schools, for comparison purposes with respect to the results in Table 2. Consistent with the example above, the estimate across all schools (51%=55% − 4%) is closer to the main unidimensional estimate for *income* (54%=57% − 3%), while the estimate for the urban sub-sample (33%=37% − 4%) is closer to the unidimensional estimate for *race* (35%=37% − 2%). This suggests that sorting by race (due to both *S* and *N*) is better at explaining school segregation in urban areas, while sorting by income has more explanatory power outside of them.

6. Sources of variation

In this section, we address considerations regarding the sources of variation we exploit, through several sensitivity analyses summarized in Table 4. For convenience, the first column reports the baseline estimates of $\hat{\Omega}_S$ for all schools in our sample, as implied by the first column of Table 2.

6.1. Are comparisons too local?

One concern is that the relative role of school features in explaining school segregation may depend on the locality of between-school comparisons. Indeed, schools within the same district are likely to be more similar than schools located in different districts. Thus, focusing exclusively on school comparisons within the same district may fail to recover the full scope of school policies affecting segregation (particularly those that vary across districts). However, an analogous argument applies to neighborhood amenities: it is likely that neighborhoods within the same district would be more similar than neighborhoods in different districts, which implies that we may also not recover the full scope of non-school policies (again, particularly those that vary across districts). Ultimately, which of these forces prevails is an empirical question. Accordingly, we assess whether the relative role of school factors changes substantially if our analysis includes school pairs that are located in different districts. Comparing the first (within-district baseline) and second (within and across districts) columns of Table 4, we do not find a systematic difference for race or income when we include schools in different districts in our analysis.[25]

A related concern is that we do not compare schools that are located in different cities. Indeed, while $|\Delta\pi_{s,s'}|$ ranges from 0 to

[25] These results corroborate our finding in Section 5.1 that pre-existing differences at the boundary (e.g., due to a major road or river) do not drive our results. Indeed, it is intuitive that boundaries separating school districts are more likely to be coincident with such barriers than boundaries within districts.

Table 4
Robustness checks.

	Baseline	Within and Across Districts	Control for Intensity of School Choice	Control for School Observables
Race	0.42	0.44	0.43	0.39
	(0.02)	(0.02)	(0.02)	(0.03)
Income	0.54	0.53	0.54	0.43
	(0.02)	(0.02)	(0.03)	(0.03)
Observations	31,617	41,332	31,617	31,617

Notes: This table shows the estimates of $\hat{\Omega}_S := \hat{\beta} - \hat{\beta}_{placebo}$ (obtained from Eqs. (14) and (15)) for different specifications and samples. The first column refers to the "all schools" results from Tables 2, which are our baseline results to which the results in the other columns should be compared. In the second column ("Within and Across Districts"), we also include boundaries separating schools from different districts. In the third column ("Control for Intensity of School Choice"), we add controls for the total number of blocks in attendance areas s and s' (a cubic B-spline for this quantity) and indicators for whether charter or magnet schools are located near either of the two attendance areas s and s'. Finally, in the fourth column ("Control for School Observables") we add as control variables the difference across schools s and s' of a wide list of observable characteristics of the schools - see footnote 29 for details. "Observations" refers to the number of unique observations used in the regressions. Standard errors, shown in parentheses, are corrected for heteroskedasticity and clustered by attendance area pair, (s, s').

0.9 in our sample of adjacent school pairs, it ranges from 0 to 1 in the full sample, containing all school pairs in the state. As with the discussion above, this raises a potential external validity issue: our findings using adjacent schools (in order to address internal validity concerns) may not be relevant to across-city comparisons. To the extent that is the case, our estimates are likely to *understate* the importance of non-school factors in explaining school segregation overall. To see this, note that the choice of the metropolitan or rural area in which to reside should depend predominantly on non-school factors, such as employment prospects. It is only once families have selected a commuting zone that school considerations are likely to become first order, with school and neighborhood amenities determining local sorting patterns. Thus, the inclusion of school comparisons across commuting zones (for example, Durham versus Charlotte) would make non-school factors even stronger determinants of school segregation.

6.2. Does the relative role of N depend on the size of the attendance areas or the presence of charter and magnet schools?

Yet another potential concern is that the relative role of S and N may depend on the degree of school choice available to parents. For instance, although North Carolina does not allow open enrollment during our period of interest, one may be concerned that there is increased scope for N to change within an urban attendance area, given that attendance areas in urban settings contain a greater number of blocks than in non-urban settings (as Table 1 shows). This could imply a larger role for N in urban settings, relative to their non-urban counterparts. This mechanical effect contrasts with our explanation for the prominent role of N in urban areas, which is that the density of neighborhood features change more intensely from one block to the next in urban relative to non-urban areas.

Another related possibility is that charter and magnet schools, which are more prevalent in urban areas, may be indirectly affecting our results. In our calculations, we did not count students who were attending those schools, potentially leading to a selection issue that affects urban areas more intensely than non-urban areas.

To rule out these alternative mechanical explanations, we flexibly control for the total number of blocks in attendance areas s and s',[26] as well as for whether charter or magnet schools are located near either of the two attendance areas s and s'.[27] The results are reported in column three of Table 4. They are statistically indistinguishable from the baseline effects in column one, supporting our explanation.[28]

6.3. To what extent does S project onto observable school characteristics?

Finally, we assess the extent to which the component we construe as being related to school factors (S) is correlated with a rich set of observable school characteristics. We do so by comparing our baseline estimate $\hat{\Omega}_S$ to the analogous coefficient in a regression that also conditions on differences between observed school characteristics.[29] Intuitively, as the characteristics are likely to be more correlated with S than with N, their inclusion in the regression should disproportionately absorb school factors and lower the value of $\hat{\Omega}_S$. That is precisely what we find for both race and income (see column four of Table 4). We view this evidence as an independent confirmation of what S represents. Moreover, the fact that $\hat{\Omega}_S$ remains substantial even with school controls suggests that unobserved school amenities are important determinants of school sorting.

7. The role of $cov(S_{s,s'}, N_{s,s'})$

Note that Ω_S attributes half of the covariance term, $2 \cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'})$, to each factor. Of course, this attribution is arbitrary. We have suggestive evidence that the covariance is positive (see Remark 1), but without further assumptions, it is unclear how to attribute it to each factor. While it is possible that the term is entirely driven by $\Delta S_{s,s'}$ affecting $\Delta N_{s,s'}$, or entirely driven by $\Delta N_{s,s'}$ affecting $\Delta S_{s,s'}$, it is more likely that some combination of the two causal relationships prevails.[30]

[26] To account for non-linearities, we add them as cubic B-splines with five equally spaced knots (so there are a total of four control variables added).

[27] In the table, we report results using a strict notion of distance: whether either type of choice school is located within one of the two attendance areas. Our results are essentially invariant to alternative notions of distance.

[28] We also consider a potential concern associated with the size of the attendance area relative to the boundary block: there should be some mechanical relationship between $\hat{\pi}_{k_1,k_1'}$ and $\hat{\pi}_{s,s'}$, given that attendance areas include boundary blocks. Reassuringly, we obtain very similar results if we construct $\hat{\pi}_{s,s'}$ without including boundary blocks in its calculation. This is not surprising, as a block accounts for a very small portion of the full attendance area.

[29] The included variables are the differences between schools s and s' of the following school characteristics: standardized mathematics and reading test scores, whether the school met adequate yearly progress under the federal No Child Left Behind act, average class size, the proportion of fully licensed teachers, the rate of teacher turnover, the proportion of teachers with 0 to 3, 4 to 10, and 11 or more years of experience, the proportion of teachers with an advanced college degree, Title I status, the proportion of classrooms connected to the Internet, the number of library books and their average age, total enrollment, and the proportion of students who are female, are limited English proficient, are classified as gifted (separately for mathematics and reading), are classified as disabled, and attend school daily.

[30] By assumption in our decomposition, there is no room for a third type of amenity originally causing both $\Delta S_{s,s'}$ and $\Delta N_{s,s'}$.

It is infeasible to estimate how the covariance should be attributed for two reasons. First, we would have to identify two causal relationships without stating *ex ante* what $\Delta S_{s,s'}$ and $\Delta N_{s,s'}$ represent in terms of observables. Second, even if we were able to uncover these relationships, we would only do so for a specific geographic area and a specific period of time, which would raise issues of external validity. For instance, it is likely that the direction of causality from $\Delta S_{s,s'}$ to $\Delta N_{s,s'}$ would dominate during periods in which educational policies are more prevalent, while the opposite direction of causality would dominate during periods in which residential policies are more prevalent. We are only able to observe a cross-sectional snapshot, reflecting the cumulative impact of both causal relationships over time.

In what follows, we consider a simple dynamic model of how this covariance came to be. Through the lens of this model, we are able to enhance the interpretation of our results by offering a theoretically sound attribution of the covariance term.

7.1. A dynamic model generating $cov(\Delta S_{s,s'}, \Delta N_{s,s'}) \neq 0$

Suppose that, for some initial period (period 0), two adjacent attendance areas differ by a small set of amenities. These amenities are considered to be "exogenous" for our purposes; they are not of direct interest, but rather provide the initial seed that generates differences in proportions across neighborhoods. A good example of an exogenous amenity is an inherent topographical feature, including the distance to a river, the degree to which the land is fertile, and the elevation of the terrain.[31] Accordingly, we model the initial difference for each pair of attendance areas s and s' as arising from a shock $\Delta\eta_0 := \Delta\eta_0^N$, which is entirely attributable to neighborhood features.[32]

People then sort based on these original differences, which begets additional differences in amenities – denoted as "endogenous." While some of these endogenous amenities evolve mechanically with socioeconomic composition (e.g., racial composition of school peers or neighbors), other endogenous amenities may vary with the socioeconomic composition via a less well-known and potentially more complex process (e.g., educational and residential policies, local taxes, and the provision of local goods and services, such as schools and venue offerings). Households may sort further based on these endogenous changes, leading to yet more endogenous changes in amenities, potentially creating a positive feedback loop. Attendance areas are observed by the researcher only after several decades of this endogenous process taking place.

The evolution of the difference in socioeconomic composition between two schools can be expressed as:

$$\Delta\pi_t - \Delta\pi_{t-1} = \Delta\eta_{t-1}^N + \psi^S[\Delta\pi_{t-1} - \Delta\pi_{t-2}] + \psi^N[\Delta\pi_{t-1} - \Delta\pi_{t-2}], \qquad (16)$$

where the relationship depends linearly on the prior shock and the endogenous shocks triggered by that prior shock. The last two terms of Eq. (16) represent endogenous shocks attributable to schools and neighborhoods, reflected by the parameters ψ^S and ψ^N, respectively. We view these parameters as being representative of the true time-varying parameters $\tilde{\psi}_t^S$ and $\tilde{\psi}_t^N$ over the long run, averaging across them from period 0 to the period in which we observe the data. Thus, ψ^S and ψ^N subsume endogenous sorting and policies that have taken place over time, including any potential frictions that limit the degree of sorting.[33]

Based on Eq. (16), we are able to develop a generic expression for $\Delta\pi_t$, the difference in socioeconomic composition between the two schools in period t, which depends only on the initial shock $\Delta\eta_0^N$, and parameters ψ^S and ψ^N. Given initial conditions $\Delta\pi_{t'} = 0$ for $t' \leq 0$ (neighborhoods are identical prior to period 0), we have $\Delta\pi_0 - \Delta\pi_{-1} = 0$. Consequently, the period 1 difference is determined only by the overall period 0 shock: $\Delta\pi_1 = \Delta\eta_0$. The general expression for $t > 1$ is $\Delta\pi_t = \sum_{w=0}^{t-1}\Psi^w\Delta\eta_0$, where $\Psi := \psi^S + \psi^N$.[34] As long as $\Psi \neq 1$, the expression simplifies to $\Delta\pi_t = \left(\frac{1-\Psi^t}{1-\Psi}\right)\Delta\eta_0$. We focus on stable non-oscillatory solutions by restricting attention to $0 \leqslant \Psi < 1$.[35] Thus, in the limit as $t \to \infty$ (long-run stable equilibrium), we have $\Delta\pi = \frac{\Delta\eta_0}{1-\Psi}$.

We now describe ΔS and ΔN in terms of these parameters:

$$\begin{aligned}
\Delta S &= \left[\psi^S + \psi^S\Psi + \psi^S\Psi^2 + \ldots\right]\Delta\eta_0^N \\
&= \psi^S\left[\sum_{w=0}^{\infty}\Psi^w\right]\Delta\eta_0^N \\
&= \frac{\psi^S\Delta\eta_0^N}{1-\Psi} \text{ and} \\
\Delta N &= \Delta\eta_0^N + \left[\psi^N + \psi^N\Psi + \psi^N\Psi^2 + \ldots\right]\Delta\eta_0^N \\
&= \Delta\eta_0^N + \frac{\psi^N\Delta\eta_0^N}{1-\Psi} \\
&= \frac{\left(1-\psi^S\right)\Delta\eta_0^N}{1-\Psi}.
\end{aligned}$$

With these expressions in hand, we can compute $var(\Delta S), var(\Delta N)$ and $cov(\Delta S, \Delta N)$, and thus $var(\Delta\pi) := var(\Delta S) + var(\Delta N) + 2 \cdot cov(\Delta S, \Delta N)$. Assuming that the shock $\Delta\eta_0^N$ is drawn from a distribution with variance σ^2, we obtain:

$$\begin{aligned}
var(\Delta\pi) &= \frac{1}{(1-\Psi)^2}\sigma^2, \\
var(\Delta S) &= \frac{\left(\psi^S\right)^2}{(1-\Psi)^2}\sigma^2, \\
var(\Delta N) &= \frac{\left(1-\psi^S\right)^2}{(1-\Psi)^2}\sigma^2, \\
cov(\Delta S, \Delta N) &= \frac{\psi^S\left(1-\psi^S\right)}{(1-\Psi)^2}\sigma^2.
\end{aligned}$$

Using these expressions, we can then compute the following ratios:

$$\frac{var(\Delta S)}{var(\Delta\pi)} = \left(\psi^S\right)^2, \qquad (17)$$

$$\frac{var(\Delta N)}{var(\Delta\pi)} = \left(1-\psi^S\right)^2, \qquad (18)$$

$$\frac{cov(\Delta S, \Delta N)}{var(\Delta\pi)} = \psi^S \cdot \left(1-\psi^S\right), \qquad (19)$$

and relate the estimand Ω_S to the model parameters:

$$\begin{aligned}
\Omega_S &= \frac{var(\Delta S) + cov(\Delta S, \Delta N)}{var(\Delta\pi)} \\
&= \left(\psi^S\right)^2 + \psi^S\left(1-\psi^S\right) \\
&= \psi^S.
\end{aligned} \qquad (20)$$

Thus, the dynamic model tells us that by identifying Ω_S we are also identifying ψ^S, which, in turn, allows us to recover the quantities in Eqs. (17)–(19). For any value γ, we define:

[31] Lee and Lin, 2017 studies the dynamic consequences of persistent natural neighborhood amenities.

[32] For expositional convenience, we omit the subscript referring to the school pair.

[33] Note that, in a context of infinite moving costs, we would have $\psi^S = \psi^N = 0$, as no endogenous sorting would take place.

[34] This can be proven by induction. For example, $\Delta\pi_2 = (1+\Psi)\Delta\eta_0$ is the period 2 expression, while $\Delta\pi_3 = (1+\Psi)\Delta\pi_2 - \Psi\Delta\pi_1 = \left(1+\Psi+\Psi^2\right)\Delta\eta_0$ is the period 3 expression.

[35] Our main conclusions are also valid in the context of oscillatory trajectories to the stable equilibrium ($-1 < \Psi \leq 0$). Many frictions in residential sorting, such as moving costs, lead us to conclude that a multiplicity of equilibria ($|\Psi| > 1$) is not realistic for most schools in our context (see Caetano and Maheshri, 2020).

Table 5
Corrected estimates – the relative role of school and neighborhood factors on school segregation (overall and by urban status).

	All schools	Urban Schools	Non-Urban Schools
Panel A: Race			
$\frac{2\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.49	0.46	0.50
$\Omega_S := \frac{var(\Delta S)+cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.42	0.35	0.45
$\Omega_S(\gamma=\Omega_S) := \frac{var(\Delta S)+2\cdot\Omega_S\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.38	0.28	0.43
$\frac{var(\Delta S)}{var(\Delta S)+var(\Delta N)}$	0.34	0.22	0.40
Panel B: Income			
$\frac{2\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.50	0.48	0.43
$\Omega_S := \frac{var(\Delta S)+cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.54	0.40	0.69
$\Omega_S(\gamma=\Omega_S) := \frac{var(\Delta S)+2\cdot\Omega_S\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.56	0.35	0.77
$\frac{var(\Delta S)}{var(\Delta S)+var(\Delta N)}$	0.58	0.31	0.83

Notes: This table reports the results from Table 2 through the lens of the dynamic model. Standard errors, calculated via the Delta method, are always below three percentage points and are omitted for clarity.

$$\Omega_S(\gamma) := \frac{var(\Delta S) + 2\cdot\gamma\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}. \quad (21)$$

The term $\Omega_S(\gamma)$ attributes the proportion γ of the covariance term $(2\cdot cov(\Delta S,\Delta N))$ to ΔS and the proportion $(1-\gamma)$ of the term to ΔN.

We are able to identify $\Omega_S(\gamma)$ for any arbitrary γ. However, the model also imposes restrictions on the value γ can take. Based on Eq. (19), the covariance ratio is the product of ψ^S and $1-\psi^S$. Since ψ^S is associated with school amenities (Eq. (17)), while $1-\psi^S$ is associated with neighborhood amenities (Eq. (18)), this suggests a theoretically sound attribution of the covariance term: $\Omega_S = \psi^S$ of the component should be attributed to ΔS, while $\Omega_N = 1-\psi^S$ of the component should be attributed to ΔN.[36] While we would ideally like to obtain a data-driven attribution of γ, that is not possible without more detailed longitudinal data. As such, we rely on a theoretical approach and leave the empirical analogue for future work.

7.2. Results through lens of dynamic model

Table 5 reports our key findings obtained through the lens of the dynamic model. Irrespective of the dimension of segregation or urban status, we find that the covariance component is positive and accounts for approximately 50% of the total variance, $var(\Delta\pi)$ (see the first row of each panel). Our finding of the covariance being positive independently corroborates Remark 1. In theory, the covariance between ΔS and ΔN could have been negative if school and neighborhood amenities had opposing effects on segregation, as would be the case if either $\psi^S < 0$ (so that $\psi^N > 0$, from $0 \leqslant \psi^S + \psi^N < 1$) or $\psi^S > 1$ (so that $\psi^N < 0$). Instead, we find $0 < \Omega_S = \psi^S < 1$ in all cases (reproduced from Table 2 and reported in the second row of each panel). This is an intuitive result: for instance, schools with higher test scores are likely to attract a disproportionate number of affluent students (all else equal), which may in turn attract a disproportionate number of affluent households without children.

The third row of each panel in Table 5 reports $\Omega_S(\gamma=\Omega_S)$, which attributes Ω_S of the covariance term to S and $1-\Omega_S$ to N. The resulting estimates constitute our headline results. They reveal even stronger gaps between urban and non-urban estimates: the role of school factors in explaining racial and income segregation is substantially smaller in urban areas (28% and 35%, respectively) than in non-urban areas (43% and 77%, respectively). As discussed in the introduction, these results are likely due to the greater complexity of neighborhood features in urban relative to non-urban settings. Features, such as specific venues or sidewalks, tend to be perceived as being more similar in non-urban areas, particularly given that residents of those places are more likely to travel by car. It is noteworthy that school sorting on the basis of income and race are more similar in urban areas but differ dramatically in non-urban areas. Indeed, in non-urban areas, neighborhood factors matter much less for school sorting on the basis of income than for sorting on the basis of race, which would occur if more affluent households use cars to access neighborhood amenities in non-urban areas more intensely than less affluent households.

For completeness, the fourth row of each panel reports estimates corresponding to an alternative measure of the importance of school factors in explaining school segregation. This quantity, $\frac{var(\Delta S)}{var(\Delta S)+var(\Delta N)}$, removes the covariance term entirely, providing a useful measure that is agnostic about the attribution of the covariance term. Note that $\Omega_S(\gamma=\Omega_S)$ can be thought of as an intermediate measure between Ω_S and $\frac{var(\Delta S)}{var(\Delta S)+var(\Delta N)}$. Regardless of the measure, we find that neighborhood factors are key for understanding school segregation, particularly in urban areas.

Table 6 reports analogous estimates by grade level. As with the results overall and by urban status, the covariance component represents approximately 50% of the total variance, irrespective of the grade level. After re-attributing the covariance term, the third row shows that school factors explain 52%, 38%, and 24% of racial segregation in elementary, middle, and secondary grades, respectively. The analogous estimates for income segregation are 65%, 46%, and 57%.

To provide context for these findings, note that attendance areas tend to be geographically smaller for earlier grades (as shown in Table 1). Thus, households with students in elementary grades have a greater number of school options to choose from, relative to households with students in middle grades (with a similar but less pronounced relationship between middle and secondary grades). Yet these households have identical housing options (and thus neighborhood amenities) from which to choose. If household valuations of school and neighborhood features are grade-invariant, then school factors should explain more of the variation in school segregation for earlier grades, which is broadly in line with the patterns we uncover. The exception is the income result for secondary grades. We conjecture that the income gap in valua-

[36] Note also that Eq. (19) rules out performing a bounding exercise in which Ω_S is recalculated assuming all ($\gamma=1$) or none ($\gamma=0$) of the covariance term is attributable to ΔS. This is due to the covariance term itself depending on γ. For instance, consider the case in which $\gamma=\psi^S$. If we had found that $\psi^S=0$ or $\psi^S=1$, then Eq. (19) would imply the covariance term would be zero.

Table 6
Corrected estimates – the relative role of school and neighborhood features on school segregation (by grade level).

	Elementary Grades	Middle Grades	Secondary Grades
Panel A: Race			
$\frac{2\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.50	0.49	0.44
$\Omega_S := \frac{var(\Delta S)+cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.51	0.42	0.32
$\Omega_S(\Omega_S) := \frac{var(\Delta S)+2\cdot\Omega_S\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.52	0.38	0.24
$\frac{var(\Delta S)}{var(\Delta S)+var(\Delta N)}$	0.52	0.34	0.18
Panel B: Income			
$\frac{2\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.48	0.50	0.50
$\Omega_S := \frac{var(\Delta S)+cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.60	0.47	0.55
$\Omega_S(\Omega_S) := \frac{var(\Delta S)+2\cdot\Omega_S\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}$	0.65	0.46	0.57
$\frac{var(\Delta S)}{var(\Delta S)+var(\Delta N)}$	0.69	0.44	0.60

Notes: This table shows the results from Table 3 through the lens of the dynamic model. Standard errors calculated via the Delta method are always below three percentage points and are omitted for clarity.

tion of school amenities for secondary grades is higher than the corresponding gap for middle grades.[37]

8. Conclusion

This article has attempted to underscore the key role that neighborhood factors play in explaining school socioeconomic segregation. Given that school and residential decisions are often made jointly, both school and neighborhood factors should affect school segregation, but little has been previously established about their relative importance. We found that 62% of school segregation by race and 44% of school segregation by income is attributable to neighborhood factors. Importantly, they tend to matter even more in urban environments, settings in which school segregation has received disproportionate attention.

Our results have implications for the efficiency and efficacy of widely implemented policies that hold educators accountable for scholastic outcomes. It is inefficient to reward or punish them for outcomes that are beyond their control. As student outcomes depend on the degree of school segregation, the first-order importance of neighborhood factors in explaining such segregation implies that a substantial portion of outcome variation is under the control of urban policymakers, especially in urban areas. Without urban policymakers playing an active role in the process, efforts to lower school segregation through well meaning educational policies are likely to be insufficient.

In future research, it would be interesting to replicate these results for additional states. Many areas of North Carolina have been subject to a variety of educational policies over the past few decades, including those providing school choice. At the same time, many school boards have repeatedly attempted to lower segregation through attendance boundary shifts in order to counteract gradual household re-sorting (Macartney and Singleton, 2018). The fact that neighborhood factors are central in explaining school segregation given this policy backdrop suggests that our conclusions about their importance may be conservative when applied to other regions.

More broadly, using Census data, our approach can be adapted to study the role of school and neighborhood factors in explaining *neighborhood* segregation. Doing so could uncover important heterogeneity between school and neighborhood sorting beyond what can be studied using our data. Related, additional demographic information about the parents of students, such as their marital status, age, and education,[38] could allow us to investigate patterns of sorting along many dimensions beyond race and income. We view this article as enabling a new line of inquiry into confronting segregation, a matter of great importance to society.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Justifying the linear-on-linear approximation

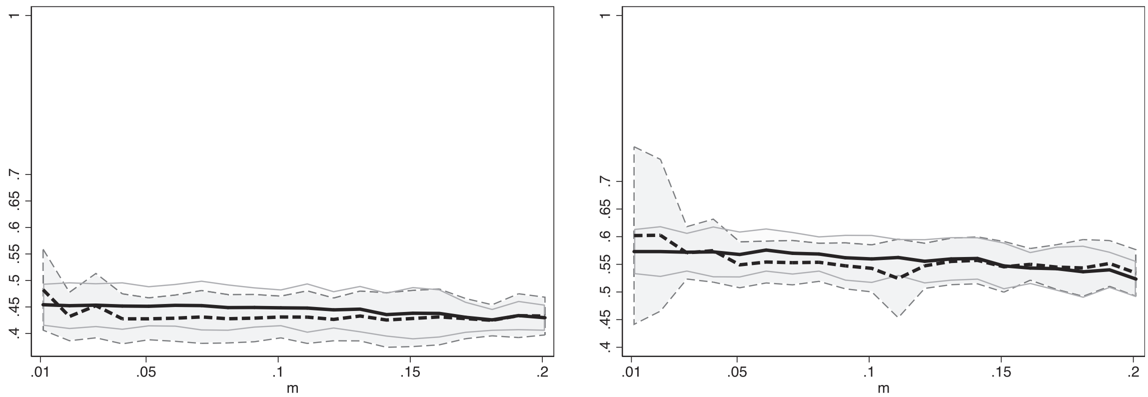
As discussed in Section 2, it is infeasible to estimate $\hat{\Omega}_S^{log}$, since $\ln\left(\frac{\hat{\pi}_{k_1}\left(1-\hat{\pi}_{k_1'}\right)}{\hat{\pi}_{k_1'}\left(1-\hat{\pi}_{k_1}\right)}\right)$ is undefined for many blocks. Indeed, $\hat{\pi}_k$ is equal to either 0 or 1 even when $0 < \pi_k < 1$. Here, we argue that $\hat{\Omega}_S$, obtained from the linear-on-linear regressions (14) and (15), offers a feasible alternative estimator to $\hat{\Omega}_S^{log}$.

It is evident that $\hat{\Omega}_S$ is always well defined, even when $\hat{\pi}_k$ is equal to 0 or 1. So it is sufficient to show that $\hat{\Omega}_S$ and $\hat{\Omega}_S^{log}$ approximately estimate the same object. In Section B.2, we provide a Monte Carlo simulation showing that this is the case even when there is only one student per block, so that $\hat{\pi}_k$ can only take values 0 or 1 irrespective of π_k. Here, we provide more direct evidence demonstrating that, whenever $\hat{\Omega}_S^{log}$ is feasible, it yields the same results in our empirical analysis as $\hat{\Omega}_S$.

We accomplish this by reducing the role of noise in the estimation of β^{log}. We aggregate across all school pairs with sufficiently similar values of $\Delta\pi_{s,s'}$. The proportion difference $\Delta\pi_{s,s'}$, which is a continuous variable bounded between -1 to 1, is discretized in intervals of width m, and we calculate the average of $\ln\left(\frac{\hat{\pi}_{k_1}\left(1-\hat{\pi}_{k_1'}\right)}{\hat{\pi}_{k_1'}\left(1-\hat{\pi}_{k_1}\right)}\right)$ for each of these intervals. For comparison, we also discretize $\Delta\hat{\pi}_{s,s'}$ in intervals of width m and calculate the average of $\Delta\hat{\pi}_{k_1,k_1'}$ for each interval in order to estimate an aggregated version of the linear-on-linear regression. The left panels of Figs. 3 and 4 in the text provide examples of this aggregation. The scatter plot in

[37] Consistent with this finding, Caetano, 2019 reports that households, particularly wealthier ones, tend to value school quality more at the secondary school level than at the middle grade level.

[38] Parental education and a student's residential location are never simultaneously reported in the NCERDC data.



(a) Race (b) Income

Fig. A.1. Relationship Between Slopes in the Aggregated Log-on-Log Regression (Dashed) and the Aggregated Linear-on-Linear Regression (Solid). *Notes*: This figure plots the slope parameter of the aggregated log-on-log regression (dashed line) and the aggregated linear-on-linear regression (solid line), along with their respective 95% confidence intervals. Block pairs and their corresponding school pairs are aggregated across all boundaries on intervals of width m of the value $\Delta\pi_{s,s'}$, where m changes in the horizontal axis of the figure. The corresponding disaggregated linear-on-linear slope estimates are 0.45 (race) and 0.57 (income), as shown in the left panels of Figs. 3 and 4.

each panel of those figures is obtained by discretizing $\Delta\pi_{s,s'}$ on the horizontal axis using intervals of $m = 0.025$ (2.5 percentage points), and calculating the average of $\Delta\pi_{k_1,k_1'}$ for each discretized value.

Fig. A.1 compares the slope of the aggregated version of the linear-on-linear regression (solid black line) and the slope of the aggregated version of the log-on-log regression (dashed black line) for different values of the aggregation interval m.[39] The corresponding 95% confidence intervals are also shown in gray. The larger the value of m, the more aggregated the data used in the regressions. As Fig. A.1 shows, the slope estimates are very similar to each other, and are in turn similar to the disaggregated slopes shown in the left panel of Figs. 3 and 4 (0.45 for race and 0.57 for income). Importantly, as m becomes smaller, the confidence interval of the log-on-log slope estimator increases while the corresponding confidence interval of the linear-on-linear slope estimator continues to be well behaved. A similar pattern is found in all stratified regressions we attempted (e.g., by urban status, by grade level).

We conclude that the linear-on-linear version of the regression yields the same interpretation of the slope as the log-on-log version of the regression, but with the advantage of being robust to noise. Thus, as discussed in Section 2.3, we can safely interpret $\Delta S_{s,s'}$ as $\left(\phi_S^A - \phi_S^B\right)(\mathbb{S}_s - \mathbb{S}_{s'})$ and $\Delta N_{s,s'}$ as $N_s - N_{s'}$, where $N_s := \ln\left(\sum_{k\in\mathcal{K}_s}\exp\left(\phi_N^A\mathbb{N}_k\right)\right) - \ln\left(\sum_{k\in\mathcal{K}_s}\exp(\phi_N^B\mathbb{N}_k)\right)$.

Appendix B. Monte Carlo

In this appendix, we use a series of Monte Carlo experiments to verify that our method works as expected, and to consider the implications of key violations of our assumptions. We first describe the Monte Carlo setup, and then discuss the results from our simulation.

B.1. Monte Carlo setup

Our simulation includes $n_S = 3,000$ pairs of attendance areas, with each pair corresponding to two schools, denoted s and s', and each attendance area containing $K = 30$ blocks. The number of students residing in block k is given by n_k. We begin by specifying the d.g.p. primitives of Eq. (2) in the main text, repeated here for convenience:

$$\pi_k = \frac{\exp\left(\phi_S^A\mathbb{S}_k + \phi_N^A\mathbb{N}_k\right)}{\exp\left(\phi_S^A\mathbb{S}_k + \phi_N^A\mathbb{N}_k\right) + \exp\left(\phi_S^B\mathbb{S}_k + \phi_N^B\mathbb{N}_k\right)}. \tag{B.1}$$

Let k represent the distance from the middle of the block to the boundary (located at 0), so that $k = -1.5$ refers to block k_2, $k = -0.5$ refers to block k_1, $k = 0.5$ refers to block k_1', and so on.[40]

The school and neighborhood amenities are set as $\mathbb{S}_k = \lambda_S \cdot 1_{\{k>0\}}$ and $\mathbb{N}_k = \frac{\lambda_N}{2\cdot K}\cdot k$, where $(\lambda_S, \lambda_N) \sim \mathcal{N}\left((0,0), \begin{pmatrix} 1 & 1 \\ 1 & 10 \end{pmatrix}\right)$.[41] We set the preference parameters to $\phi_S^A = 3, \phi_N^A = 2.5, \phi_S^B = 2$, and $\phi_N^B = 2$. Note that preferences for $\mathbb{S}$ are assumed to be more intense than preferences for $\mathbb{N}$. Moreover, type A tends to have more intense preferences than type B for both amenities, which implies that the majority of students in the population are of type A.[42] Finally, $S_k := \left(\phi_S^A - \phi_S^B\right)\cdot\mathbb{S}_k$ and $N_k := \left(\phi_N^A - \phi_N^B\right)\cdot\mathbb{N}_k$ are positively correlated to each other: blocks with school amenities that disproportionately attract students of type A tend to also have neighborhood amenities that disproportionately attract students of type A.

Given these primitives, one can calculate $\pi_k, N_k, \Delta S_{s,s'}$ and $\Delta N_{s,s'}$, and thus Ω_S in Eq. (7) from the main text, reproduced here for convenience:

$$\Omega_S := \frac{var(\Delta S_{s,s'}) + cov(\Delta S_{s,s'}, \Delta N_{s,s'})}{var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2\cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'})} \tag{B.2}$$

The parameterizations above describe the population, with key quantities $\pi_k, \pi_s, \pi_{s'}$ and Ω_S. Although Ω_S is calculated directly using Eq. (B.2), it can also be estimated via $\Omega_S^{\log} = \beta^{\log} - \beta^{\log}_{\text{placebo}}$ under Assumption 2′, using the population quantities π_k, π_s and $\pi_{s'}$. We find that Ω_S agrees with $\Omega_S^{\log}$ to six decimal places. This is not surprising, given that Assumption 2′ is valid in this baseline case.

[39] We weight the aggregated regressions by the number of block pairs in each interval.

[40] Doing so ensures that the distance (in terms of k) between any two adjacent blocks is the same: for instance, the distance between k_1 and k_1' is the same as the distance between k_2 and k_1.

[41] We assume that the variance of λ_N is much larger than the variance of λ_S to account for the division by $2\cdot K = 60$ in the definition of $\mathbb{N}_k$.

[42] This implication follows from the normalization $\sum_{\tilde{k}}\exp\left(\delta_{\tilde{k}}^{\tau}\right) = n^{\tau}$. See the discussion preceding Eq. (2) in the main text.

As researchers do not observe the population, we designed the Monte Carlo to take that into account. We exploit the exact source of randomness we discuss in the main text; namely that only one or two students typically reside within a given block. This implies that we do not actually observe π_k, but only an estimate of it. For each Monte Carlo iteration i, instead of observing the population quantity π_k for each block, we observe n_k independent draws of a Bernoulli distribution with probability π_k, which allows us to estimate the realization $\hat{\pi}_k^i$. For instance, if $\pi_k = 0.5$ but $n_k = 1$ for some block k, then $\hat{\pi}_k^i$ can only be equal to 0 or 1, and it will take either value in a given iteration with 50% probability.

Thus, for each iteration of the Monte Carlo, we draw a random sample from the population for all blocks k across all attendance area pairs (s, s'), under the assumption that each block k contains only n_k students. Each student within block k is assigned to type A (as opposed to type B) based on n_k independent draws from the Bernoulli distribution with probability π_k. For each Monte Carlo iteration $i, \hat{\pi}_k^i$ is calculated as the number of type A students drawn in block k divided by the number of draws n_k. Next, we estimate $\hat{\Omega}_S^i := \hat{\beta}^i - \hat{\beta}^i_{placebo}$, where $\hat{\beta}^i$ and $\hat{\beta}^i_{placebo}$ are obtained for each iteration i from Eqs. (14) and (15), respectively. We repeat this process a total of $I = 10,000$ iterations.

B.2. Baseline results

In Fig. B.1 we compare $\hat{\Omega}_S^I = \frac{1}{I}\sum_i \hat{\Omega}_S^i$ with Ω_S for different values of n_k. Given that Ω_S is a population parameter, it is by definition invariant to the value of n_k. However, while $\hat{\Omega}_S^I$ can change with n_k, it is in practice remarkably similar for different values of n_k. We also show that the 95% confidence interval narrows as n_k increases; though even for $n_k = 100, \Omega_S$ lies well within the confidence interval.

This suggests that our method allows us to circumvent the issue of small samples that makes it infeasible to estimate the log-on-log regression (Eq. (8)).[43] Indeed, our method performs very well irrespective of the value of n_k. While $\hat{\Omega}_S^I = 0.6010$ for $n_k = 1$ and $\hat{\Omega}_S^I = 0.6014$ for $n_k = 100$, the true value of the parameter is $\Omega_S = 0.5972$.

To provide some context, Fig. B.2 shows a plot analogous to Fig. 5 from a typical iteration of the Monte Carlo with $n_k = 1\ \forall\, k$. It shows the proportion of students of type A for each block k_l. This figure looks very similar to Fig. 5. In particular, the slope as we approach the boundary from the left is very similar to the slope as we approach the boundary from the right. We will show below how Fig. B.2 would look very different from Fig. 5 under violations of Assumption 2′.

B.3. Geographic features coinciding with boundaries

In this section we consider one specific type of violation from our identifying assumptions. We assume that boundaries coincide with geographic features for all 3,000 boundary pairs. We report results for the case in which people do not want to reside near that geographic feature (e.g., a major road), although we also find similar conclusions for the case in which people prefer to reside near it (e.g., a lake). Specifically, we use the parameter values from the baseline case, with the following exception: instead of the neighborhood component being represented simply by $\phi^\tau \cdot \mathbb{N}_k$, as in the baseline case, we define it to be $\phi^\tau \cdot \mathbb{N}_k + \theta^\tau \cdot |d_k|$, where $|d_k|$ represents the absolute value of the distance from block k to the boundary. Higher values of θ^τ imply that people of type τ prefer residing farther from the boundary with a greater intensity. We

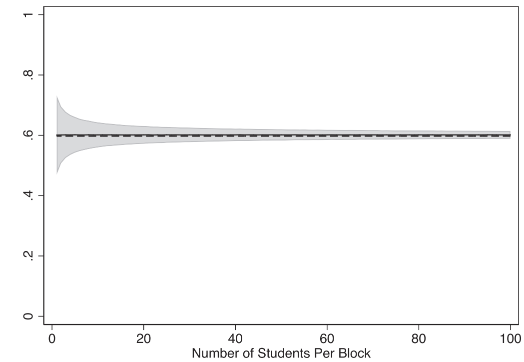


Fig. B.1. $\hat{\Omega}_S^I$ (solid) and Ω_S (dashed). *Notes*: This figure plots $\hat{\Omega}_S^I$ (solid curve) and Ω_S (dashed curve) for each value of n_k. There is a total of $I = 10,000$ iterations for each value of n_k.

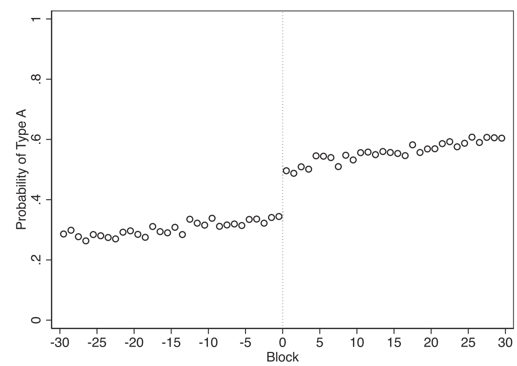


Fig. B.2. Analogous Plot to Fig. 5 for a typical iteration of the Monte Carlo. *Notes*: This figure is analogous to Fig. 5, for a typical iteration of the Monte Carlo with $n_k = 1$. It shows the proportion of students of type A for each block indexed based on their distance to the boundary, calculated across all attendance area pairs. For each pair, the school on the right is the one with the higher school proportion of type A students.

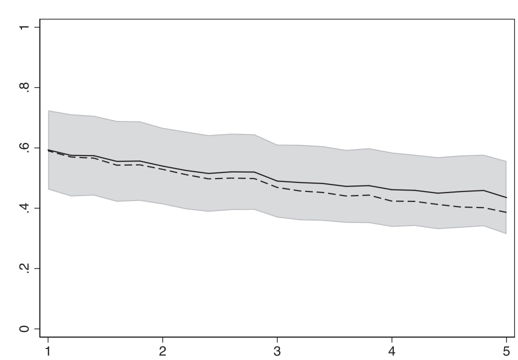
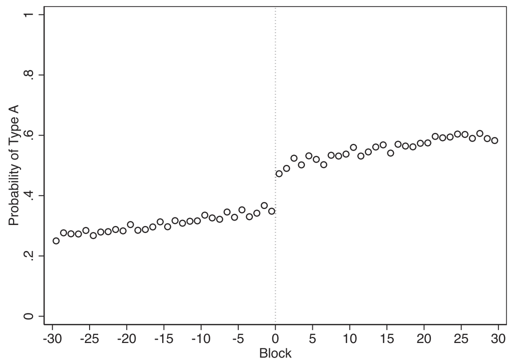
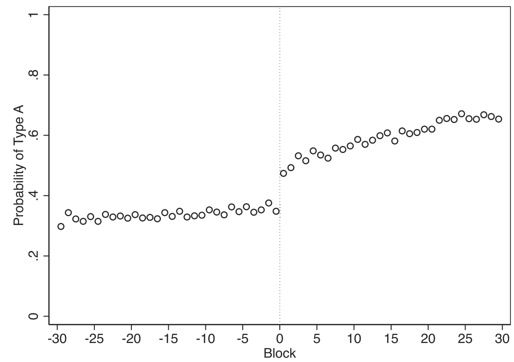


Fig. B.3. $\hat{\Omega}_S^I$ (solid) and Ω_S (dashed) for Different Values of ρ: Distance-to-Boundary. *Notes*: This figure plots $\hat{\Omega}_S^I$ (solid curve) and Ω_S (dashed curve) for each value of ρ. We hold constant $\theta^B = 0.01$ and set $\theta^A = \rho\theta^B$. There is a total of I = 10,000 iterations for each value of ρ.

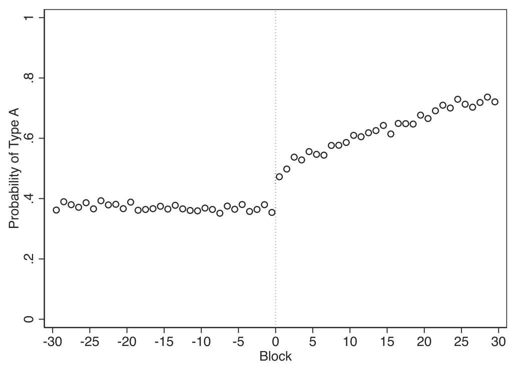
[43] To see why the regression is infeasible, note that the left-hand-side of Eq. (8), $\ln\left[\frac{\hat{\pi}^i_{k_1}\left(1-\hat{\pi}^i_{k'_1}\right)}{\hat{\pi}^i_{k'_1}\left(1-\hat{\pi}^i_{k_1}\right)}\right]$, is undefined for $n_k = 1$. In practice the regression is not feasible for $n_k \leqslant 100$, as one can always find at least one block k with either $\hat{\pi}_k^i = 0$ or $\hat{\pi}_k^i = 1$, especially for blocks with low or high values of π_k.



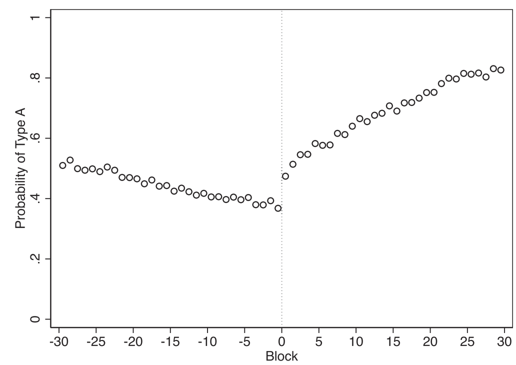
(a) $\rho = 1$



(b) $\rho = 2$



(c) $\rho = 3$



(d) $\rho = 5$

Fig. B.4. Simulated Versions of Fig. 5 for Different Values of ρ: Distance-to-Boundary. *Notes*: These panels show simulated figures analogous to Fig. 5 for the distance-to-boundary analysis. We hold constant $\theta^B = 0.01$ and set $\theta^A = \rho\theta^B$, and change the values of ρ.

report the case in which $\theta^A \geqslant \theta^B$, although a similar conclusion can be drawn from the opposite case. We carry out several different Monte Carlo experiments, considering different preference gaps between θ^A and θ^B.

The results are shown in Fig. B.3. In the horizontal axis, ρ represents the gap between θ^A and θ^B. Specifically, we compare $\hat{\Omega}^I_S$ and Ω_S as we change $\rho := \frac{\theta^A}{\theta^B}$ with $\theta^B = 0.01$. There is no bias for $\rho = 1$, but the bias increases as ρ increases.

We now show how Fig. B.2 (or its empirical analogue, Fig. 5) serves as a good diagnostic tool for detecting this potential bias. Fig. B.4 shows what Fig. B.2 would look like for selected hypothetical values of ρ. When $\rho = 1$, we see that the figure looks very similar to Fig. B.2 (the baseline case). When $\rho = 2$, we already see evidence that Fig. B.4 looks different from Fig. B.2. In particular, the two sides of the boundary have very different slopes. This pattern becomes even clearer when ρ grows further, with a pronounced difference in the slopes across the boundary.

Fig. B.4 is obtained from a typical Monte Carlo iteration, and it is shown here simply for concreteness in the discussion. In reality, there are I such figures, one for each iteration. More formally, for each value of ρ, we test the equality of the slopes on the left-hand-side and right-hand-side of the boundary for all iterations. We use the sample of observations for the half of each attendance area closer to the boundary. In all $I = 10,000$ iterations, we are able to reject the null hypothesis that the slopes are the same for $\rho \geqslant 2$ at the 95% level of confidence. For $\rho = 2$, we calculate $\Omega_S = 0.5328$ and $\hat{\Omega}_S = 0.5461$. We believe a conservative conclusion from this exercise is that Fig. 5 has the power to detect biases due to this concern on the order of two percentage points or larger.

B.4. Distance to school

In the following Monte Carlo experiment, we study the implications of another violation from our identifying assumptions. We consider the scenario in which parents also care about the distance between their residence and assigned school. They may care about it, for instance, because of commuting to school, or rather because the school serves as a coordinated location for students to interact outside school hours (e.g., using the playground).

We keep the same parameter values as in the baseline case, except for the following change: instead of the school component of the utility function being represented simply by $\phi^\tau \cdot \mathbb{S}_k$, as before, we define it to be $\phi^\tau \cdot \mathbb{S}_k - \theta^\tau \cdot |d_k|$, where $|d_k|$ represents the absolute value of the distance from block k to the school assigned to block k. We assume that the school location is in the middle of the attendance area, and we report the results for the case in which $\theta^A \geqslant \theta^B$.[44]

Fig. B.5 shows what happens to $\hat{\Omega}_S$ and Ω_S as the preference gap (represented on the horizontal axis) increases. Specifically, we compare $\hat{\Omega}_S$ and Ω_S as we change $\rho := \frac{\theta^A}{\theta^B}$ with $\theta^B = 0.01$. As before, there is no bias when $\rho = 1$, and the bias increases as ρ grows.

Once again, we find that Fig. B.2 is a good diagnostic tool for detecting whether our estimates will be biased due to this reason. To see why, Fig. B.6 shows what Fig. B.2 would look like for selected hypothetical values of ρ. For $\rho = 1$, the plot looks very similar to Fig. B.2 in the baseline case, as expected. For $\rho = 2$, it

[44] The conclusions from the opposite case ($\theta^A \leqslant \theta^B$) are very similar.

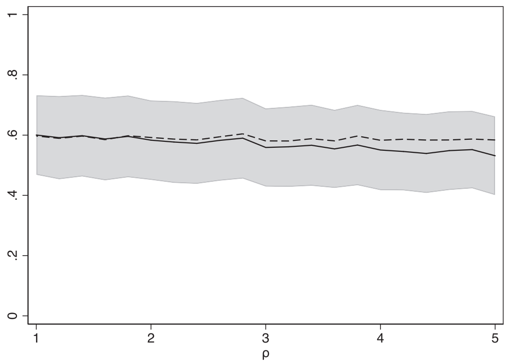


Fig. B.5. $\hat{\Omega}_S$ (solid) and Ω_S (dashed) for Different Values of ρ: Distance-to-School. *Notes*: This figure plots $\hat{\Omega}_S$ (solid curve) and Ω_S (dashed curve) for each value of ρ. We hold constant $\theta^B = 0.01$ and set $\theta^A = \rho\theta^B$. The school's location is assumed to be in the middle of the attendance area.

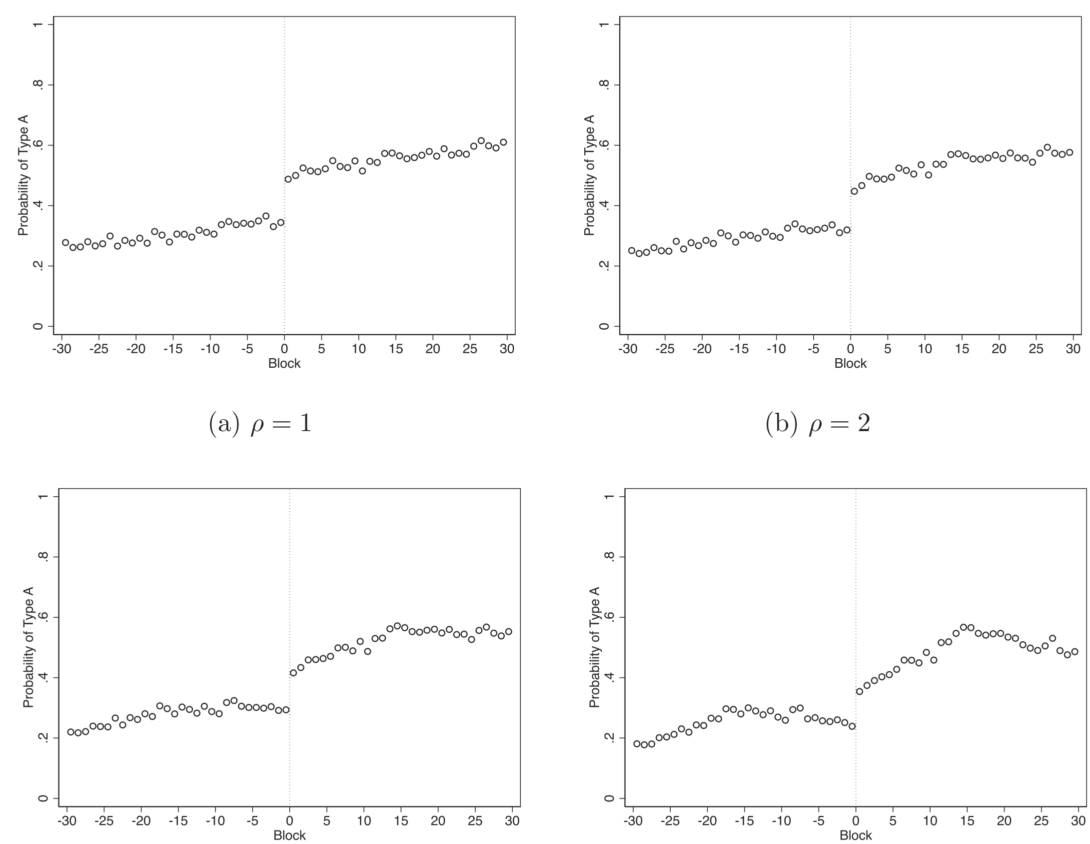
already looks very different, and this difference only grows as ρ grows. In particular, the two sides of the boundary have very different slopes.

As in the previous Monte Carlo experiment, we test the equality of the slopes on the left-hand-side and right-hand-side of the boundary for all iterations and for all values of ρ. In all $I = 10,000$ iterations, we are able to reject the null hypothesis that the slopes are the same for $\rho \geqslant 2$ at the 95% level of confidence. For $\rho = 2$, we calculate $\Omega_S = 0.5843$ and $\hat{\Omega}_S = 0.5778$. We believe a conservative conclusion from this exercise is that Fig. 5 has the power to detect biases due to this concern on the order of one percentage point or larger.

Remark 2. The approach of using Fig. 5 as a diagnostic check may also be relevant to the boundary fixed effects literature. For instance, a common approach to allay the concern raised in Section B.3 is to drop from the analysis boundaries that are close to observable features, such as roads or rivers. Our approach complements this approach for three reasons: (i) not all observed features anticipated to be barriers necessarily render the identifying assumptions invalid (false negative); (ii) it is possible that other boundaries should be dropped because of unobserved or unanticipated barriers (false positive); and (iii) Fig. 5 allows us to indirectly gauge whether the identifying assumption is a good approximation, in the sense that there are not enough boundaries coinciding with geographic features for this issue to be of practical concern.

Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jpubeco.2020.104335.



(a) $\rho = 1$

(b) $\rho = 2$

(c) $\rho = 3$

(d) $\rho = 5$

Fig. B.6. Simulated Versions of Fig. 5 for Different Values of ρ: Distance-to-School. *Notes*: These panels show simulated figures analogous to Fig. 5 for the distance-to-school analysis. We hold constant $\theta^B = 0.01$ and set $\theta^A = \rho\theta^B$, and change the values of ρ.

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