What Determines School Segregation? The Crucial Role of Neighborhood Factors*

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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 66% of racial segregation and 42% of economic segregation across schools, mattering even more 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. *JEL Codes: I21, J15, R23*

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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, Kain and Rivkin 2009; Johnson 2011; Billings, Deming and Rockoff 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, Ladd and Vigdor 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 has seen increasingly widespread adoption. 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, especially in urban areas (Orfield et al. 2014), where school choice has been disproportionately embraced.

One potential reason why education policies have been ineffective at reducing school segregation is that it may be partially determined by non-school factors. 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 availability of nearby desirable venues (Jacobs 1961; Glaeser, Kolko and Saiz 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 more affluent families value the lake more highly than their less affluent counterparts. As a result, the socioeconomic composition of the schools would then 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 live around 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 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 paper, 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 question of interest 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, Ferreira and McMillan (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 66% of school racial seg-

regation and 42% of school economic segregation. These percentages are larger in urban areas (78% and 69%, respectively) than in non-urban areas (60% and 17%, 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, Haughwout and Van Der Klaauw 2014). In contrast, these features are perceived to be more similar from one block to the next in non-urban areas, as families residing in them (particularly those that are affluent) tend to use cars as their primary mode of transportation. This may explain the larger gap by urban status for income compared to race.

We also find that neighborhood features tend to play a smaller role in elementary grades than in later grades. We speculate this is due to the fact that households with students in elementary grades have a greater number of options to choose from regarding school features (given smaller attendance areas) but face the same set of options in terms of neighborhood features. In addition, the evidence indicates that school and neighborhood factors tend to attract a disproportionate number of the same type of parents, suggesting that feedback loops originally created by neighborhood factors intermingle with those created by school factors, and vice-versa, leading to even more segregation. This positive correlation between school and neighborhood factors is responsible for about half of the school segregation by race and income.

Our findings suggest that, in the absence of schemes to break the connection between residence and school by restricting parental school 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 the paper is organized as follows: The next section discusses our identification strategy, and Section 3 describes the data used in our analysis. Section 4 presents our results, which are subsequently interpreted through the lens of a dynamic model in Section 5. Section 6 explores and rules out several potential issues with our analysis, and Section 7 then concludes.

2 Identification Strategy

To identify the role of school and neighborhood factors in explaining school segregation, we exploit Census block-level variation at the boundary between two school attendance areas. It is helpful to visualize our approach using Figure 1. Consider two blocks, k_0 and k_0', which are adjacent to each other but are served by different schools, s and s', respectively. We define π_k as the proportion of students of a given type (e.g., white) in block k, and π_s as the analogous proportion for the entire attendance area served by school s. Our identification strategy involves comparing how this proportion varies across the boundary at the block level (from π_{k_0} to $\pi_{k_0'}$) to how it varies at the attendance area level (from π_s to $\pi_{s'}$).[1] More precisely, we consider the regression equation:

$$\Delta\pi_{k_0,k_0'} = \alpha + \beta \cdot \Delta\pi_{s,s'} + \text{error}\,. \tag{1}$$

where $\Delta\pi_{k_0,k_0'} := \pi_{k_0} - \pi_{k_0'}$ and $\Delta\pi_{s,s'} := \pi_s - \pi_{s'}$.

The slope coefficient β in equation (1) is our parameter of interest. Below, we discuss the assumptions under which β identifies the relative importance of school factors in explaining school segregation. We begin by expressing these proportion differences in terms of a component due to school factors (ΔS) and one due to neighborhood factors (ΔN):

$$\Delta\pi_{s,s'} = \Delta S_{s,s'} + \Delta N_{s,s'}, \tag{2}$$

and, more generally, for any two blocks k and k':

$$\Delta\pi_{k,k'} = \Delta S_{k,k'} + \Delta N_{k,k'}. \tag{3}$$

[1] Block k_1 depicted in Figure 1 is used later to correct for a potential source of bias in our approach.

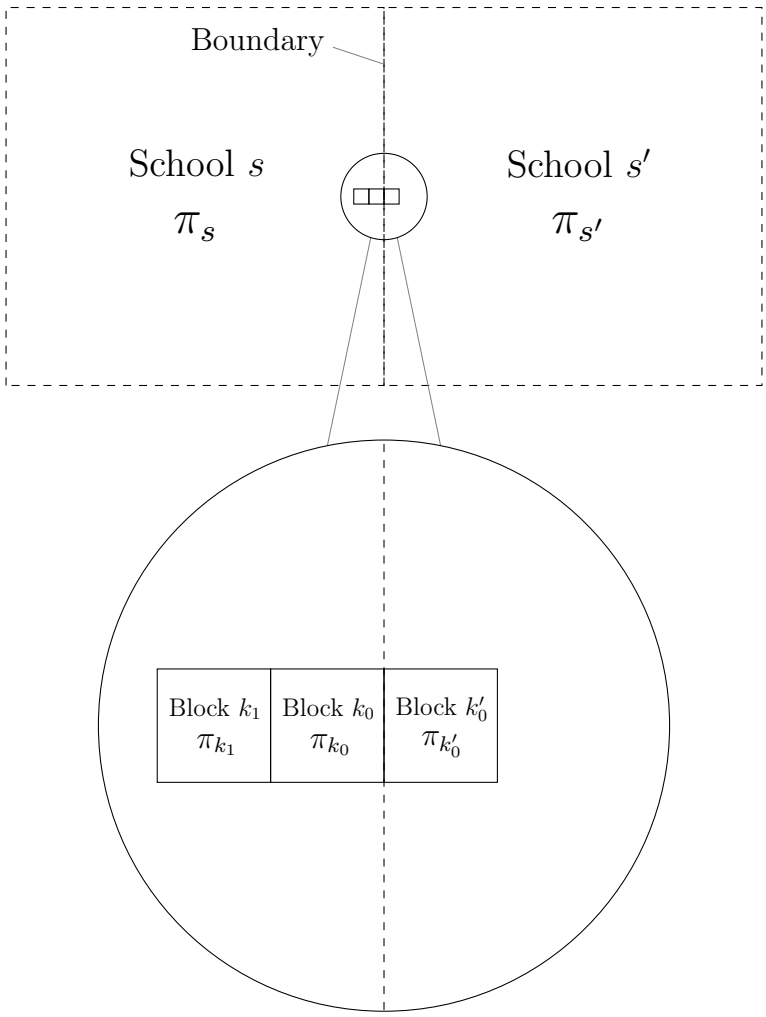


Figure 1: Visualizing Sources of Variation

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_1, k_0 and k_0', along with the analogous proportions for the associated schools s and s'. Blocks k_0 and k_0' are adjacent to each other but located in different attendance areas. Blocks k_1 and k_0 are adjacent to each other and located in the same attendance area s.

As discussed in Appendix A in the context of a discrete choice framework, ΔS and ΔN have a straightforward interpretation.[2] In the case of race, we have $\Delta S := (\phi_S^{\text{white}} - \phi_S^{\text{non-white}}) \cdot (\mathbb{S}_s - \mathbb{S}_{s'})$, where $\mathbb{S}_s$ denotes the school-amenity of school s and ϕ_S^τ denotes the preference of group τ over that school amenity.[3] For $\Delta S_{k,k'}$ to be nonzero, it is not enough for blocks k and k' to have different school amenities; these school amenities must also be valued differently by white and non-white students. Indeed, this difference in school amenities must attract a

[2]As Appendix B shows, the additive separability of equations (2) and (3) is not exact. However, it provides a very good approximation for interpretation purposes.

[3]The corresponding quantity for income is $\Delta S := (\phi_S^{\text{advantaged}} - \phi_S^{\text{disadvantaged}}) \cdot (\mathbb{S}_s - \mathbb{S}_{s'})$.

disproportionate number of students of a given type for the racial composition between the blocks to differ. Thus, whenever we use the expression "school factors," we are referring to the combination of school amenities and preferences for those amenities. The expression for "neighborhood factors" (ΔN) is defined analogously.

Our goal is to identify the relative role of $\Delta S_{s,s'}$ and $\Delta N_{s,s'}$ in explaining $var(\Delta \pi_{s,s'})$ in equation (2), where the variance is calculated across all boundaries contained in the sample. We decompose $var(\Delta \pi_{s,s'})$ as

$$var(\Delta \pi_{s,s'}) = var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2 \cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'}) \,. \tag{4}$$

Note that 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.

The relative role of $\Delta S_{s,s'}$ in explaining school segregation is defined as

$$\Omega_S := \frac{var(\Delta S_{s,s'}) + cov(\Delta S_{s,s'}, \Delta N_{s,s'})}{var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2 \cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'})} \,, \tag{5}$$

and the relative role of $\Delta N_{s,s'}$ in explaining school segregation is thus given by $\Omega_N := 1 - \Omega_S$.[4,5] The ordinary least squares estimator of β in equation (1) is our estimator of Ω_S. It can be written as:[6]

$$\beta_{ols} = \frac{cov(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta S_{k_0,k_0'} + \Delta N_{k_0,k_0'})}{var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2cov(\Delta S_{s,s'}, \Delta N_{s,s'})} \,. \tag{6}$$

To connect these quantities, we write:

$$\Delta S_{k_0,k_0'} = \Delta S_{s,s'} + \Delta \nu_{k_0,k_0'} \,, \tag{7}$$

[4]Note that Ω_S attributes half of the covariance term to each factor. In Section 5 we show how we can also identify a more intuitive parameter that allows for the relative attribution of the covariance term to differ depending on the size of $var(\Delta S_{s,s'})$ with respect to $var(\Delta N_{s,s'})$.

[5]Given the potential for the covariance term to be negative, interpreting Ω_S as a proportion may not always be appropriate, since it is able to take on values outside of the $[0, 1]$ interval. For instance, it is possible that $\Omega_S > 1$, which would indicate that school segregation would be higher if it were only arising from school factors. This would occur only if school and neighborhood factors influence school segregation in opposite directions (in other words, a negative covariance). In the context of our paper, this is not a concern: the proportion interpretation is correct, as the covariance term is always inferred to be positive (see Section 5.2 for details).

[6]This equation is obtained by noting that $\beta_{ols} = \frac{cov(\Delta \pi_{s,s'}, \Delta \pi_{k_0,k_0'})}{var(\Delta \pi_{s,s'})}$.

so that $\Delta S_{k_0,k_0'}$ is equal to $\Delta S_{s,s'}$ for the corresponding attendance areas with some error.

We invoke the following identifying assumptions:

Assumption 1. *$cov(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta \nu_{k_0,k_0'}) = 0$, where $\Delta \nu_{k_0,k_0'}$ is defined in equation (7).*

Assumption 1 states that the difference in school amenities at the boundary is representative of the difference in school amenities between the two attendance areas up to a random error.

Assumption 2. *$cov(\Delta \pi_{s,s'}, \Delta N_{k_0,k_0'}) = 0$.*

Assumption 2 states that the (highly local) difference in neighborhood factors between two adjacent blocks, $\Delta N_{k_0,k_0'}$, is uncorrelated with the (non-local) school-level difference in student composition, $\Delta \pi_{s,s'}$.

Assumptions 1 and 2 allow us to simplify equation (6):

$$\begin{aligned} \beta_{ols} &= \frac{cov(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta S_{k_0,k_0'})}{var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2 \cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'})} \\ &= \frac{var(\Delta S_{s,s'}) + cov(\Delta S_{s,s'}, \Delta N_{s,s'})}{var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2 \cdot cov(\Delta S_{s,s'}, \Delta N_{s,s'})} \\ &= \Omega_S. \end{aligned} \tag{8}$$

Intuitively, as one moves across the boundary from k_0 in attendance area s to k_0' in attendance area s', only school factors can systematically change the values of both π_s and π_{k_0}. Thus, the slope coefficient from the regression in equation (1) represents the degree to which segregation across schools is explained by school factors.

2.1 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_0 and k_0' 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

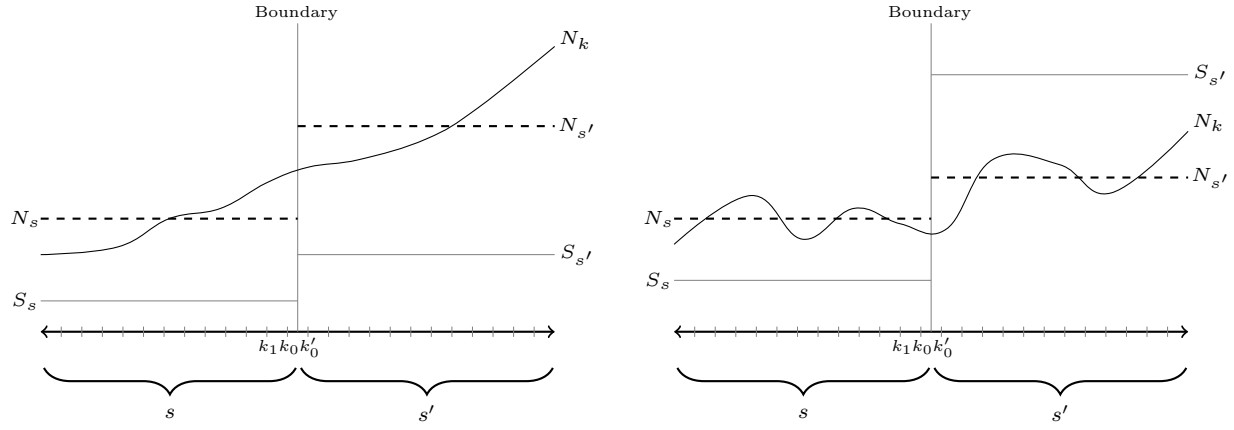
to separately identify these two sources, as they are both attributable to school factors. More formally, anything that affects $\Delta\pi_{k_0,k_0'}$ because of the difference in school amenities is attributed to $\Delta S_{s,s'}$, and not to $\Delta N_{k_0,k_0'}$. This rules out concerns related to post-determined differences at the boundary, but concerns may still abound with respect to pre-determined differences driving our results, such as major highways or rivers coinciding with a boundary. Below, we relax this assumption to accommodate some of these concerns, and Section 6.1.1 rules out remaining issues in detail.

To better understand Assumption 2, consider the example depicted in Figure 2. For simplicity, we interpret the figure in terms of race, but the intuition is analogous for income. Each panel depicts a unique 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. For simplicity, we consider examples of boundaries for which school factors do not vary within attendance area, trivially satisfying Assumption 1. However, doing so is not necessary. 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 Figure 2. From the figure, note that $\Delta N_{k_0,k_0'} = N_{k_0} - N_{k_0'}$ 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 $cov(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta N_{k_0,k_0'}) = 0$. Departing from this simple example, it is clear that this assumption might fail to hold using actual data: indeed, the slope at the boundary for every boundary must be just so in order for the covariance to equal zero. In general, $cov(\Delta N_{s,s'}, \Delta N_{k_0,k_0'})$ is likely to be positive (as is the case for Panel

[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_0, k_0'). 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 living close to it more than non-whites do, though at slightly varying degrees depending on the distance.



(a) Boundary 1 (b) Boundary 2

Figure 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_1, k_0 and k_0', as also described in Figure 1.

(a)), and $cov(\Delta S_{s,s'} + \Delta N_{s,s'}, \Delta N_{k_0,k_0'})$ 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 Figure 2. Consider block k_1, which is adjacent to block k_0 and is served by the same school s. Using this block pair, we can construct an additional block-level difference in proportion: $\Delta\pi_{k_1,k_0}$. This difference does not systematically depend on the school component, since both blocks are contained within the same attendance area. Thus, the ordinary least squares estimator of the slope coefficient of the analogous regression to equation (1) (by regressing $\Delta\pi_{k_1,k_0}$ on $\Delta\pi_{s,s'}$) is:

$$\beta_{placebo} = \frac{cov(\Delta\pi_{s,s'}, \Delta N_{k_1,k_0})}{var(\Delta S_{s,s'}) + var(\Delta N_{s,s'}) + 2cov(\Delta S_{s,s'}, \Delta N_{s,s'})}. \quad (9)$$

We propose a novel alternative to Assumption 2:

Assumption 2′. $cov(\Delta\pi_{s,s'}, \Delta N_{k_0,k_0'}) = cov(\Delta\pi_{s,s'}, \Delta N_{k_1,k_0})$

A sufficient condition for this assumption to hold is for N to vary around the boundary in a

[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.

linear fashion from k_1 to k_0' (i.e., in Figure 2, the portion of the N_k curve from k_1 to k_0 must have the same slope as the portion of the N_k curve from k_0 to k_0'). Given the close proximity of blocks k_1 and k_0' (with only block k_0 separating them), we view this local approximation as plausible. One potential issue, which we consider in detail in Section 6.1.1, is that attendance boundaries may separate neighborhoods beyond their school allocation (e.g., due to a major highway or river). In that case, the slope from k_1 to k_0 may be systematically lower than the slope from k_0 to k_0', 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 Assumptions 1 and $2'$, we form the corrected estimator of Ω_S as:

$$\tilde{\beta} := \beta_{ols} - \beta_{placebo}. \tag{10}$$

Remark 1. *In order for Assumption $2'$ to be valid, it is crucial to use blocks (instead of larger geographic areas) as the unit of our analysis, as we need k_1 and k_0' to be sufficiently close to each other. However, choosing blocks raises a potential concern. In practice, our estimate of $\Delta\pi_{k,k'}$ may differ from the population parameter due to the small size of blocks. For instance, if the population proportion is 70% and we observe only one student in the block, the block proportion can only take the value 0 or 1, rather than 0.7. Our approach discussed above is designed to circumvent this potential issue. Let the measurement error in block k be defined as ϵ_k. Assumption 2 can be stated instead as $cov(\Delta\pi_{s,s'}, \Delta N_{k_0,k_0'} + \Delta\epsilon_{k_0,k_0'}) = 0$, and Assumption $2'$ can be stated instead as $cov(\Delta\pi_{s,s'}, \Delta N_{k_1,k_0} + \Delta\epsilon_{k_1,k_0}) = cov(\Delta\pi_{s,s'}, \Delta N_{k_0,k_0'} + \Delta\epsilon_{k_0,k_0'})$. Measurement error does not diminish the plausibility of these assumptions, as this noise is likely to be random. We discuss this point further in Section 6.1.3.*

2.2 What is contained in ΔS, ΔN and $cov(\Delta S, \Delta N)$?

Recall that $\Delta S_{k_0,k_0'}$ is an index of whatever amenities vary discontinuously at the boundary, and $\Delta N_{k_0,k_0'}$ is an index of whatever amenities do not vary discontinuously at the boundary (both mediated by differential preferences between household types). Under Assumption 1, $\Delta S_{k_0,k_0'}$ is representative of $\Delta S_{s,s'}$, which implies that $\Delta S_{s',s'}$ represents the discontinuity at the boundary up to an error that is random across boundaries. We now make explicit which elements are contained in ΔS, ΔN and $cov(\Delta S, \Delta N)$. To do so, we now expand upon our

discussion in the introduction, by considering some concrete examples.[10]

Suppose that, for some initial period, two adjacent attendance areas differ from each other only because attendance area s' is more elevated and thus provides a better view of the city on average. If white households value a better view more than their non-white counterparts, then sorting ensues, leading white students to disproportionately reside in attendance area s'. This sorting would be attributable to ΔN under our framework. It could also give rise to follow-on responses independently of any school-related changes, which would be classified under ΔN as well. Some non-mutually exclusive examples: (a) white households may prefer to reside near other white households; (b) white households may invest more in their house (e.g., mowing lawns, buying a new roof); and (c) attendance area s' may endogenously adjust its features differently than attendance area s to cater to those residing nearby (e.g., venues, greenery, types of buildings, sidewalks, additional housing supply).

The initial sorting could also lead schools s and s' to differentially cater to their new student bodies and parents, potentially resulting in further (now school-induced) sorting of white (non-white) parents or would-be parents to attendance area s' (s). If so, this would lead to a discontinuity in the proportion of students who are white at the boundary, as in Figure 5. The actual discontinuity we observe includes not only the sorting due to this initial difference in school features, but also any further sorting arising from several overlapping positive feedback loop mechanisms, analogous to the examples given for ΔN above. Non-mutually exclusive examples (which would intensify the discontinuity at the boundary even further): (a') white families may prefer to attend schools with predominantly white students; (b') following the sorting due to the initial difference in school quality, if white families invest more in their house, then the ensuing housing quality differential across the boundary would attract a disproportionate number of white households; and (c') sorting from initial differences between the schools could beget further differential school catering and sorting. To summarize, all complementary positive feedback loops, such as those contained in the preceding examples, are included in ΔS as long as they manifest as discontinuities in the racial composition at the boundary.

It is also informative to consider a few examples of changes partly induced by ΔS that do

[10]For additional insight, Section 5 provides a dynamic model to help formalize the ideas we discuss here.

not show up as a discontinuity at the boundary. These are rightly attributed in our framework to the covariance term between ΔS and ΔN, since they simultaneously intermingle in positive feedback loops that arise from both ΔS and ΔN. A couple of examples: (i) there is a park in the center of attendance area s', and white families sorting because of school features disproportionately sort towards the center of attendance area s', relative to the boundary (perhaps because they disproportionately value *both* sending their kids to a predominantly white school and residing near a park relative to simply sending their kids to such a school); and (ii) certain venues (e.g., coffee shops, grocery stores, yoga studios) may decide to locate in the middle of attendance area s' in order to cater to their clientele (predominantly white families who sorted because of S in the first place), and additional white households may disproportionately want to locate close to such venues, leading yet more venues to locate there.

Note that, given the preceding examples, there is no reason to expect a further discontinuity at the boundary. To see why, consider the second example in which attendance area s' gentrifies due to initial differences in school amenities. Provided the boundary is sufficiently distant from the location of the attendance area where the venues are located, there is little difference in the distance to the venues from block k_0' versus block k_0.[11] Thus, the discontinuity at the boundary will not account for the full difference in racial composition across schools initiated by ΔS. This is why our framework incorporates the *correlation* between the discontinuity at the boundary ($\Delta\pi_{k_0,k_0'}$) and the variation across the two corresponding attendance areas ($\Delta\pi_{s,s'}$). The portion of the S-initiated difference that does not show up at the boundary but is correlated with the difference between the attendance areas, $\Delta\pi_{s,s'}$, is part of the covariance term. Of course, there are analogous examples initiated by ΔN rather than by ΔS, which are equally attributed to the covariance term.

[11] Incidentally, if there are barriers at the boundary that make the trip for those residing in block k_0 systematically more difficult than for those residing in block k_0', then our approach correctly attributes this difference to S. However, as discussed in Section 6.1.1, we find no evidence that boundaries provide such stark neighborhood divisions in our data.

3 Data

To determine the extent to which 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 about 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, critically 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). Crucial to our research design, 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 by different schools in the same district.[15] It also allows us to determine the share of students within

[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, each 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.

[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 them are served by the same school. Depending on the grade level, this covers between 67% and 71% of all such 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. Note that boundary blocks k_0 and k_0' (and interior blocks k_l and k_{l-1} for all $l = 1, 2, 3, ...$) in our sample must be adjacent to each other – i.e., they cannot be separated by a block that is dropped from our sample.

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,

[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

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.

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.

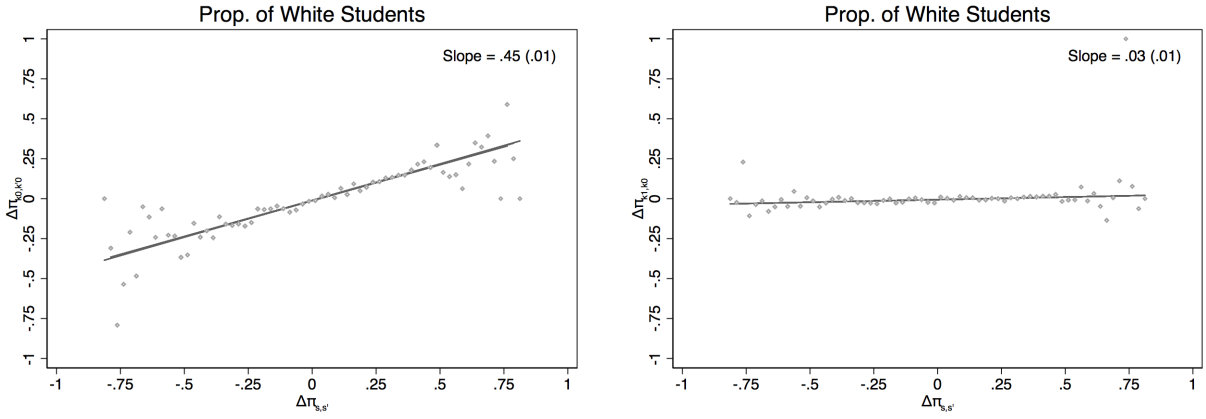
4 Results

In this section, we implement the approach detailed in Section 2 to estimate the relative role of school features in explaining school segregation, both in terms of race (white vs. non-white students: β_{ols}^{white}) and income (economically advantaged vs. economically disadvantaged students: β_{ols}^{adv}).

schools located in (by descending share) Charlotte, Fayetteville, Greensboro, Raleigh, Durham, Winston-Salem, Burlington, and Wilmington.

4.1 All Schools

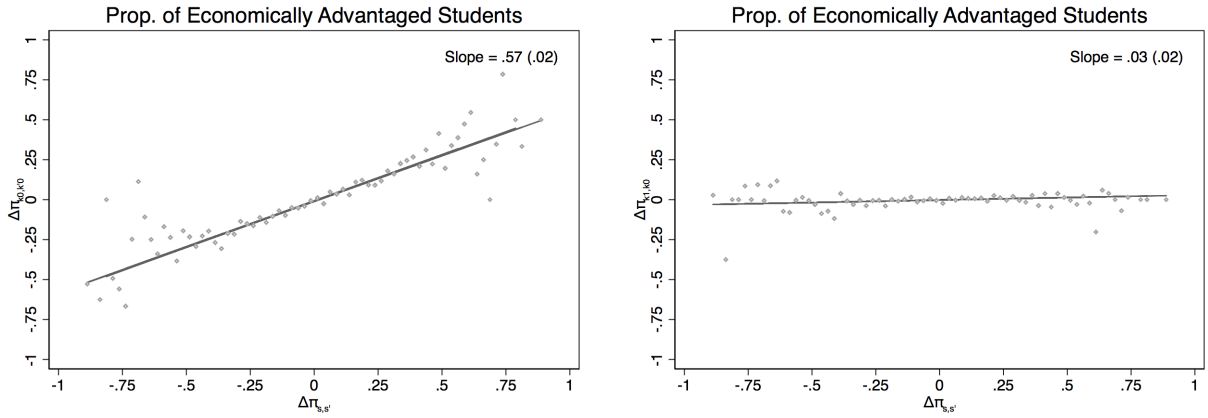
Our main results for race are presented in Panel (a) of Figure 3. The horizontal axis measures the difference in the proportions of white students between schools s and s' ($\Delta\pi^{white}_{s,s'}$), while the vertical axis measures the difference in the proportions of white students between boundary blocks k_0 and k_0' ($\Delta\pi^{white}_{k_0,k_0'}$). The scatter plot shows averages of $\Delta\pi^{white}_{k_0,k_0'}$ across all boundaries with similar values 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 Figure 3 suggests that 45% of racial school segregation is due to school factors. Panel (a) of Figure 4 reports the analogous results for income, revealing that 57% of economic school segregation is due to school factors.



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

Figure 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_0 and k_0' 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_0 who are white relative to the analogous proportion in block k_0'. 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_0 and k_0', it considers blocks k_1 and k_0. These results were obtained from a sample of 31,617 block pairs along with their associated schools.



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

Figure 4: The Relative Role of School Factors on School Segregation by Income

Notes: See the notes for Figure 3, which presents the analogous results by race.

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 Figure 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_0 and k_0' (which are served by different schools), we calculate the difference between adjacent blocks k_1 and k_0 (which are served by the same school). The placebo estimates for race and income are both equal to 3%. Thus, our corrected 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 leads us to conclude 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.)

Table 2: The Relative Role of School Factors on School Segregation

	All Schools		Urban Schools		Non-Urban Schools	
	β_{ols}	$\beta_{placebo}$	β_{ols}	$\beta_{placebo}$	β_{ols}	$\beta_{placebo}$
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. β_{ols} is defined in equation (8), and $\beta_{placebo}$ is defined in equation (9). "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'). *** denotes significance at the 1% level; and * denotes significance at the 10% 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.)

Table 3: The Relative Role of School Factors on School Segregation by Grade

	Elementary Grades		Middle Grades		Secondary Grades	
	β_{ols}	$\beta_{placebo}$	β_{ols}	$\beta_{placebo}$	β_{ols}	$\beta_{placebo}$
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. β_{ols} is defined in equation (8), and $\beta_{placebo}$ is defined in equation (9). "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'). *** denotes significance at the 1% level.

5 Interpretation

In this section we present a simple dynamic model that explores how school segregation emerges. We interpret our findings through the lens of the model, and then provide context with respect to policies that move or eliminate school attendance boundaries.

5.1 Dynamic Model

As discussed, both school and neighborhood amenities may differ across two attendance areas s and s', which would lead to segregation. It is useful to consider how such differences emerge in the first place. Initially (in period 0), suppose the two adjacent attendance areas differ due to a small set of amenities. These amenities are considered to be "exogenous" for our purposes, as they are not of primary interest but rather the seed of the data generating process. They may be inherent, for example, from topographical differences, such as the distance to a river, the degree to which the land is fertile or the elevation of the terrain.[18] As suggested by these examples, we assume that the initial differences are due entirely to non-school factors. More precisely, the difference for each pair of attendance areas s and s' is modeled as arising from the shock $\Delta\eta_0 := \Delta\eta_0^N$, entirely attributable to neighborhood

[18]Lee and Lin 2017 studies the dynamic consequences of persistent natural neighborhood amenities such as these.

features.[19]

People then engage in sorting based on these original differences, which beget further differences. We denote these additional sorting-based differences in amenities as "endogenous." While some of these endogenous amenities change 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 process (e.g., local taxes and the provision of local goods and services, such as schools and venue offerings). Households may further sort based on these endogenous changes, leading to additional endogenous changes in amenities, potentially creating a positive feedback loop. Attendance areas are observed by the researcher only after numerous decades of this endogenous process taking place.

The evolution of the difference in socioeconomic composition between two schools is given by the expression:

$$\Delta\pi_t - \Delta\pi_{t-1} = \Delta\eta^N_{t-1} + \psi^S \left[\Delta\pi_{t-1} - \Delta\pi_{t-2}\right] + \psi^N \left[\Delta\pi_{t-1} - \Delta\pi_{t-2}\right] . \tag{11}$$

We assume that the relationship depends linearly on the prior shock and the endogenous shocks triggered by that prior shock. The last two terms of equation (11) 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 $\tilde{\psi}^S_t$ and $\tilde{\psi}^N_t$ 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 prevent people from sorting as much as they would like.[20]

The component of $\Delta\pi$ that is due to school amenities (ΔS) is represented by the terms that depend on ψ^S. Analogously, the component of $\Delta\pi$ that is due to neighborhood amenities (ΔN) is represented by the terms that depend on the initial shock $\Delta\eta^N_0$ and ψ^N. Assuming $0 \leq \psi^S + \psi^N < 1$, we have:[21]

[19]For expositional convenience, we omit the subscript referring to the pair of schools.

[20]For instance, in a context of infinite moving costs, we would have $\psi^S = \psi^N = 0$.

[21]See Appendix D for details. Assuming $0 \leq \psi^S + \psi^N < 1$ implies that schools converge to a stable equilibrium.

$$\frac{var(\Delta S)}{var(\Delta \pi)} = (\psi^S)^2\,, \tag{12}$$

$$\frac{var(\Delta N)}{var(\Delta \pi)} = (1-\psi^S)^2\,, \tag{13}$$

$$\frac{cov(\Delta S, \Delta N)}{var(\Delta \pi)} = \psi^S \cdot (1-\psi^S)\,, \tag{14}$$

$$\Omega_S = \psi^S\,. \tag{15}$$

5.2 Interpretation of Results

This simple dynamic model allows us to interpret our results from Section 4. Indeed, Assumptions 1 and $2'$ in conjunction with equation (15) imply that $\tilde{\beta}$ (from equation (10)) is a consistent estimator of ψ^S. Consequently, we are able to obtain estimates of the key quantities in equations (12) through (14).

Table 4 reports these estimates overall and by urban status for segregation by race (Panel A) and income (Panel B). Irrespective of the dimension of segregation or school urban status, we find that the covariance component is positive and accounts for approximately 50% of the total variance, $var(\Delta\pi)$ (see row 3 of each panel). 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 $0 \leq \psi^S + \psi^N < 1$) or $\psi^S > 1$ (so that $\psi^N < 0$). Instead, we find $0 < \Omega_S = \psi^S < 1$ in all cases (Ω_S is shown in the penultimate row of each panel). This is an intuitive result: for example, it is likely that schools with higher test scores attract a disproportionate number of affluent students (all else constant), which may in turn attract a disproportionate number of affluent households without children if they disproportionally prefer to locate near other affluent households.

One complication that arises when interpreting our original parameter of interest, Ω_S (given by equation (5)), is that it attributes half of the covariance component to school and neighborhood factors. A potentially more compelling parameter is one that attributes a higher proportion of the covariance to the factor that most explains school segregation. Accordingly, we define the more general measure $\Omega_S(\gamma) := \frac{var(\Delta S)+2\cdot\gamma\cdot cov(\Delta S,\Delta N)}{var(\Delta\pi)}$, where γ

Table 4: Corrected Estimates – The Relative Role of School and Neighborhood Factors on School Segregation (Overall and by Urban Status)

Panel A: Race			
	All schools	Urban Schools	Non-Urban Schools
$\frac{var(\Delta S)}{var(\Delta \pi)}$	0.18	0.12	0.20
$\frac{var(\Delta N)}{var(\Delta \pi)}$	0.34	0.42	0.25
$\frac{2 \cdot cov(\Delta S, \Delta N)}{var(\Delta \pi)}$	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
$\frac{var(\Delta N)}{var(\Delta S)+var(\Delta N)}$	0.66	0.78	0.60
Panel B: Income			
	All schools	Urban Schools	Non-Urban Schools
$\frac{var(\Delta S)}{var(\Delta \pi)}$	0.29	0.16	0.48
$\frac{var(\Delta N)}{var(\Delta \pi)}$	0.21	0.36	0.10
$\frac{2 \cdot cov(\Delta S, \Delta N)}{var(\Delta \pi)}$	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
$\frac{var(\Delta N)}{var(\Delta S)+var(\Delta N)}$	0.42	0.69	0.17

Notes: This table reports the results from Table 2 through the lens of the dynamic model discussed in Section 5.1. Standard errors, calculated via the Delta method, are always below three percentage points and are omitted for clarity.

denotes the proportion of the covariance term attributed to school factors (with $\Omega_S(1/2) := \Omega_S$). We propose a specific candidate for the value of γ: $\gamma^\star := \frac{var(\Delta S)}{var(\Delta S)+var(\Delta N)}$. To illustrate the difference between $\Omega_S(1/2)$ and $\Omega(\gamma^\star)$, consider an example in which $var(\Delta S)$ is two times larger than $cov(\Delta S, \Delta N)$ and four times larger than $var(\Delta N)$. In this scenario, $\Omega_S = 2/3$ but $\Omega_S(4/5) = 4/5$. In general, Ω_S tends to bias our findings toward a 50-50 split between school and neighborhood factors, which motivates the correction. Our correction attributes the proportion of segregation to school factors in a way that is independent from the value of the covariance: $\Omega(\gamma^\star) = \gamma^\star = \frac{var(\Delta S)}{var(\Delta S)+var(\Delta N)}$.

Correcting for this bias, the final row of each panel in Table 4 reports $\Omega_N(\gamma^\star) := 1-\Omega_S(\gamma^\star)$, revealing that neighborhood factors explain 66% and 42% of overall school segregation by race and income, respectively. The role of neighborhood factors in explaining racial and income segregation is substantially larger in urban areas (78% and 69%, respectively) than in non-urban areas (60% and 17%, respectively). As discussed in the introduction, these results are likely due to the higher complexity of neighborhood features in urban relative to non-urban settings. Features, such as specific venues or sidewalks, tend to be perceived as

Table 5: Corrected Estimates – The Relative Role of School and Neighborhood Features on School Segregation (By Grade Level)

Panel A: Race			
	Elementary Grades	Middle Grades	Secondary Grades
$var(\Delta S)/var(\Delta\pi)$	0.26	0.18	0.10
$var(\Delta N)/var(\Delta\pi)$	0.24	0.34	0.46
$2 \cdot cov(\Delta S, \Delta N)/var(\Delta\pi)$	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
$\frac{var(\Delta N)}{var(\Delta S)+var(\Delta N)}$	0.48	0.66	0.72
Panel B: Income			
	Elementary Grades	Middle Grades	Secondary Grades
$var(\Delta S)/var(\Delta\pi)$	0.36	0.22	0.30
$var(\Delta N)/var(\Delta\pi)$	0.16	0.28	0.20
$2 \cdot cov(\Delta S, \Delta N)/var(\Delta\pi)$	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
$\frac{var(\Delta N)}{var(\Delta S)+var(\Delta N)}$	0.31	0.56	0.40

Notes: This table shows the results from Table 3 through the lens of the dynamic model discussed in Section 5.1. Standard errors calculated via the Delta method are always below three percentage points and are omitted for clarity.

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 richer households use cars to access neighborhood amenities in non-urban areas more intensely than poorer ones.

Table 5 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 correcting for the covariance bias, we find that neighborhood factors explain 48%, 66% and 72% of racial segregation in elementary, middle and secondary grades, respectively. The analogous estimates for income segregation are 31%, 56% and 40%.

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 valuation of school amenities for secondary grades is higher than the corresponding gap for middle grades.[22]

5.3 Boundary Changes and Open Enrollment

In light of our interpretation that neighborhood factors limit the ability of education policymakers to influence school segregation, it is worth considering two key policies at their disposal that go beyond redistributing funding and inputs across schools.

First, there is ample evidence that school boards manipulate attendance area boundaries to affect segregation, both upon the overturning of earlier court-ordered desegregation measures (Billings, Deming and Rockoff 2014) and subsequently according to political affiliation (Macartney and Singleton 2018). However, such policy is not a panacea for confronting school segregation. As Lutz (2011) and Reardon et al. (2012) show, residential sorting (due to both S and N studied above) can rapidly undo the effects of boundary changes in the medium run, requiring continual action by boards to achieve long-run aims. Moreover, as noted by Macartney and Singleton (2018), the set of feasible boundaries to choose from will be restricted according to the cost of transporting students over large distances and parental opposition to unusually shaped attendance areas, making it unlikely that any adjustments would deviate strongly from already established boundaries.

The second policy is an outright elimination of attendance area boundaries via the adoption of open enrollment (Cullen, Jacob and Levitt 2006). Doing so lessens the dependence of school segregation on neighborhood factors, but does not eliminate it altogether if travel costs are important. Further, some families may respond to this policy by sorting to another district or to a private school, potentially exacerbating school segregation. During this

[22]Consistent with this finding, Caetano (2018) reports that households, particularly wealthier ones, tend to value school quality more at the secondary school level than at the middle grade level.

sorting process, both the S and N components we consider will likely factor into families decisions.

Regarding our dynamic model, we view boundary changes and open enrollment policies as a form of reset in terms of the initial conditions $\Delta\eta_0$. Endogenous processes represented by ψ^S and ψ^N will dominate in the long run.

6 Addressing Potential Concerns

We now assess the extent to which our results are robust to potential concerns that might be raised in the context of our application. We first discuss possible issues regarding the validity of our identification strategy, and then consider those related to the interpretation of our results.

6.1 Issues Regarding Validity

6.1.1 Is Assumption 2′ valid?

In Section 2, we show that Assumption 2′ (our main identifying assumption) is a substantially weaker form of Assumption 2, which is related to the one often made in the boundary fixed effects literature. We also discuss how post-determined amenities that change as a function of school differences at the boundary are completely attributable to school factors under our approach. This is in stark contrast to the boundary fixed effects literature.

Notwithstanding that contrast, a key potential concern raised by that literature may also affect our approach. Blocks at the boundary may coincide with particular geographical features, such as a river, lake or major highway, making them systematically different from interior blocks. In this scenario, differences in the socioeconomic composition of those living in block k_0 and those living in block k_0' would reflect not only S but N as well, which would imply a violation of Assumption 2. Assumption 2′ would also be violated, as the difference between k_0 and k_0' would be larger than the difference between k_1 and k_0. Importantly however, this would bias our estimates of the role of S upward, making our conclusion that N plays a key role a conservative one. In any case, we provide suggestive evidence that these local differences at the boundary, if they exist, are not first order in our analysis.

Figure 5 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}.[23] This average is calculated across all boundaries for each block k_l (k'_l), where l reflects the number of degrees of separation from block k_0 (k'_0) within the corresponding attendance area.[24] In the plot, we assign the school with the largest proportion of students who are white to the right hand attendance area (s').[25] As expected, there is a positive discontinuity at the boundary in the proportion of students in a block who are white, highlighting the role of S in explaining sorting patterns. The plot also reveals a positive slope for both attendance areas, suggesting that neighborhood amenities in attendance area s' tend to disproportionately attract white families relative to s. These findings corroborate our conclusion in Section 5.2 that $cov(\Delta S, \Delta N) > 0$.

Importantly, as one approaches the boundary from the left (block k_0), the slope is similar to the slope as one approaches it from the right (block k'_0). This strongly suggests that preexisting differences do not play an important role in our analysis, and that Assumption $2'$ (N varies linearly at the boundary) is valid. We now explore this logic in greater detail.

Figure 5 looks very different from what it would look like if major highways, lakes or rivers commonly coincided with attendance area boundaries. For instance, consider a case in which boundaries coincide with a disamenity, which attracts a disproportionately low number of white students (e.g., a major highway). If there were a sufficiently large number of such boundaries, then one would expect 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). Alternatively, consider the case of a coincident amenity, which attracts a disproportionately high number of white students (e.g., a picturesque lake). One would then expect a positive slope when approaching the boundary from the left and a negative slope

[23]Note that Figure 5 is the empirical analog of the theoretical Figure 2 aggregated across all boundaries, given that only $\pi_k = S_k + N_k$ is observed directly (rather than S_k or N_k).

[24]Block k'_2 is indexed as "2" because it is the nearest block (in terms of the Euclidian distance) to block k'_0, among all blocks located within attendance area s' that are adjacent to block k'_1 but not to block k'_0. We use an analogous definition for each block (k_{30} to k'_{30}). Note that each boundary k_0, k'_0 has many different "paths" going from k_{30} to k'_{30}. We truncate the plot at 30 to avoid any potential selection issue, as some attendance areas have paths with only about 30 blocks. Results are unchanged if we use different notions of distance.

[25]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 whites disproportionately.

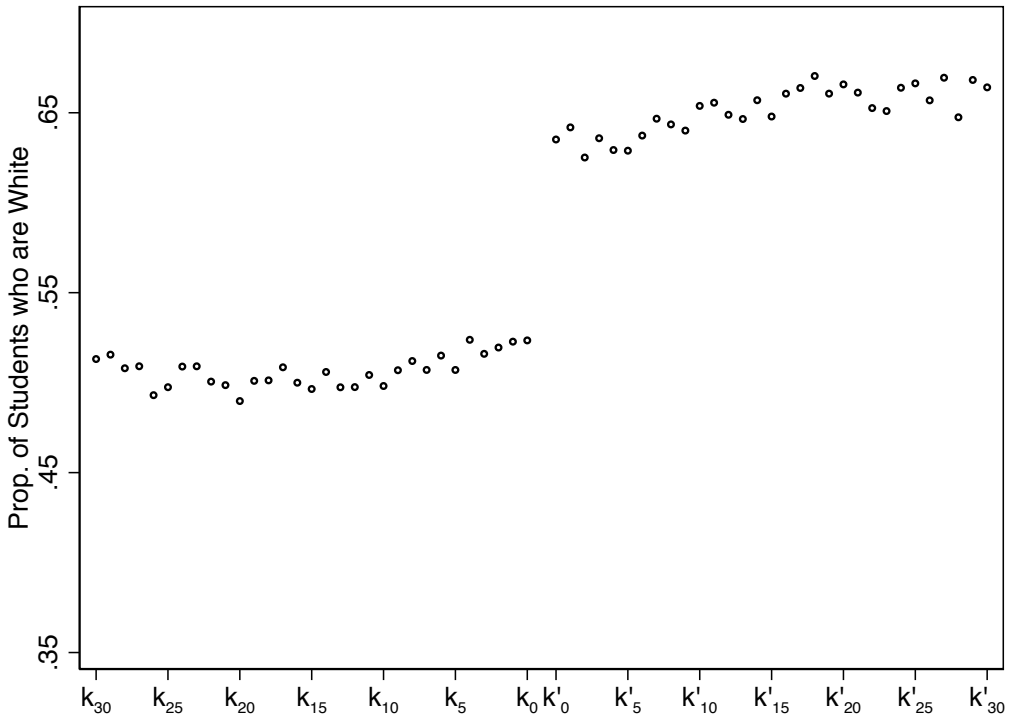


Figure 5: Proportion of Elementary Students who are White in Each Block

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 block k_0 (k'_0) in their corresponding attendance area. See footnote 24 for details on how l is measured.

when approaching it from the right (i.e., opposite signed slopes once again).

In general, if attendance boundaries divide neighborhoods in ways beyond those related to the school allocation, then what it means to reside on the left versus the right side of the boundary would be entirely different. Those living in block k_0 would have much less access to amenities available in attendance area s' than those living in block k'_0, and vice-versa. If that was the case for a large enough number of boundaries, then the slopes on both sides would be unrelated to each other, as they would constitute essentially separate self-contained areas. We do not find that to be the case in our sample.

Appendix Figure E.1 presents analogous plots for middle and secondary school students, and also for the proportion of students in each block who are economically advantaged. All plots lend credence to the notion that the two sides of the boundary look like, on average, a single neighborhood that happens to be served by two different schools. Furthermore, it is worth noting that attendance areas for later grades are larger than for earlier grades, which

makes them more likely to contain boundaries coinciding with major highways or rivers. Yet the patterns for secondary schools are similar to those for lower grades.

Additional pertinent evidence is presented in Figure 6. We estimate β_k by race across all elementary schools for each $k = \{k_{30}, ..., k_0, k_0', ..., k_{30}\}$ from the regressions:

$$\Delta\pi_{k_0,k} = \alpha_k + \beta_k.\Delta\pi_{s,s'} + \text{error}_{k_0,k}\,, \tag{16}$$

reporting the corrected estimate $\tilde{\beta}_k := \beta_k - \beta_{k_1}$ for each value of k. It is worth noting that the resulting figure looks strikingly similar to Figure 5, though it exploits entirely different variation. The first point to the right of the boundary is equal to $\tilde{\beta}$ from our main results (equation (10)). However, this figure allows us to understand how our estimate of $\tilde{\beta}_k$ would change if we used a block farther away from the boundary in either direction, rather than the block k_0' right at the boundary. As one moves farther away from k_0' towards the right of the figure (within attendance area s'), $\tilde{\beta}_k$ likely starts incorporating variation due to ΔN as well. In particular, similar estimates are obtained if we drop the blocks closest to the boundary from the analysis and rely instead on predicting the value of $\tilde{\beta}_{k_0}$ and $\tilde{\beta}_{k_0'}$ by estimating the limits $\lim_{l\to 0}\tilde{\beta}_{k_l}$ and $\lim_{l\to 0}\tilde{\beta}_{k_l'}$, respectively. This suggests that the blocks at the boundary are not special enough to bias our estimates. Appendix Figure E.2 shows analogous figures by race and income for elementary, middle and secondary schools, and the conclusions are unchanged.

Remark 2. *In order to guard against pre-determined amenities biasing estimates, the prior literature typically drops boundaries that are close to observable features, such as roads or rivers. We instead carry out the spatial robustness check in Figure 5 for several reasons: (i) not all observed features anticipated to be barriers necessarily render Assumption 2′ invalid (false negative); (ii) it is possible that other boundaries should be dropped because of unobserved or unanticipated barriers (false positive); and (iii) Figure 5 allows us to indirectly gauge whether the linearity assumption (Assumption 2′) is a good approximation, irrespective of whether some boundaries coincide with barriers (observed or unobserved).*

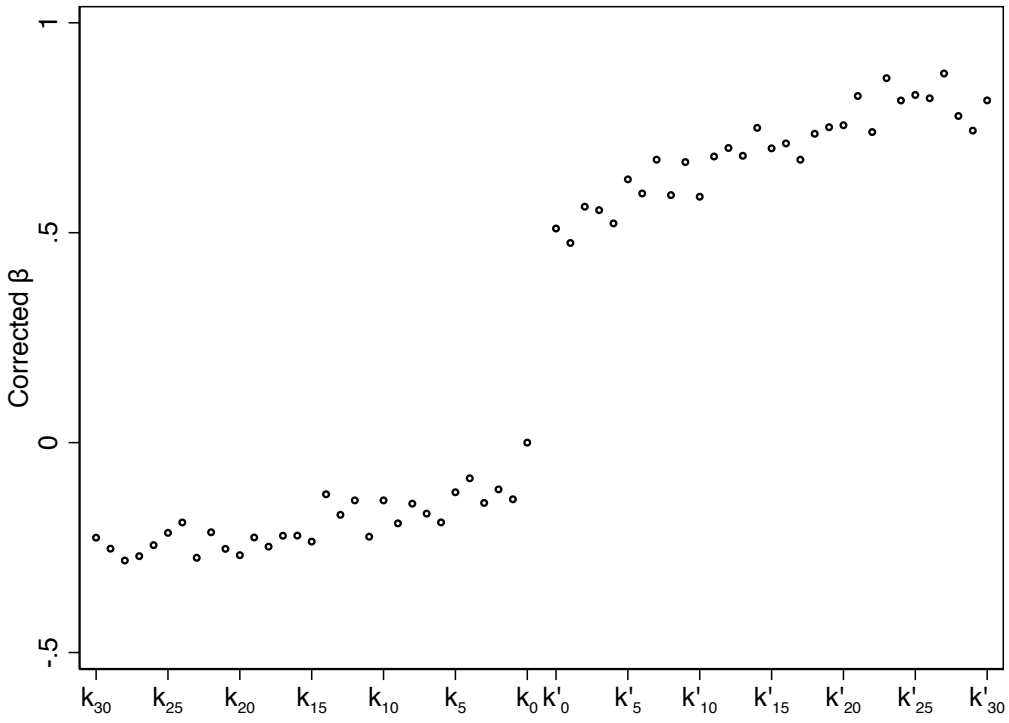


Figure 6: Corrected β Depending on the Reference Block k – Race, Elementary Schools

Notes: This figure plots $\tilde{\beta}_k := \beta_k - \beta_{k_1}$ for each $k = \{k_{30}, ..., k_0, k'_0, ..., k_{30}\}$, where β_k is estimated from equation (16). See footnote 24 for details on how k is measured.

6.1.2 Is Assumption 1 valid?

Assumption 1 states that the block-level difference $\Delta S_{k_0,k'_0}$ is representative of the overall difference in school factors between the two corresponding attendance areas, $\Delta S_{s,s'}$. Recall that for groups defined by race, $\Delta S_{k,k'} := (\phi^{\tau}_{k,S} - \phi^{\tau'}_{k,S}) \cdot (\mathbb{S}_k - \mathbb{S}_{k'})$, where $\mathbb{S}_k$ denotes the school amenity of block k and $\phi^{\tau}_{k,S}$ denotes the preference over it of those from group τ considering residing in block k.[26] Thus, for Assumption 1 to be valid, two conditions must hold: (i) $\mathbb{S}_{k_0} - \mathbb{S}_{k'_0}$ is representative of $\mathbb{S}_s - \mathbb{S}_{s'}$; and (ii) $\phi^{\tau}_{k_0,S} - \phi^{\tau'}_{k'_0,S}$ is representative of $\phi^{\tau}_{s,S} - \phi^{\tau'}_{s',S}$.

In Section 2.2, we discuss in detail why $\mathbb{S}_{k_0} - \mathbb{S}_{k'_0}$ is representative of $\mathbb{S}_s - \mathbb{S}_{s'}$. This is implied by our definition of ΔS. It simply involves an understanding of what is included in ΔS and, by implication, what is included in ΔN and $Cov(\Delta S, \Delta N)$, which we provide in that section.

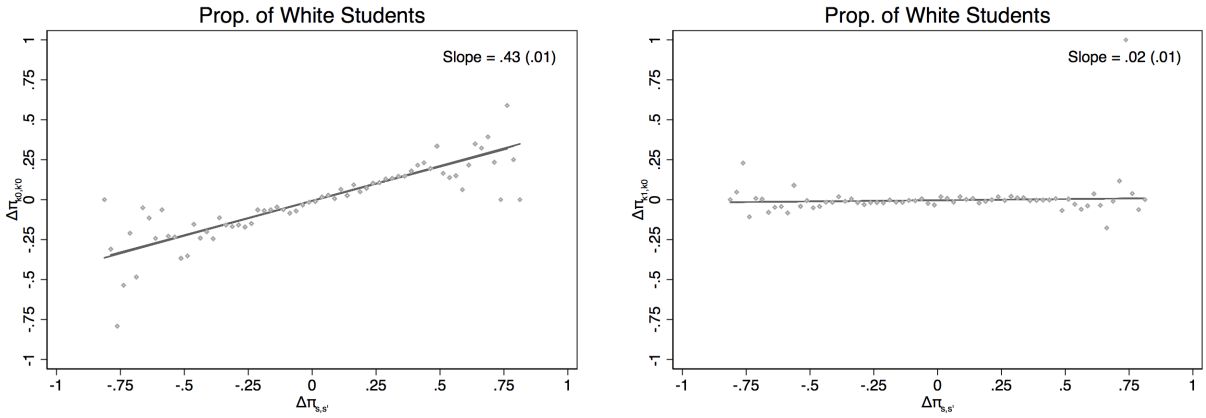
[26] See Appendix C for a generalized model where $\phi^{\tau}_{k,S}$ can vary with each block k.

We now turn our attention to the second condition. In essence, it would fail to hold if the sorting due to S (captured by the difference in the student population between representative blocks K_s and $K_{s'}$) is not reflected by the difference in student population between the boundary blocks k_0 and k_0'. As discussed in Section 6.1.1, Figure 5 suggests that there is nothing particularly special about blocks at the boundary (on average), when considering race or income on their own. This implies that the condition is likely to hold. However, there is a nuance that could call this conclusion into question.

Essentially, Figure 5 cannot rule out the condition failing in multiple dimensions. Dimensions other than race might be affected by sorting at the boundary, and that could correlate with the difference between the two attendance areas in terms of race, $\Delta\pi_{s,s'}^{white}$. For instance, it is possible that households in block k_0' are the poorest ones in their attendance area (because they would be willing to incur the price difference to reside in block k_0' versus block k_0, but otherwise would not be willing to additionally pay to be closer to nicer neighborhood amenities). The differences associated with income and race together may correlate more with $\Delta\pi_{s,s'}^{white}$ than the differences in race alone.

To assess whether this multidimensional issue presents a problem for our analysis, we estimate versions of equation (1) using two dimensions simultaneously. In particular, we calculate the extent to which $\Delta\pi_{s,s'}^{white}$ helps predict $\Delta\pi_{k_0,k_0'}^{richwhite}$, where π_s^{white} is defined as before and $\pi_k^{richwhite}$ represents the proportion of students in block k who are both economically advantaged and white, compared to all other types (non-white of any income or economically disadvantaged white).

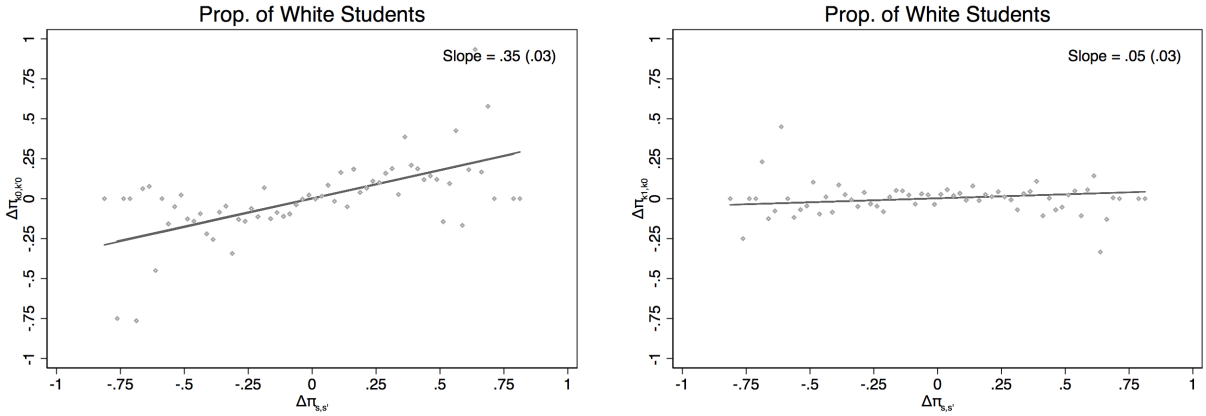
The results are presented in Figure 7. The slope estimate in the left panel (43%) is very similar to our main unidimensional estimate for race in Figure 3 (45%). The same is true when restricting the analysis to urban schools only, as the slope estimate in the left panel of Figure 8 (35%) is again very close to the corresponding race-only estimate in Table 2 (37%). For both cases, the placebo estimates are in line with the unidimensional estimates reported in Table 2. Thus, there is essentially no difference in the extent to which $\Delta\pi_{s,s'}^{white}$ explains $\Delta\pi_{k_0,k_0'}^{richwhite}$ or $\Delta\pi_{k_0,k_0'}^{white}$. We view this as lending further credence to Assumption 1.



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

Figure 7: The Effect of $\Delta\pi^{white}_{s,s'}$ on $\Delta\pi^{richwhite}_{k_0,k_0'}$ – All Schools

Notes: See the notes for Figure 3, which presents the analogous results for the effect of $\Delta\pi^{white}_{s,s'}$ on $\Delta\pi^{white}_{k_0,k_0'}$.



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

Figure 8: The Effect of $\Delta\pi^{white}_{s,s'}$ on $\Delta\pi^{richwhite}_{k_0,k_0'}$ – Urban Schools Only

Notes: See the notes for Figure 3, which presents the analogous results for the effect of $\Delta\pi^{white}_{s,s'}$ on $\Delta\pi^{white}_{k_0,k_0'}$ on all schools.

For completeness, we also regress $\Delta\pi^{richwhite}_{k_0,k_0'}$ on $\Delta\pi^{richwhite}_{s,s'}$. The corresponding plots are contained in Appendix Figures E.3 and E.4. Interestingly, the estimate across all schools (55%) is very close to the main unidimensional estimate for *income* in Figure 4 (57%), while the estimate for the urban sub-sample (37%) is identical to the unidimensional estimate for *race*. Intuitively, sorting by race (due to both S and N) is better at explaining school

segregation in urban areas, while sorting by income appears to do a better job outside of them.

6.1.3 Are results biased from noisy measures at the block level?

Another potential issue with our approach is that bias may arise from exploiting variation across blocks, in which very few students typically reside. This can be best understood by way of example. Suppose that all boundary block pairs are associated with population differences $\Delta\pi_{k_0,k_0'} = 0.3$, and each block contains one student. In that case, the sample difference estimate of $\Delta\pi_{k_0,k_0'}$ for a single pair of blocks is constrained to take the value -1, 0 or 1. The deviation of the sample difference estimate from its unmeasured population counterpart represents noise from small sample sizes, which could potentially lead to bias. However, as we argue in Remark 1, our estimates are unlikely to be affected by the presence of even substantial noise, since it is averaged away when aggregating across a sufficiently large number of block pairs.

The graphical evidence in Figures 3 and 4 bears this out. Taking averages of $\Delta\pi_{k_0,k_0'}$ across boundaries by bin of $\Delta\pi_{s,s'}$ (which is measured at the school level and not affected by small sample noise) produces a pattern that closely tracks the fit of the disaggregated ordinary least squares regression. Indeed, Figure B.1 in Appendix B explicitly shows that the slope from a regression based on aggregated values is statistically indistinguishable from its disaggregated counterpart, regardless of bin width. We take this as evidence that our estimates are not biased by small sample noise.[27]

6.2 Issues of Interpretation

Table 6 summarizes the robustness tests we carry out regarding interpretation. For convenience, the first column reports the baseline estimates of $\tilde{\beta}$ for all schools in our sample, as implied by the first column of Table 2.

[27] We have also performed different robustness checks by controlling for the number of students in the block pairs and in the school pairs using cubic B-splines, and the slope estimates barely change. These results are available upon request.

6.2.1 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.[28] Comparing the first (within-district baseline) and second (within and across districts) columns of Table 6, we do not find a systematic difference for race or income when we include schools in different districts in our analysis.[29]

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

Yet another 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

[28] Another related concern is that our identification strategy does not allow us to compare, for instance, one school from Charlotte, NC to another school from Raleigh, NC. Again, although school amenities may vary more non-locally than locally, the same is true for non-school amenities. In fact, it is intuitive that most people choose the city in which they will reside based on non-school factors, such as their job prospects.

[29] These results corroborate our finding in Section 6.1.1 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 the district.

Table 6: Robustness Tests

	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 $\tilde{\beta}$ (equation (10)) 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 32 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').

of N in urban areas, which is that neighborhood features change more intensely from one block to the next in urban relative to non-urban areas.

Another 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',[30] as well as for whether charter or magnet schools are located near either of the two attendance areas s and s'.[31] The results are reported in column three of Table 6. They are statistically indistinguishable from the baseline effects in column one, supporting our explanation.

[30]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).

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

6.2.3 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 $\tilde{\beta}$ to the analogous coefficient in a regression that also conditions on differences between school characteristics.[32] 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 $\tilde{\beta}$. That is precisely what we find for both race and income (see column four of Table 6). We view this evidence as an independent confirmation of what S represents.

7 Conclusion

This paper 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 66% of school segregation by race and 42% 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

[32] 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.

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,[33] could allow us to investigate patterns of sorting along many dimensions beyond race and income. We view this paper as enabling a new line of inquiry into confronting segregation, a matter of great importance to society.

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

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Appendices

A A Simple Model of School and Neighborhood Choice

Our framework is based upon a simple 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. 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 $\tau \in \{A, B\}$ observes the vector of school-related amenities $\mathbb{S} = [\mathbb{S}_1, \ldots, \mathbb{S}_K]'$ and the vector of neighborhood-related amenities $\mathbb{N} = [\mathbb{N}_1, \ldots, \mathbb{N}_K]'$, where k indexes the K neighborhoods in their choice set (each of which is assigned to a school indexed by s).[34] Each household selects the option that maximizes its utility:

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

where δ_k^τ corresponds to the mean utility of households of type τ for neighborhood k, and ζ_k^τ 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.[35] This yields the familiar expression for the proportion of students residing in neighborhood k who are of type A:

[34] 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 are different from each other because of many school and neighborhood amenities, so that $\mathbb{S}$ and $\mathbb{N}$ should be understood as indexes of all these corresponding amenities. Moreover, some amenities inherently conflate school and neighborhood amenities, such as the block 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 $\mathbb{N}$.

[35] This assumption is made only for didactic purposes. We present a more general model in Appendix C, which allows for substitutability to be different for surrounding neighborhoods.

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

where $n_k^\tau = n^\tau . \frac{exp(\delta_k^\tau)}{\sum_{\tilde{k}} exp(\delta_{\tilde{k}}^\tau)}$. Similarly, the proportion of students attending school s who are of type A is:

$$\pi_s = \frac{n_s^A}{n_s^A + n_s^B} \,,$$

where $n_s^\tau = n^\tau . \frac{\sum_{k \in \mathcal{K}_s} exp(\delta_k^\tau)}{\sum_{\tilde{k}} exp(\delta_{\tilde{k}}^\tau)}$ and $\mathcal{K}_s$ denotes the set of blocks k that are associated with attendance area s. Given representative blocks K_s and $K_{s'}$ for s and s', respectively, we denote $\mathbb{S}_s := \mathbb{S}_{K_s}$ and $\mathbb{N}_s := \mathbb{N}_{K_s}$. Under the normalization $\sum_{\tilde{k}} exp(\delta_{\tilde{k}}^\tau) = n^\tau$, we write:

$$\begin{aligned} \pi_s &= \frac{exp(\phi_S^A \mathbb{S}_s + \phi_N^A \mathbb{N}_s)}{exp(\phi_S^A \mathbb{S}_s + \phi_N^A \mathbb{N}_s) + exp(\phi_S^B \mathbb{S}_s + \phi_N^B \mathbb{N}_s)} \\ &= \frac{exp(\delta_s^A)}{exp(\delta_s^A) + exp(\delta_s^B)} \,, \end{aligned} \tag{A.2}$$

where $\delta_s^\tau := \phi_S^\tau \mathbb{S}_s + \phi_N^\tau \mathbb{N}_s$ represents the mean utility of households of type τ for attendance area s.

For school segregation to exist in our sample of schools, the proportion of students of a given type must vary across schools. Consider two schools s and s'. For $\pi_s \neq \pi_{s'}$, there must be something different across the two school attendance areas that is valued differently by type. This intuition can be made precise. Recall equations (2) and (3) in Section 2:

$$\Delta\pi_{s,s'} = \Delta S_{s,s'} + \Delta N_{s,s'} \,,$$
$$\Delta\pi_{k,k'} = \Delta S_{k,k'} + \Delta N_{k,k'} \,.$$

The key quanitites are defined as $\Delta S_{s,s'} := (\phi_S^A - \phi_S^B)(\mathbb{S}_s - \mathbb{S}_{s'})$ and $\Delta N_{s,s'} := (\phi_N^A - \phi_N^B)(\mathbb{N}_s - \mathbb{N}_{s'})$. Note that $\Delta S_{s,s'}$ and $\Delta N_{s,s'}$ are not the same as $\Delta\mathbb{S}_{s,s'}$ and $\Delta\mathbb{N}_{s,s'}$: the former represent both differences in the level of amenities across school attendance areas and differences in preferences across groups, while the latter represent only differences in the level of amenities across attendance areas. In Appendix B, we explain how equations (2) and (3) in Section 2 serve as good approximations for interpretation purposes given these intuitive definitions of $\Delta S_{s,s'}$ and $\Delta N_{s,s'}$.

B Justifying the Interpretation of $\Delta S_{s,s'}$ and $\Delta N_{s,s'}$

In this appendix, we justify why $\Delta S_{s,s'} := (\phi_S^A - \phi_S^B)(\mathbb{S}_s - \mathbb{S}_{s'})$ and $\Delta N_{s,s'} := (\phi_N^A - \phi_N^B)(\mathbb{N}_s - \mathbb{N}_{s'})$ given in Appendix A are good approximations for interpretation purposes.

We begin by explicitly deriving the components of $\Delta\pi_{k,k'}$ and $\Delta\pi_{s,s'}$, based on the discrete choice model in Appendix A. Using equation (A.2), we have that $\delta_k^A - \delta_k^B = ln\left(\frac{\pi_k}{1-\pi_k}\right) = S_k + N_k$, where $S_k := \left(\phi_S^A - \phi_S^B\right)\mathbb{S}_k$ and $N_k := \left(\phi_N^A - \phi_N^B\right)\mathbb{N}_k$. Given the two adjacent blocks k and k' in attendance areas s and s', we have $\delta_k^A - \delta_k^B - \left(\delta_{k'}^A - \delta_{k'}^B\right) = ln\left(\frac{\pi_k(1-\pi_{k'})}{\pi_{k'}(1-\pi_k)}\right) = \Delta S_{s,s'} + \Delta N_{k,k'}$, where $\Delta S_{s,s'} := S_s - S_{s'}$ and $\Delta N_{k,k'} := N_k - N_{k'}$. Analogously, we can write $\delta_s^A - \delta_s^B - \left(\delta_{s'}^A - \delta_{s'}^B\right) = ln\left(\frac{\pi_s(1-\pi_{s'})}{\pi_{s'}(1-\pi_s)}\right) = \Delta S_{s,s'} + \Delta N_{s,s'}$, where $\Delta S_{s,s'} := S_s - S_{s'}$ and $\Delta N_{s,s'} := N_s - N_{s'}$.

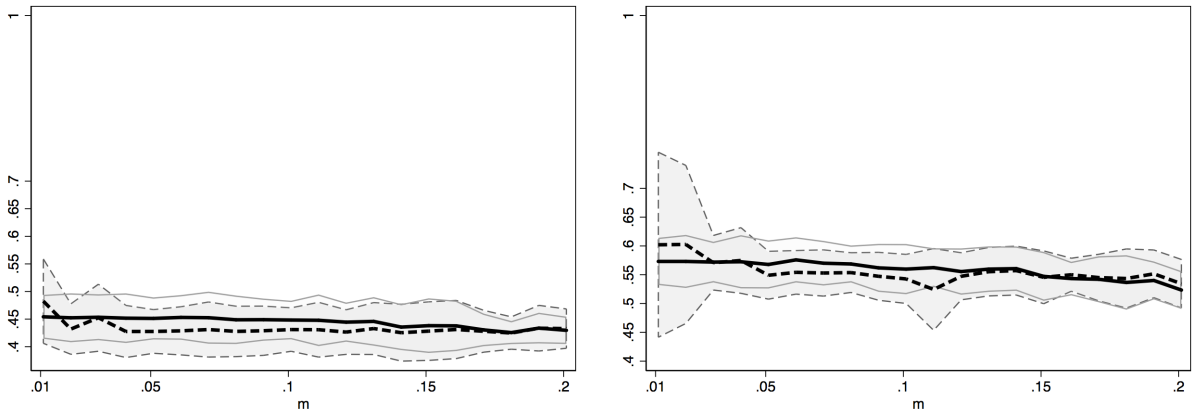
Thus, the exact equations are $ln\left(\frac{\pi_s(1-\pi_{s'})}{\pi_{s'}(1-\pi_s)}\right) = \Delta S_{s,s'} + \Delta N_{s,s'}$ and $ln\left(\frac{\pi_k(1-\pi_{k'})}{\pi_{k'}(1-\pi_k)}\right) = \Delta S_{k,k'} + \Delta N_{k,k'}$, instead of $\Delta\pi_{s,s'} = \Delta S_{s,s'} + \Delta N_{s,s'}$ (equation (2)) and $\Delta\pi_{k,k'} = \Delta S_{k,k'} + \Delta N_{k,k'}$ (equation (3)), respectively. However, we would like to avoid using $ln\left(\frac{\pi_k(1-\pi_{k'})}{\pi_{k'}(1-\pi_k)}\right)$ because this ratio is often not defined for our estimates of π_k and $\pi_{k'}$. Indeed, as discussed in Remark 1, $\hat{\pi}_k = 0$ and $\hat{\pi}_k = 1$ often occur in our sample even if $0 < \pi_k < 1$. Thus, this measure is highly affected by noise.

Here, we argue that the slope of the linear-linear regression ($\Delta\hat{\pi}_{k_0,k_0'}$ on $\Delta\hat{\pi}_{s,s'}$, as in equation (1)) and the slope of the log-log regression ($ln\left(\frac{\hat{\pi}_{k_0}\left(1-\hat{\pi}_{k_0'}\right)}{\hat{\pi}_{k_0'}\left(1-\hat{\pi}_{k_0}\right)}\right)$ on $ln\left(\frac{\hat{\pi}_s(1-\hat{\pi}_{s'})}{\hat{\pi}_{s'}(1-\hat{\pi}_s)}\right)$) are approximately the same when noise is not present. To see this, we reduce the role of noise by aggregating, across all boundaries, all school pairs with sufficiently similar values of $\Delta\pi_{s,s'}$. $\Delta\pi_{s,s'}$, which in principle can vary from -1 to 1, is divided in intervals of width m, and we aggregate $ln\left(\frac{\hat{\pi}_{k_0}\left(1-\hat{\pi}_{k_0'}\right)}{\hat{\pi}_{k_0'}\left(1-\hat{\pi}_{k_0}\right)}\right)$ and $ln\left(\frac{\hat{\pi}_s(1-\hat{\pi}_{s'})}{\hat{\pi}_{s'}(1-\hat{\pi}_s)}\right)$ for each of these intervals. For comparison, we aggregate $\Delta\hat{\pi}_{k_0,k_0'}$ and $\Delta\hat{\pi}_{s,s'}$ in order to estimate an aggregated version of the linear-linear regression.

Figure B.1 compares the slope of the aggregated version of the linear-linear regression (solid black line) and the slope of the aggregaged version of the log-log regression (dashed black line) for different values of the aggregation interval m.[36] The corresponding 95% confidence intervals are also shown in grey. The larger the value of m, the more aggregated

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

the data used in the regressions. To provide more context, we use $m = 0.025$ in the scatter plots of Figures 3 and 4. As Figure B.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 Figures 3 and 4 (0.45 for race and 0.57 for income). Importantly, as m gets smaller the confidence interval of the log-log slope estimator increases while the corresponding confidence interval of the linear-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).



(a) Race (b) Income

Figure B.1: Relationship Between Slopes in the Aggregated Log-Log Regression and the Aggregated Linear-Linear Regression

Notes: This figure plots the slope parameter of the aggregated log-log regression (dashed line) and the aggregated linear-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-linear slope estimates are 0.45 (race) and 0.57 (income), as shown in the left panels of Figures 3 and 4.

We conclude that running the linear-linear version of the regression yields the same interpretation of the slope as running the log-log version of the regression, but with the advantage of being more robust to noise. Thus, we can safely interpret $\Delta S_{s,s'}$ as $(\phi_S^A - \phi_S^B)(\mathbb{S}_s - \mathbb{S}_{s'})$ and $\Delta N_{s,s'}$ as $(\phi_N^A - \phi_N^B)(\mathbb{N}_s - \mathbb{N}_{s'})$, as discussed in Appendix A.

C More General Discrete Choice Model

In this appendix, we outline a more general model than the one presented in Appendix A, allowing for spillovers from other neighborhoods. The model setup differs only in the way that δ_k^τ is defined. Otherwise, all other expressions and results from the main text hold.

Assume each household h of type τ observes the vector of school-related amenities $\mathbb{S} = [\mathbb{S}_1, \ldots, \mathbb{S}_K]'$ and the vector of neighborhood-related amenities $\mathbb{N} = [\mathbb{N}_1, \ldots, \mathbb{N}_K]'$, where $k \in [1, K]$ indexes the neighborhoods in their choice set (each of which are assigned to a school indexed by s). Each household selects the option that maximizes its utility:

$$u_k^{h,\tau} = \underbrace{\phi_{k,S}^\tau \mathbb{S} + \phi_{k,N}^\tau \mathbb{N}}_{\delta_k^\tau} + \zeta_k^{h,\tau}, \tag{C.1}$$

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 the shared effect of $\mathbb{S}$ and $\mathbb{N}$ on the population of type τ households in neighborhood k. The mean utility depends on the preference parameter vectors $\phi_{k,S}^\tau = [\phi_{k,1,S}^\tau, \ldots, \phi_{k,K,S}^\tau]$ and $\phi_{k,N}^\tau = [\phi_{k,1,N}^\tau, \ldots, \phi_{k,K,N}^\tau]$. Each element depends on a household's type τ (allowing preferences to differ across types) and is specific to the neighborhood k chosen (weighting the exposure to different components of the amenity vector according to the selected location).[37]

As we are interested in comparing one household type to its complement (e.g., white vs. non-white, or advantaged vs. disadvantaged), we consider two types $\tau, \tau' \in \{A, B\}$, where $\tau' \neq \tau$. Household h will choose to reside in neighborhood k if $u_k^{h,\tau} > u_{\tilde{k}}^{h,\tau}\ \forall\ k \neq \tilde{k}$. As is standard in discrete choice problems, we assume that $\zeta_k^{h,\tau}$ is independently and identically drawn from the extreme value distribution. This assumption results in the exact same expressions we obtained in Appendix A.

The only difference between this model and the more restricted model in Section 2 is that we now allow households who choose block k to experience school and neighborhood amenities from other blocks at different rates than if they had chosen block $\tilde{k}$. Thus, rather

[37] The weighting is easily motivated by the distance to the amenity in question. It is reasonable to expect that someone living in a house located one mile from a park would derive greater value from the park than someone living in a house that is ten miles away from it.

than $\Delta S := (\phi_S^A - \phi_S^B) \cdot (\mathbb{S}_s - \mathbb{S}_{s'})$, we have $\Delta S := (\phi_{s,S}^A - \phi_{s',S}^B) \cdot \mathbb{S}$, where $\phi_{s,S}^\tau$ reflects the representative value of $\phi_{k,S}^\tau$ considering all blocks in attendance area s, with an analogous definition for neighborhood factors.

D Derivation of Dynamic Model Results

Recall the expression that governs the evolution of $\Delta\pi_t$, given by equation (11):

$$\Delta\pi_t - \Delta\pi_{t-1} = \Delta\eta_{t-1} + \psi^S \left[\Delta\pi_{t-1} - \Delta\pi_{t-2}\right] + \psi^N \left[\Delta\pi_{t-1} - \Delta\pi_{t-2}\right] ,$$

where $\Delta\eta_0 := \Delta\eta_0^N$ and $\Delta\eta_t = 0 \ \forall \ t \neq 0$.

We now 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 $\Psi := \psi^S + \psi^N$.[38] 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 $0 \leq \Psi < 1$.[39] Thus, in the limit as $t \to \infty$ (long-run stable equilibrium), we have $\Delta\pi = \frac{\Delta\eta_0}{1-\Psi}$.

We now decompose $\Delta\pi$ into its constituent elements ΔS and ΔN. Attributing the initial shock $\Delta\eta_0^N$ to ΔN, the components of $\Delta\pi$ are:

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

where $\Delta\pi = \Delta S + \Delta N$ as in Section 2. With these expressions in hand, we can compute

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

[39] Our main conclusions are also valid in the context of oscillatory trajectories to the stable equilibrium ($-1 < \Psi \leq 0$). Moreover, many frictions in residential sorting, such as moving costs, lead us to conclude that multiplicity of equilibria ($|\Psi| > 1$) is not realistic for most schools in our context (see Caetano and Maheshri 2019).

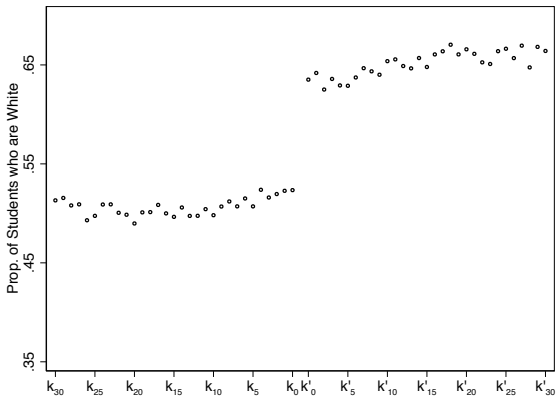
$var(\Delta\pi)$, $var(\Delta S)$, $var(\Delta N)$ and $cov(\Delta S, \Delta N)$. Assuming that the shock $\Delta\eta_0^N$ is drawn from a distribution with variance σ^2, we obtain:

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

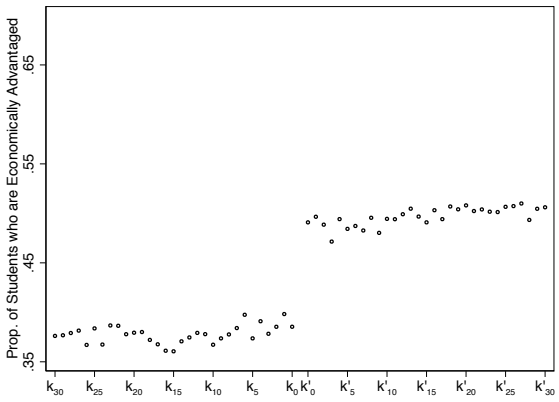
In turn, we can compute Ω_S:

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

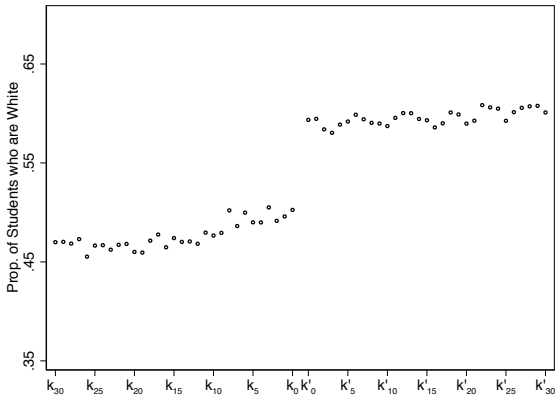
E Supporting Figures



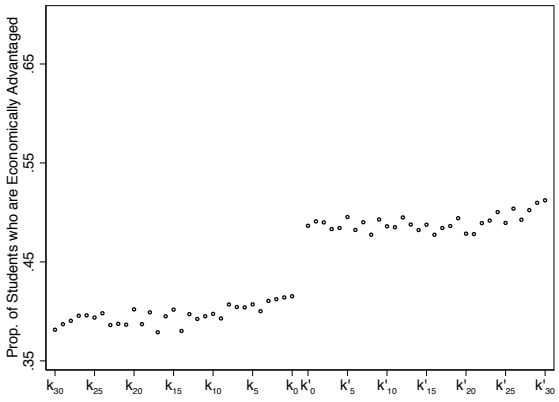
(a) White, Elementary



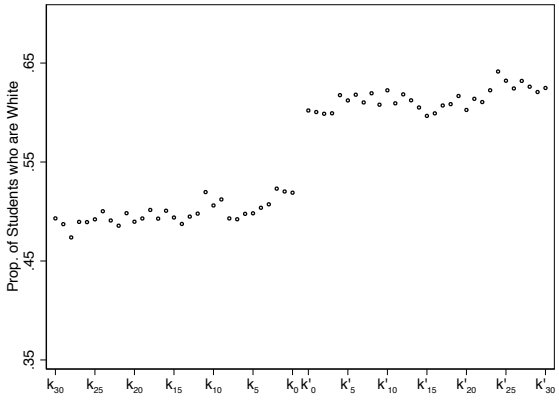
(b) Economically Advantaged, Elementary



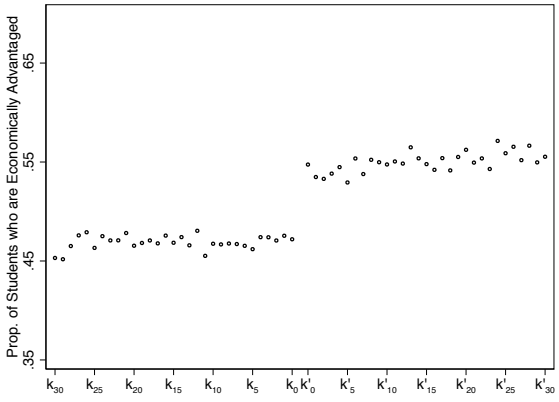
(c) White, Middle



(d) Economically Advantaged, Middle



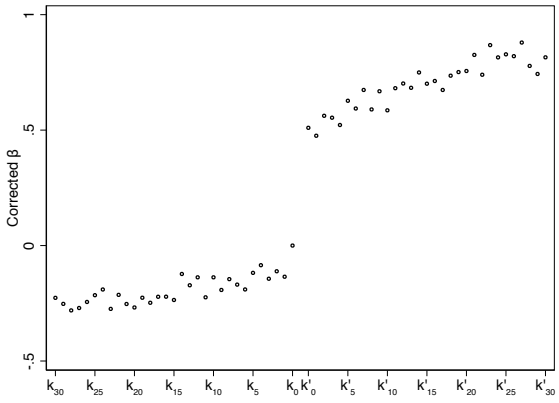
(e) White, Secondary



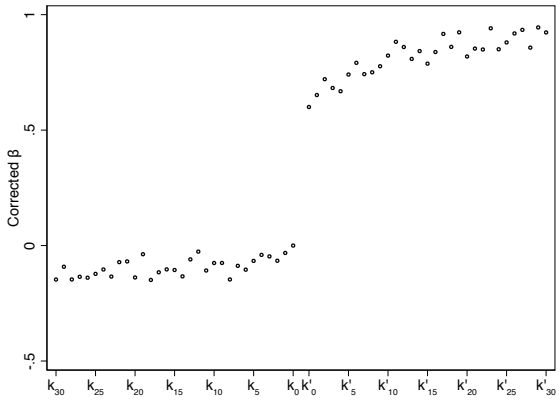
(f) Economically Advantaged, Secondary

Figure E.1: Proportion of Students of a Given Type in Each Block

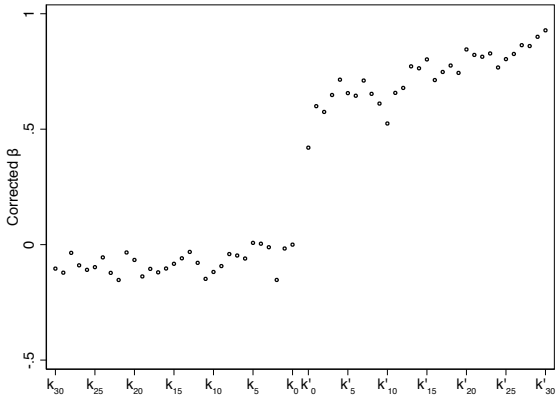
Notes: This figure plots the average proportion of students who are white across all blocks of type k_l (k'_l) (each block representing a different boundary). The index l reflects the number of degrees of separation from block k_0 (k'_0) in their corresponding attendance area. See footnote 24 for details on how l is measured.



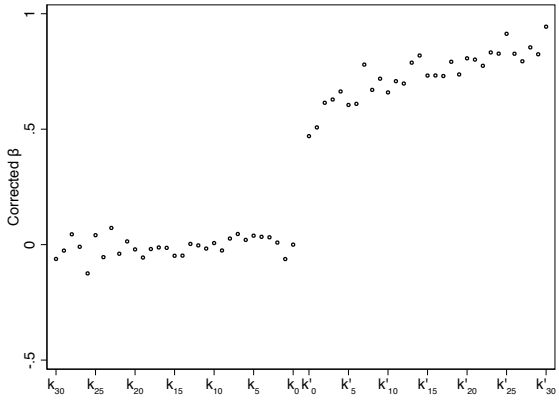
(a) White, Elementary



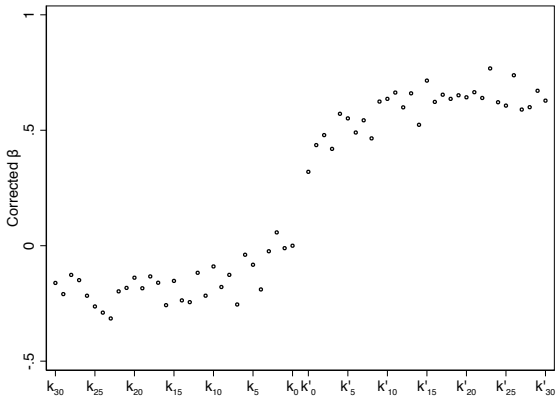
(b) Economically Advantaged, Elementary



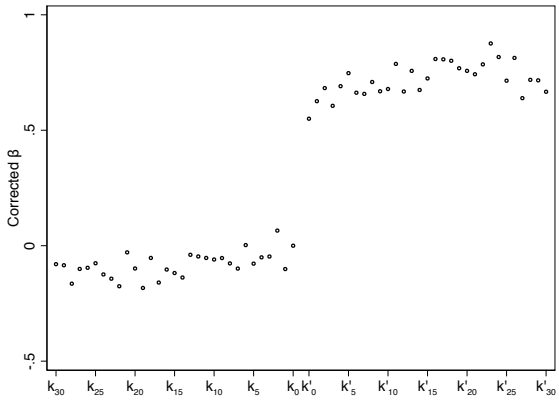
(c) White, Middle



(d) Economically Advantaged, Middle



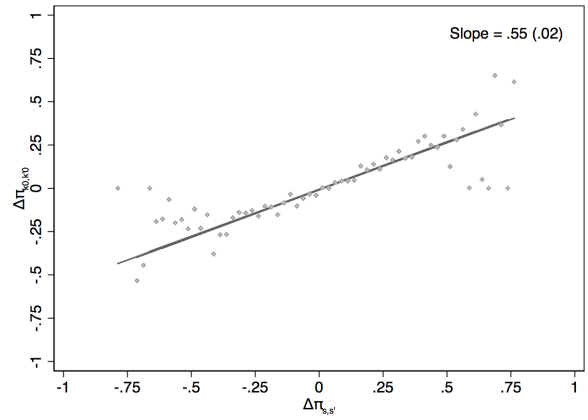
(e) White, Secondary



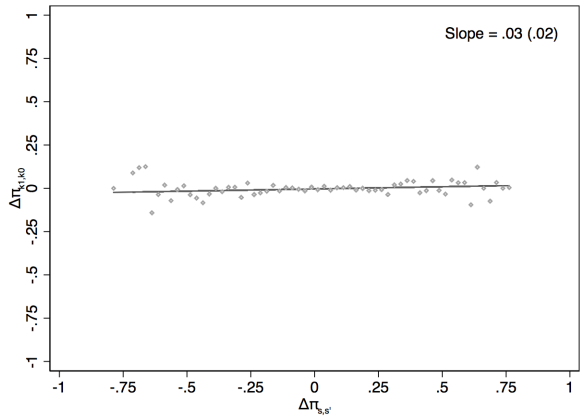
(f) Economically Advantaged, Secondary

Figure E.2: Corrected βs Depending on the Reference Block k

Notes: This figure plots $\tilde{\beta}_k := \beta_k - \beta_{k_1}$ for each $k = \{k_{30}, ..., k_0, k'_0, ..., k_{30}\}$, where β_k is estimated from equation (16). See footnote 24 for details on how k is measured.



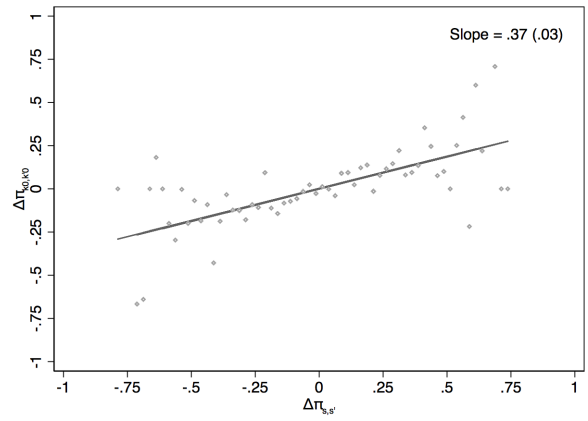
(a) Blocks in Different Attendance Areas



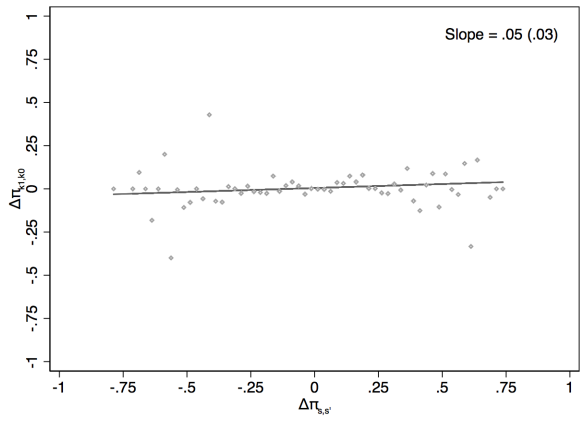
(b) Blocks in the Same Attendance Area

Figure E.3: The Effect of $\Delta\pi^{richwhite}_{s,s'}$ on $\Delta\pi^{richwhite}_{k_0,k'_0}$ – All Schools

Notes: See the notes for Figure 3, which presents the analogous results by race.



(a) Blocks in Different Attendance Areas



(b) Blocks in the Same Attendance Area

Figure E.4: The Effect of $\Delta\pi^{richwhite}_{s,s'}$ on $\Delta\pi^{richwhite}_{k_0,k'_0}$ – Urban Schools Only

Notes: See the notes for Figure 3, which presents the analogous results by race and for all schools.