School Attendance Boundaries and the Segregation of Public Schools in the US

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Abstract

Public school assignment policy is determined by local education agencies, typically using school attendance boundaries. I provide evidence that local agencies exhibit demand for racial desegregation of school boundaries as a function of commuting costs, and that this demand is responsive to desegregation court orders and local attitudes toward racial diversity. To do so, I develop empirical techniques for the economic analysis of spatial school boundary data, linked to census block demographics. My findings suggest that school boundaries are a remarkably active area of local policy that has impacts on educational equity and is responsive to costs and local preferences.

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1 Introduction

Over the second half of the twentieth century, the United States embarked on, then retreated from, a concerted effort to integrate schools. The landmark *Brown* decision in 1954 held that the then status quo system of "separate but equal" schools for black and white children was unconstitutional. Through the 1960s, 1970s, and early 1980s, many school districts implemented, under federal judicial oversight, ambitious programs designed to create "unitary" school systems (Coleman, Campbell, Hobson, McPartland, Mood, Weinfeld and York 1966, Welch and Light 1987, Clotfelter 2004, Reber 2005, Rivkin and Welch 2006, Cascio, Gordon, Lewis and Reber 2008, Johnson 2015). However, since the late 1980s federal enforcement of local school integration efforts has declined. Judicial oversight of desegregation plans has largely been withdrawn, and most school districts have been left to make policy decisions affecting school integration locally (Orfield and Eaton 1997, Jackson 2009, Lutz 2011, Reardon, Grewal, Kalogrides and Greenberg 2012, Billings, Deming and Rockoff 2014, Reardon and Owens 2014).

Local programs intended to encourage school integration typically involve the reform of school assignment policy. Even in today's era of expanding school choice, most student assignment systems continue being comprised at least partially, if not completely, of *school attendance boundaries* – zoning maps that assign public schools to students based on the location of their residence. These maps partition school attendance rights based on geography, creating a link between residential segregation patterns and segregation in schools. This link need not be perfect, however. Just as it is the case with the gerrymandering of congressional districts, school boundaries can be drawn in a myriad of ways, potentially affording local leaderships the ability to influence racial diversity in schools with the simple drawing of a line on a map.

I study whether local education agencies manipulate school attendance boundaries to combat or perpetuate school segregation. Specifically, I use geographic information systems (GIS) data on the 2013-14 school boundaries of nearly every urban school district in the country, combined with 2010 census block data on the racial composition of neighborhoods, to understand how school boundaries affect racial segregation in school assignments. I begin by developing tools to measure school boundary desegregation and apply them to the data. I present evidence consistent with most school districts preserving the link between residential and school segregation by drawing school boundaries that replicate the racial composition of neighborhoods. However, a sizable minority of local governments appear to desegregate boundaries to ameliorate this link, tilting the scale in the direction of increased racial integration in school assignments. Very few districts appear to manipulate boundaries to exacerbate segregation.

Next, I examine what school boundaries reveal about local governments' preferences for school integration. I do it using data on the commuting cost of school boundary desegregation, the status of court desegregation orders, and the beliefs of local white residents regarding the causes of racial inequality. I discipline the analysis with a simple model of the tradeoff local governments face when drawing school boundaries, motivated by a historical stylized fact: given residential segregation, costly student busing is often needed to integrate schools (Welch and Light 1987). I estimate cross-sectional models of school district demand for integrated school boundaries as a function of commuting cost and taste shifters, generating novel evidence on districts' school boundary drawing behavior. I address endogeneity in cost using a novel instrument based on the variability in school district jurisdiction shapes, which drives desegregation commuting costs, as I demonstrate.

The key findings of the revealed preference analysis are that, (i) districts are more likely to desegregate school boundaries if desegregation can be achieved at a lower commuting cost; (ii) controlling for cost, active desegregation orders lead to more intense school boundary desegregation, but no such association is present for districts that have been released from judicial oversight; and (iii) intolerant racial attitudes on the part of local white residents are robustly correlated with less school boundary desegregation. Taken together, the evidence suggests that school boundary manipulation is a remarkably active area of local education policy which reflects the influence of both local cost and preference factors, with important implications for racial equity in the country's thousands of local school systems.

While the era of judicial remedies for school segregation has been studied extensively, there is relatively little known about the role played by school boundaries (Saporito and Sohoni 2006, Sohoni and Saporito 2009, Richards 2014, Saporito and Riper 2016). I evaluate existing school boundaries by comparing their residential racial composition to counterfactuals that implement "neighborhood schools" in a strict mathematical sense – hypothetical zones that minimize the distance travelled between school locations and student residences. By definition, these counterfactuals replicate the segregation of neighborhoods in the immediate area surrounding schools. These counterfactuals are also correctly scaled to make comparisons between school and neighborhood segregation, since segregation indices are not scale invariant and tracts and school boundaries are seldom of similar scale (Lee, Reardon, Firebaugh, Farrell, Matthews and O'Sullivan 2008). I show that variation in a boundary desegregation index based on these counterfactuals is correlated with racial integration in school enrollments, as well as various measures of system-wide inequality in access to school resources, suggesting that school boundary desegregation is a policy lever that is effective at influencing equity in local schooling.

I model a district's choice of school boundaries as an equity-efficiency trade-off. Districts draw school boundaries to maximize a value function defined over the level of racial integration and aggregate commuting distance, with relative weights that may vary across districts capturing preference heterogeneity. While district objectives are typically more complicated than this, this simple model captures the first order concerns of the boundary setting process. Concerns for commuting efficiency and equity are often cited as competing objectives during the boundary setting process, and modeling equity in terms of racial segregation is closer to the available census block data. As such, these weights characterize district effective preferences for racially integrated schools, in terms of their willingness to increase aggregate student transportation costs. The districts' budget constraints are also heterogeneous – in some places the travel cost of increasing integration may be high due to the geography of residential segregation, while in other places, where the spatial configuration of race across the jurisdiction is different, boundaries can be drawn to increase school integration relatively cheaply. Realized school boundary choices are therefore generated by a district-specific mix of taste and cost shifters.

I decompose the variance of boundary desegregation into cost and preference components, allowing me to study the behavior of local policymakers. I measure the commuting cost of desegregating school boundaries with a simple algorithm approximating the district-specific increase in total home-school distance that is needed to increase racial integration by one unit. In other words, I measure the marginal cost of desegregation, conditional on the spatial distribution of residential racial composition. I use these cost estimates to model the demand for school boundary desegregation across school districts. OLS estimates of a regression of boundary desegregation on cost show a significant negative coefficient that is robust to the addition of various controls including district racial composition, residential segregation, region, population density, among others.

I address simultaneity concerns in the OLS demand model by instrumenting the cost of school boundary desegregation with a measure of the *bizarreness* of districts' geographic jurisdiction – a concept borrowed from the literature on congressional gerrymandering (Chambers and Miller 2010). I show that districts with bizarrely shaped jurisdictions tend to face higher desegregation costs (the first stage), conditional on covariates. I argue that variability in cost that is driven by the geographic shape of districts is unlikely to be directly linked to local policymaker preferences, making it excludable from the second stage demand equation. 2SLS demand elasticity estimates are negative and of larger magnitude than OLS, providing two insights: (1) there is measurement error in the price measure; and (2) unobserved preferences for desegregation are negatively correlated with desegregation costs. The latter implication suggests that communities with strong preferences for desegregated school systems have urban geographies that are easier to integrate, perhaps precisely due to a greater historical tolerance toward racial diversity.

These results indicate that school districts are responsive to the cost of integrating schools by desegregating school attendance boundaries. Districts are more likely to desegregate boundaries if it is cheaper to do so. My preferred estimates suggest that a one standard deviation increase in cost leads to a 1.23 standard deviation decrease in school boundary desegregation. This has important implications for schooling equity policy at higher levels of government. For instance, it suggests that federal school transportation subsidies would lead local governments to enact better integrated school attendance boundary maps.

I next examine the relationship between school boundaries and judicial oversight over desegregation. I estimate that the small number of districts that remain under a court desegregation order have significantly higher realized levels of school boundary desegregation. Active orders are associated with a 0.53 standard deviation higher school boundary desegregation controlling for cost and other covariates. On the other hand, the considerably larger number of districts that were formerly under supervision but have since been released, show no statistically significant difference in integration effort compared to similar districts that never faced a court order. Taken together, these results suggest that school boundary decisions respond to federal and state pressure to alleviate racial imbalance in schools, but that school assignment policy is sufficiently flexible such that districts revert to neighborhood schools when outside government pressure subsides. These findings are consistent with earlier work on the resegregation of schools that accompanied the end of the federal oversight era (Clotfelter 2004, Lutz 2011, Reardon et al. 2012).

Finally, I examine the relationship between school boundary desegregation and local attitudes toward racial minorities on the part of white residents. Following the earlier work of

Cutler, Glaeser, and Vigdor (1999) and Card, Mas, and Rothstein (2008), I use census tract level data on racial attitudes from the General Social Survey to construct a school district level index of racial intolerance on the part of local white residents. I find that racial intolerance from whites is highly predictive of lower levels of school boundary desegregation, both in univariate models, and controlling for a range of district observables including desegregation cost, the status of desegregation orders, neighborhood segregation, racial composition, population density, and US region effects. Estimates suggest that, conditional on controls, a one standard deviation increase in racial intolerance is associated with a 0.35 standard deviation decrease in school boundary desegregation. This finding underscores the continuing role of white animus toward racial diversity as a barrier to the integration of schools.

A central assumption in this study is that policymakers view residential composition as fixed when enacting school boundaries. However there is evidence consistent with a long-run causal effect of school attendance boundaries on residential segregation (Black 1999, Bayer, Ferreira and McMillan 2007). If neighborhoods and real estate markets react swiftly to school attendance boundary challenges, that would threaten the basis of the measures and results presented here. I argue that the long-run endogeneity of residential composition is not a threat to the findings of this study. First, school boundary changes tend to happen frequently, often due to the construction of new schools or to rectify imbalances in school enrollment and capacity. I measure residential demographics in 2010 to evaluate 2013 school boundary maps. This partly alleviates concerns for bias due to endogenous residential sorting in my evaluation, specially in cases in which the maps were enacted recently. However, this logic also implies that my analysis may be more sensitive to cases in which school boundaries have not changed for extended periods of time.

Second, I present direct evidence of the medium-run impact of school boundaries on residential racial composition, using the prominent case of Charlotte Mecklenburg Schools (CMS) school district in North Carolina (reported in the Appendix). In 2002, CMS reverted its decades old desegregated school boundary map to a neighborhood schools plan. Using a research design similar to Billings, Deming, and Rockoff (2014), I estimate the impact of this change on residential segregation by comparing census blocks in the same neighborhood that used to be assigned to the same school but were reassigned to different schools. I implement this design to estimate the impact of school boundaries on block racial composition and real estate values. The results suggest that a 1 p.p. increase in the minority share of school boundaries leads to a 0.15 p.p. increase in the share of minorities in a census block, and no discernible impact on real estate values. I interpret these findings as evidence that sorting equilibrium in the housing market is not highly sensitive to school boundaries in the short to medium run. This finding reassures the validity of the main analysis.

This paper provides a contribution to several literatures. One is the research on the effect of school desegregation policies. This work nearly exclusively focuses on court-ordered policies in a much earlier era. There is much less work on the effect of districts' unsupervised choice of student assignment systems on segregation (Richards 2014, Saporito and Riper 2016).[1] My

[1] The findings in the education literature on school boundaries are largely consistent with the results of this paper. In particular, Richards (2014) uses a similar empirical approach leveraging a different dataset,

work also relates to the mechanism design literature on student assignment based on deferred acceptance assignment algorithms and parental school preference rankings (Abdulkadiroglu, Pathak and Roth 2009, Pathak 2011, Ellison and Pathak 2016). The recent growth in this literature demonstrates that student assignment policy is an active area of both empirical and theoretical research. Moreover, deferred acceptance algorithms frequently incorporate priorities over students living within school boundaries (Dur, Kominers, Pathak and Sonmez 2013).

This paper is also related to the political economy literature on diversity and governance (Alesina, Baqir and Hoxby 2004). There is relatively little work in this literature on school boards, though this hyperlocal level is where much of the action occurs. One challenge is that it can be difficult to measure policy choices at this level, which this paper partially addresses by genarating district level indices aimed at capturing local government behavior. Macartney and Singleton (2017) estimate the effect of the partisan composition of school boards on segregation, finding that a higher Democratic share leads to lower segregation in the district. They provide suggestive evidence that the mechanism at play is changes in school boundaries. My measurement of districts' actual policies is complementary to theirs, and strengthens the notion that school boundaries are levers that districts use to achieve this goal.

Due to the focus on the strategic drawing of boundaries, this paper is also closely related to the congressional gerrymandering literature in political science and economics. The seminal work on optimal gerrymandering in economics has focused on purely theoretical aspects (Friedman and Holden 2008), ignoring the inherent geographic aspect of drawing congressional district boundaries. On the other hand, political scientists have focused on the geographic shape of congressional districts (Chambers and Miller 2010) or more recently on generating a statistical distribution of partisan bias by randomly generating districts that satisfy legal requirements (Chen and Cottrell 2016). My paper contributes to this literature by expanding the concept of boundary optimization to a different set of intentionally drawn boundaries.

The rest of the paper proceeds as follows. Section 2 describes the historical background of school segregation and local governance, as well as institutional details of school attendance boundary policy. Section 3 develops minimum travel distance SAB counterfactuals and implements an index to describe the distribution of desegregation policy. Section 4 presents a model of school attendance boundary choice. Section 5 analyzes the travel cost of desegregation and develops an algorithm to estimate prices. Section 6 studies desegregation demand shifters, characterizing observable drivers of heterogeneity in policy. Section 7 presents the case study of abrupt boundary changes in Charlotte, estimating the causal effect of school boundary racial composition on neighborhood racial composition. Section 8 concludes.

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documenting a similar distribution of desegregation and a link between boundary desegregation and desegregation orders. This literature has taken a stronger stance that district inaction to desegregate boundaries – by sticking to neighborhood schools – amounts to segregative policy.

2 Background

The Supreme Court's landmark Brown v. Board of Education decision in 1954 placed a mandate to end the racial segregation of schools, ruling that the 'separate but equal' school doctrine was unconstitutional. While the *Brown* decision marked the end of de jure segregation of schools, actual desegregation efforts did not begin until subsequent Supreme Court decisions forced school districts to act against de facto school segregation in the following decades. During this time many districts were placed under court desegregation orders and school segregation decreased dramatically across the nation (Clotfelter 2004).

More recent Supreme Court rulings have pushed in the opposite direction, severely altering the legal basis of court-ordered desegregation plans. Board of Education v. Dowell (1991) established that desegregation decrees were not permanent. The court ruled that school districts could be released from oversight by demonstrating they had complied in good faith and that vestiges of past discrimination had been eliminated, regardless of contemporaneous segregation levels. Many of the school districts formerly under desegregation orders were declared "unitary" by the courts, and were subsequently released from judicial oversight (Lutz 2011). While a small number of desegregation orders remain open today, the vast majority of districts that were once under court oversight have been released from it (Reardon et al. 2012). Today, most school districts have freedom to choose whether or not to encourage school integration. Local desegregation efforts therefore depend on the views of local school boards and communities, as well as the feasibility and transportation cost of desegregation, given existing residential segregation patterns.

But the end of the era of court desegregation orders was not intended to signal the end of *Brown*'s mandate. The Supreme Court made this point clear in PICS v. Seattle School Dist. No. 1, (2007). Parents brought legal action challenging a student assignment desegregation plan that used individual racial classification to allocate slots in oversubscribed high schools. The court ruled that the *individualized* use of race in student assignments was unconstitutional. Supreme Court Justice Anthony Kennedy joined the majority opinion of the Court, but emphasized that the decision should not be understood as prohibiting local authorities from considering the racial makeup of schools in student assignment policy. Kennedy recognized that public school districts have a compelling interest in both achieving diversity and avoiding racial isolation in schools. He went on to recommend policy alternatives to achieve school integration. Notably, it was Kennedy's consideration that the manipulation of school attendance boundaries may be an effective way of achieving integration:[2]

> "School boards may pursue the goal of bringing together students of diverse backgrounds and races through other means, including strategic site selection of new schools; *drawing attendance zones with general recognition of the demographics of neighborhoods*; allocating resources for special programs; recruiting students and

[2] These recommendations were published by the Department of Education as part of a memorandum entitled "Guidance on the Voluntary Use of Race to Achieve Diversity and Avoid Racial Isolation in Elementary and Secondary Schools" (Department of Education, 2011), that has since been rescinded by the Trump administration.

faculty in a targeted fashion; and tracking enrollments, performance, and other statistics by race.", Parents Involved in Cmty. Sch. v. Seattle Sch. Dist. No. 1, 551 U.S. 701, 720 (2007)

School attendance boundaries (zones) are the most common student assignment mechanism in US public school systems. Formally, they are school district policies that link public school attendance rights with student residential addresses. Thus they are frequently represented as maps that partition the district's jurisdiction into multiple school zones, although sometimes they are published as lists linking street names and schools. Available data suggests that 95% of public schools in the U.S. operate school attendance boundary plans, although the degree to which boundaries bind varies.[3] In some districts adherence to student assignments based on school boundaries is highly strict, while in others boundaries serve only as a default option from which parents can opt out easily.[4] It is also common for school systems implementing centralized school choice mechanisms to use school boundaries to ration seats at oversubscribed schools.[5]

The National Center of Education Statistics (NCES) reports that only about 20% of parents in 2017 had any degree of choice when finding a public school for their child.[6] This likely suggests that at least 80% of student assignments in the country's public schools are based, at least partly, on school attendance boundaries. But despite being virtually ubiquitous across public education agencies, local school district officials set school boundary policy with little federal or state government oversight. There is no regulation on the geographic shape school boundaries must take, or demographic constraints they must satisfy. Unlike congressional districting, school boundaries need not be contiguous or compact, they are not required to have equal population, and they need not be demographically representative of a larger geography. As such, many school districts draw discontiguous attendance boundaries for which spatially separate neighborhoods are given the same school assignment. Such discontiguous school boundaries are typically associated with student busing schemes.[7]

Locally elected school district boards are in charge of the enactment, maintenance, and updating of school attendance boundaries. While school boundary maps are typically stable over time, changes are often necessary. Most school districts change their boundaries every few years. School boundary redistricting is typically brought about by demographic change, school capacity imbalances or new school construction. But school districts may also be compelled

[3]Panel B in Table A.1, provides the basis for this claim, showing that only about 5% of schools in the available nationwide data are 'open enrollment', in the sense that residences play no role in student assignment. Moving from column (1) to column (2) shows that more than half of open enrollment schools are located in small districts, typically rural, districts that administer a single school, know as 'de facto' school districts

[4]Fairfax County Schools in Virginia is a school district with strict school boundary assignment, see http://boundary.fcps.edu/boundary/.

[5]Washington DC Public Schools and San Francisco Unified School District are two prominent examples of large districts with centralized school choice that combine the use of school boundaries. For San Francisco see http://www.sfusd.edu/en/enroll-in-sfusd-schools/how-student-assignment-works/the-assignment-process.html. For Washington DC see https://www.myschooldc.org

[6]See Table 206.30 in the 2017 NCES Digest of Education Statistics.

[7]In Panel B of Table A.1, I show that about 12% of school boundaries in the 2013-14 SABS were discontiguous.

to change school boundaries to accommodate changes in school programming requirements or school closings precipitated by changes in school funding or natural disasters (Brown and Knight 2005).

It is common for districts to hire consulting firms providing dedicated redistricting software to model school boundary changes. Consulting services typically allow district officials to impute constraints such as travel distance limits, natural barriers, appropriate street crossings, pre-assignment of areas or neighborhoods to certain schools, and demographic makeup of school boundaries.[8] These services use optimization algorithms from the operations research literature to generate feasible school boundary change proposals that meet the requirements of the school board (Caro, Shirabe, Guignard and Weintraub 2004).

School board objectives during the redistricting process vary greatly between localities, but a common theme is a discussion of commuting distance, racial or ethnic equity and correlated issues. School redistricting is politically fraught for local school boards because school boundary systems are tightly linked to real estate values and notions of neighborhood schools, walkability, and sense of community (Black 1999, Kane, Staiger and Samms 2003, Kane, Staiger and Riegg 2005, Bayer et al. 2007). Local hearings designed to gather community input on proposed boundary changes can be heated, to the extent that school board members have been replaced following lengthy redistricting disagreements (Samuels 2011, Schlenker 2017). Discussions regarding daily travel distance are always present in local redistricting debates, including concerns of the cost district-supplied busing or the burden on parents required to provide transportation for their children. Redistricting proposals are almost always guided by transportation efficiencies, meaning that the location of existing schools (and the site selection of new ones) are also important determinants of school boundary choices.

While commuting efficiency is a natural objective of redistricting, racial equity and diversity are also frequently at the forefront of local redistricting debates. Sometimes racial integration is addressed directly in these discussions, such as considerations to maintain unitary status required by agreements linked to the lift of court desegregation orders (Siegel-Hawley 2013). Some districts explicitly target socioeconomic integration in school assignments using student subsidized lunch status, which is correlated with race (Samuels 2019). Frequently, the most vociferous opposition to boundary changes are wealthy communities that have enjoyed exclusive access to high-quality public schools for years (Hannah-Jones 2016, Lareau, Weininger and Cox 2018). There is anecdotal evidence that school boundary maps have been amended "last-minute" prior to their enactment to satisfy the preferences of powerful members of the community (Siegel-Hawley 2013). While perhaps not directly motivated by issues of racial segregration, redistricting objectives that protect the interests of privileged factions are likely to have detrimental effects on the prospect of school integration.

[8] Some known school redistricting consulting firms offering these services are: EdData OnPass Pro, Zillion, SchoolSite, Maptitude, Cropper GIS, among others.

3 Data and Measurement

I study school boundaries using the NCES 2013-14 School Attendance Boundary Survey (SABS), a nationally representative survey of local school assignment policies.[9] This survey is the Department of Education's first attempt to collect and harmonize the school boundary maps of all public school districts in the country, with 90% of surveyed districts reporting. Each observation in this dataset corresponds to a school's attendance boundary polygon measured in longitude-latitude space. Using GIS software, I link school boundaries to 2010 census blocks and compute the 2010 fraction of 5 to 9 year old school boundary residents that are Black or Hispanic (henceforth, I refer to these two groups as "minorities").

In addition to school boundaries, the analysis makes use of 2013-14 data on school locations and other school and district level characteristics from the NCES Common Core of Data. I link school district level data on the status of court desegregation orders made publicly available by Reardon et al. (2012), via the Stanford Education Data Archive. I also utilize geolocated survey data from the General Social Survey to measure local attitudes toward racial inequality at the school district level over the period 1998-2016.[10] Finally, I make use of 2010 block group data to measure median household income and adult educational attainment at the school district level.

The analysis focuses on elementary school boundaries because they are more numerous than middle or high schools, generating a richer context for the district's school boundary drawing problem. Additionally, elementary schools are often feeder schools, such that the boundaries of middle and high schools are approximate unions of elementary school boundaries. In this sense elementary school boundaries usually generate the most consequential student assignments across all K-12 grade levels. Appendix Table E.2 shows that the distribution of district observables is similar for the limited number of districts for which we observe multiple middle and high school boundaries.

The sample also restricts attention to school districts facing considerable leeway when drawing school boundaries by limiting the sample to districts administering at least 5 elementary schools. The final analysis sample contains 1,486 school districts, accounting for 11.8 million students or about 52% of the elementary school population. I refer the reader to Appendix A and Table E.1 for a detailed description of the data building procedures and sample selection of both school and districts. These sample restrictions imply that the results of this analysis apply mostly to large urban school districts; they cannot be extrapolated to the large number of school districts that administer only one school per grade level.[11]

[9]The SABS recently released a second wave of this survey covering boundaries for the 2015-16 school year. I focus on the first wave for 2013-14 given my use of 2010 census block data to measure residential composition.

[10]The geolocated GSS data provide the code of the census tract of survey respondents' residence. They are restricted-access use and obtaining them involves a full IRB review and adherence by NORC's privacy protection guidelines. On average, there are 22 GSS survey observations per school districts, with an interquartile range of 10 to 27 observations.

[11]In the school year 2013-14 16,608 districts reported non-zero enrollment to the Common Core of Data, the vast majority of which administer a single school per grade.These school districts have little scope for school boundary desegregation policy.

Table 1 Panel C summarizes the characteristics of school districts in the final analysis sample. The average district in the sample administered approximately 15 elementary schools and had a total 5-to-9-year-old population of about 6,954 that was 27.4% minority. Median household income in the average district is approximately $60,000 (2010 USD). Out of the 1,486 in the sample, 94 school districts remain under active court supervision over school desegregation efforts, while 164 district were previously under judicial oversight but have since been released.

3.1 School boundary desegregation, an illustrative example

School districts face a fundamental trade-off when devising the attendance boundaries of the schools they administer. While minimizing the daily distance students must travel to school is a natural objective, such plans will replicate existing patterns of residential racial segregation. If the district is interested in ameliorating the link between neighborhood and school segregation generated by school boundaries, it must partly sacrifice the minimum distance objective. The following example illustrates this point by introducing the concept of "neighborhood schools" counterfactuals.

How would a school district's leadership go about drawing school attendance boundaries? As an example, Panel (1) of Figure 1 shows a map of Springfield School District No. 186 in Illinois. It consists of the census blocks that make up the district's jurisdiction, with colors denoting the fraction of residents in a given block that are minorities; darker shades correspond to a higher proportion minority. Notably, Springfield is residentially segregated in a manner reminiscent of an archetypical American city (Cutler, Glaeser and Vigdor 1999). Near downtown, there is a pocket of residences that are almost exclusively inhabited by minorities. In contrast, residents in the outskirts of the city tend to be almost exclusively non-minority. The red circles in this map denote the location of this district's elementary schools.

A natural objective of school boundaries is to minimize the distance that students must travel daily to school. The black lines in Panel (2) of Figure 1 show what school attendance boundaries would look like if student allocations focused on minimizing distance, known as the *Voronoi mapping*.[12] Generically, minimum distance boundaries consist of as many "neighborhoods" as there are schools, with schools located approximately in the center of each neighborhood. This hypothetical school assignment is a "neighborhood schools" rule in a mathematically strict sense – blocks are literally assigned to the nearest school, defined using the Euclidean metric ("distance as the crow flies").[13] For all districts in the data, I assume that these simple counterfactuals approximate the distribution of school boundary racial composition in a minimum commuting cost assignment policy. I refer readers interested in a discussion on the discrepancy between Euclidean and actual commuting distance, as well as the role of school capacity to the Appendix,

[12] Defining a set of points (school locations) and partitioning a space into minimum distance zones around them is known as the Voronoi map, see also Richards (2014).

[13] The neighborhood counterfactuals also provide the correct geographic scale to make sensible comparisons between neighborhood and school segregation. The reason is that segregation indices are not scale invariant – smaller geographies have more scope for segregation than larger geographies. This problem has arisen in the literature comparing school and census tract segregation (Reardon et al. 2012).

where I provide several robustness checks on this assumption.[14]

A problematic aspect of neighborhood schools assignments is that they replicate residential racial segregation patterns in the school system. To see this, Panel (3) of Figure 1 summarizes the racial composition of school boundaries generated by the minimum distance assignment. Noticeably, under neighborhood schools there would be two schools near the center of the jurisdiction with a more than 60% minority population assignment, while schools closer to the outer edge of the district would be assigned a population that is less than 20% minority. Such a large disparity in racial composition between different school zones amounts to a high level of school boundary segregation, which can be summarized using an index.

Panel (3) of Figure 1 reports a racial integration index based on the the variance-ratio index of segregation, defined as:

$$Variance\ Ratio = \frac{E[q_{sj}|URM = 1] - Q_j}{1 - Q_j} = E[q_{sj}|URM = 1] - E[q_{sj}|URM = 0], \quad (1)$$

where the expectation operates at the student level, q_{sj} is the fraction of students in school s in school system j that are underrepresented minorities (URM). The isolation index, the average exposure to minorities q_{sj} when restricting attention to the URM population, can be written as the conditional expectation $E[q_{sj}|URM = 1]$, where URM is a student level indicator of being minority. Variance ratio adjusts this term by Q_j, the district-wide URM share of the population. The adjustment is intuitive. In a perfectly integrated system all schools would have a composition equal to Q_j. On the other hand, in a perfectly segregated school system URM students are only exposed to themselves, so the isolation index would equal one. The variance ratio therefore measures excess isolation relative to a complete segregation benchmark.

It is a remarkable fact of algebra that the variance ratio index also coincides with the second equality, which is the difference in average school exposure to URMs between URM and non-URM students. In other words, the variance ratio index can also be interpreted as a gap in exposure to URM students. It bears mentioning that this characterization of the variance ratio also coincides with the OLS slope coefficient of a student level regression of q_{sj} on the URM indicator. In other words, the variance-ratio index can also be interpreted as how predictive a student's own race is of the racial composition of her school peers. In addition, seminal studies have established that the variance ratio index can be derived as the correct measure of segregation in an econometric model in which racial gaps in student outcomes are generated by racial gaps in school resources (Card and Rothstein, 2007; Reardon and Owens, 2014).

I define integration I as one minus the variance ratio, so that $I = 1$ corresponds to perfect racial integration, and $I = 0$ to perfect segregation.[15] Under a neighborhood schools counterfactual assignment, Springfield's primary school boundaries have $I^o = 0.821$, meaning that that

[14] Figures E.2 and E.3 in the appendix provide evidence that neighborhood boundary counterfactuals defined by applying Dijkstra's algorithm to the U.S. road network are very similar to the Euclidean neighborhoods used throughout the paper.

[15] In Appendix Table E4, I show that my main results are robust to defining integration based on the dissimilarity index.

minority students have about 18 p.p. higher exposure to minorities than whites. I also report average commuting distance to school, defined as the population-weighted average distance between block centroids and school locations. With neighborhood schools boundaries, the average student would travel $D^o = 1.12$ kilometers to get from home to their assigned school.

Could this district draw boundaries that are more racially integrated? In order to achieve higher levels of school boundary integration, Springfield would have to manipulate boundaries away from commuting efficiency – improving integration at the cost of higher daily school travel distance. Panel (4) of Figure 1 shows black lines denoting the school attendance boundaries Springfield implemented during the 2013-14 school year. Most of the school zones in this map have similar racial compositions – between 20-40% minority each. Racial integration in this map is $I = 0.978$, so schools are 97.8% as integrated as they could possibly be, which is higher than integration in the neighborhood schools counterfactual plan by $I - I^o = 0.157$. Relative to the neighborhood schools counterfactual, Springfield's primary school boundaries are considerably *desegregated*.

Springfield achieves school integration by drawing discontiguous boundaries and accepting longer daily travel distances. Note that in Panel (4), the center of the district is fragmented into several small polygons – these are neighborhoods that are assigned to schools outside their immediate vicinity. Springfield's desegregation plan is two-pronged. It assigns predominantly minority residents from downtown to schools located in the low-minority outskirts of the district. It also does the opposite for school's located downtown, bringing in students from the mainly non-minority suburbs. This results in more integration but also higher distance travelled per capita – average distance travelled per student in Springfield's chosen boundaries is $D = 1.899$ kilometers, meaning that students travel an average excess distance of $D - D^o = 0.771$ kilometers relative to the minimum distance counterfactual.

4 The Distribution of School Boundary Desegregation

Generalizing the intuition of the above example, I compute neighborhood schools counterfactual boundaries for each of the 1,486 districts in the sample, enabling the systematic evaluation of existing school boundary policy across school districts. I develop two methods of evaluating school boundaries relative to the counterfactuals.

Figure 2 presents scatter plots of the school boundaries of four school districts. In the horizontal axis I plot the racial composition of school neighborhoods ordered from lowest to highest fraction minority. The vertical axis measures the racial composition of schools' attendance boundaries, also ranked by racial composition. This bivariate relationship is informative of the link between residential and school segregation. If the OLS slope between these two variables equals one, school boundaries are consistent with an assignment policy that perfectly replicates neighborhood segregation patterns. The plots report the OLS slope β and the integration index of assignments I, the vertical axis, and neighborhoods I^o, the horizontal axis.

The top left panel of Figure 2 corresponds to the example presented above, Springfield School District No. 186 in Illinois. Their school boundaries are highly integrative, manifested here as an

OLS slope below one, implying that the correlation between neighborhood and assignment composition is drastically ameliorated. The figure elucidates how Springfield's boundaries achieve such an integrated system: three schools with relatively high neighborhood minority share receive assignments with a considerably lower minority share. The rest of the schools tend to be in low-minority neighborhoods receiving relatively higher minority assignments. Similarly, the district plotted on the top right of Figure 2, Midland Independent School District (ISD) in Texas, also desegregates boundaries by swapping students' school assignments between neighborhoods.

The bottom panels of Figure 2 show that not all districts are willing to increase daily travel to achieve school integration. The bottom left shows a large urban school district, Philadelphia City School District, which replicates neighborhood segregation patterns in its 148 school zones almost exactly. On the other hand, there are districts whose boundaries appear to exacerbate segregation. Dysart Unified School District in Arizona, the bottom right panel of Figure 2, seems to do this by sending additional minority students to schools that are located in high minority neighborhoods. In Dysart, a neighborhood schools assignment would be more integrated than its 2013-14 boundaries.

I summarize the distribution of school boundary desegregation across school districts by computing the OLS gradients exemplified in Figure 2 for all districts j in the sample and plotting the empirical distribution of $1 - \hat{\beta}_j$ in the histogram presented in Figure 3. In this scale, values close to zero correspond to OLS coefficients close to one – districts that do not desegregate. Higher positive values in this scale represent districts with school boundaries that are increasingly set toward desegregation, and vice versa. Because sample size (i.e. number of schools) varies considerably between districts, I shrink the $\hat{\beta}_j$ estimates toward the grand mean using Empirical Bayes.[16]

Figure 3 presents the empirical distribution of school boundary desegregation, showing that on average school boundaries tend reflect neighborhood segregation. The mean district has an OLS desegregation index of 0.13, which suggests that approximately 87% of a unit increase neighborhood minority share carries through to the composition of school boundaries. But the mean masks considerable heterogeneity in school boundary desegregation across districts. The distribution has a thick right tail, indicating that a sizable minority of school boundary systems achieve more desegregation than the mean district. A much smaller fraction of school districts have boundaries that are more segregated than neighborhoods. The evidence thus suggests that school boundaries whose racial composition markedly differ from that of neighborhoods tend to partially ameliorate segregation. This finding is important, as it is prima facie evidence that some districts may be willing to depart from neighborhood schools to achieve more equitable school compositions.

The OLS approach to measuring school boundary desegregation is useful for a visually intuitive analysis, but it does not have a close connection with the existing literature on racial segregation. I therefore develop an alternative measure based on the variance ratio index of

[16] I compute the signal-to-noise ratio needed for the shrinkage weights in the Empirical Bayes procedure using the estimated robust standard errors from a pooled school level model of the school boundary minority share on neighborhood minority share interacted with school district indicators.

segregation defined in equation (1). I decompose the racial integration of school assignments into the following components,

$$\underbrace{I_j}_{\text{Boundary integration}} = \underbrace{I_j^o}_{\text{Neighborhood integration}} + \underbrace{I_j - I_j^o}_{\text{Boundary desegregation}}. \quad (2)$$

The first component, I_j^o, is the level of neighborhood integration produced by the commuting efficient school boundary counterfactuals. The second component is the difference in integration between existing boundaries I_j and neighborhood integration I_j^o, interpreted as boundary desegregation. If this component is positive, the district's school boundaries are more racially integrated than one would expect given the integration of neighborhoods.

Table 1 summarizes the distribution of each of these components across districts in the sample. The boundaries of the mean district have an integration level of 0.92.[17] With a mean of 0.91, the neighborhood component (I^o) explains almost all of the mean school boundary integration. This means that average boundary desegregation ($I - I^o$) is only 1 percentage point. Although scaled differently, these patterns are consistent with the regression-based evidence presented above. For reference, I summarize the neighborhood-assignment OLS gradient index at the bottom of Panel A.[18] Table 1 also describes additional district characteristics, among them the distribution of average commuting distance to school in the existing and counterfactual school boundaries. Populated census blocks are 2.5 kilometers away from their assigned school on average. If blocks were instead systematically assigned to the school that is closest, average distance would be 2 km. Existing school boundaries thus make students travel an average excess distance of about 0.4 kilometers.

4.1 Boundary desegregation and racial gaps in school characteristics

So far the analysis has been based on school boundary comparisons using census block demographic data. One way of validating this approach is to link the boundary desegregation index to school enrollment data. I first examine whether school boundary desegregation is predictive of realized levels of school integration in enrollment. Then, I inspect the correlation of boundary desegregation and district racial gaps in school characteristics and student outcomes.

Table 2 reports regression estimates of district racial gaps on boundary desegregation. For each outcome, I report estimates of a model controlling only for neighborhood integration and one that controls for log population, population percent minority, log median household income, and US region fixed effects. The estimates in the top panel show that school boundary desegregation is robustly correlated with narrower racial gaps in important school characteristics. The outcome in columns (1) and (2) is the segregation of school enrollments, as defined in equation

[17]As a point of reference, Charlotte-Mecklenburg Schools (NC) moved from integrated boundaries to a neighborhood schools scheme in 2002. The policy change led to a 20 point drop in the integration of CMS schools, from 0.801 to 0.610. Billings et al. (2014) document that considerable negative effects on student outcomes were caused by this change in school boundaries.

[18]In Table E4, I show that my main results are hold whether I use the segregation index-based measure in equation (2) or this regression-based measure of school boundary desegregation.

(1). The coefficient on boundary desegregation is consistently in the -0.80 to -0.90 range and precisely estimated, implying that school boundary desegregation is associated with lower segregation in schools. A one percentage point increase in boundary desegregation (of census blocks) is associated with about a -.82 decrease in school segregation (in enrollment) . This evidence is consistent the claim that desegregated school boundaries result in desegregated schools, even in light of the potential of household non-compliance with school boundary assignments.

Moreover, multiple studies have documented that school segregation is linked to racial gaps in exposure to experienced teachers and student tracking programs (Jackson 2009, Card and Giuliano 2015, Card and Giuliano 2016). There is also a well-documented link between school segregation and racial gaps in student outcomes like student grade repetition and achievement in standardized exams (Card and Rothstein 2007, Hanushek and Rivkin 2006, Johnson 2015). If boundary desegregation is negatively correlated with realized school segregation, it should also be associated with narrower racial gaps in school characteristics and student outcomes.

I operationalize this test by constructing a dataset of racial gaps in exposure to experienced teachers and participation in the "Gifted and Talented" (GT) program using school data from the US Department of Education's Office of Civil Rights (OCR). Additionally, I collect district level gaps in student achievement from the Stanford Education Data Archive (SEDA). District racial gaps in school characteristics are defined in a similar manner to segregation:

$$Gap_j^Y = E[Y_{sj}|URM = 0] - E[Y_{sj}|URM = 1] \tag{3}$$

where the expectation is taken at the student level; Y_{sj} is a characteristic of school s administered by district j; and URM is a student level indicator of being an underrepresented minority. I compute the sample analog of this equation using school level enrollment counts by race.

Columns (3) and (4) at the top of Table 2 present estimates for district racial gaps in teacher experience, measured as the fraction of school teachers in their first or second year in the profession. The mean of the teacher experience gap is negative and near zero, consistent with minority students having slightly higher exposure to inexperienced teachers than their non-minority counterparts. The coefficient on boundary desegregation is positive, implying that it is associated with narrower racial gaps in teacher experience. Columns (5) and (6) examine the association between boundary desegregation and the racial gap in exposure to the Gifted and Talented (GT) program. This gap has a positive mean, implying that non-minority students are more likely to be exposed to the GT program than minorities. Boundary desegregation is predictive of smaller district racial gaps in this outcome. Together, these results are consistent with a link between boundary desegregation and greater racial equity in public education systems.

The bottom of Table 2 presents models of racial gaps in student outcomes. Columns (1) and (2) regress racial gaps in student grade retention rates – the share of students in a school that were held back a grade – on boundary desegregation. The mean of this dependent variable is negative, meaning that on average minority students are somewhat more likely to attend schools with higher student retention than their counterparts. Boundary desegregation is associated with lower gaps in student retention, although imprecisely so. Columns (3)-(6) link to racial gaps in student standardized test scores. Interestingly, boundary desegregation is associated with wider racial gaps in student achievement. One explanation consistent with this is reverse causality: segregated districts with large achievement gaps may implement desegregation efforts in hopes of remedying existing racial inequity. Identifying the causal effect of school boundary policy on student outcomes, while important, is beyond the scope of this study.

5 School Boundary Choice and the Demand for Desegregation

The evidence presented thus far indicates that school boundaries are consequential to the equity of public education systems and that school districts vary in the extent to which their school boundaries replicate residential segregation. To explain such variation in policy, I posit a simple theory of school boundary choice modeled as a trade-off between two competing interests for the school district's leadership: commuting distance efficiency and school integration.

The literature has documented that parents dislike distant schools (Abdulkadiroglu, Pathak, Schellenberg and Walters 2017). Long school commutes can limit school readiness and have historically been a burden borne by minority households (Johnson 2019). Furthermore, school districts often bear the cost of providing daily student transportation, be it via traditional student busing or by subsidizing the cost of public transit. It is thus natural to consider commuting distance efficiency a feature of school boundaries that policymakers care for. On the other hand, the racial integration of schools continues to be a controversial topic in many localities. Desegregation initiatives may anger local elites and cause upheaval during community input meetings, which can be costly for districts (Siegel-Hawley 2013). But districts that allow severe school segregation to take place bear the risk of criticism by local advocates, which may escalate to negative media coverage ands costly litigation. Thus, holding all else equal, school districts are likely to prefer an "equitable" school assignment policy, or at least be indifferent to one.

There is a mechanical trade-off between school boundary integration and commuting efficiency: given housing segregation patterns, improving racial integration relative to neighborhood schools necessarily entails increases in commuting distance. This point is made clear in the literature; student busing expenses have been frequently cited as one of the most salient costs associated with school desegregation efforts (Coleman et al. 1966, Welch and Light 1987, Clotfelter 2004). The trade-off can also be examined empirically. Figure 4 shows a binned scatter plot summarizing the bivariate relationship between school boundary desegregation and excess travel distance to school, relative to neighborhood schools. The excess distance variable must be positive by construction – it is defined relative to distance efficient boundaries – but the positive relationship detailed in the plot casts light on the integration-distance trade-off. On average, districts that draw boundaries making students travel 1 kilometer more than neighborhood schools tend to be about 2 percentage points more desegregated than districts whose boundaries produce no excess distance. This relationship is statistically precise, showing that desegregated boundaries in the data are more likely to be inefficient in terms of commuting, as one would expect when neighborhood segregation is common.

To be sure, school boundary setting involves locally heterogenous objectives and constraints, many of which are not modeled explicitly. While objectives regarding commuting distance are natural and likely ubiquitous, other potential objectives – such as preserving socioeconomically-determined neighborhood borders, or improving socioeconomic integration – may vary from place to place. To the extent that districts' other objectives are correlated with racial integration, the current approach is parsimonious and more closely linked to the available empirical data, since population by race is the only data available at a sufficiently granular spatial level. Thus, when I refer to district "preferences" for school boundary desegregation, it is in an effective sense, as measured by willingness to depart from commuting efficiency.

I formalize the school boundary choice problem with a simple utility maximization model. Consider a district policymaker j with the task of setting school attendance boundaries. The policymaker chooses school boundaries to maximize a utility function $u_j(I, D)$ defined over school integration (I) and distance travelled to school per student (D). Assume that $\frac{\partial u_j}{\partial I} \geq 0$ and $\frac{\partial u_j}{\partial D} < 0$ for all j's. Each district has a benchmark set of boundaries which minimize travel distance. I denote the distance-integration pair generated by distance efficient boundaries (D_j^o, I_j^o). Relative to this benchmark, a district can obtain more integration by accepting longer travel distances. Denote the maximum increase in integration achievable for a given increase in travel distance per student $h_j(D - D_j^o)$. Function $h_j(\cdot)$ has the following properties: (i) $h_j(0) = 0$; (ii) $\frac{\partial h_j}{\partial D} \geq 0$; and (iii) $\frac{\partial^2 h_j}{\partial D^2} \leq 0$.

Given this framework, the district's decision problem can be written as

$$\max_{D} \; u_j(I, D) \text{ s.t. } I \leq I_j^o + h_j(D - D_j^o), \tag{4}$$

with first order condition

$$h_j'(D_j - D_j^o) = -\frac{\partial u_j / \partial D}{\partial u_j / \partial I}. \tag{5}$$

This first order condition defines the district's policy rule for setting school boundaries. The left hand side of equation (5) is the marginal rate of transformation between commuting distance and school integration – the slope of the district's budget constraint. The right hand side is the district's marginal rate of substitution between distance and integration – the inverse willingness to pay for integration in units of travel distance. Figure 5 illustrates the logic of the model using a familiar indifference curve plot in integration-distance space. Starting from minimum distance school boundaries, the district gradually increases integration at the cost of higher distance. The district's chosen school boundaries are defined by the point in which the marginal cost of integration in terms of distance is equal to the marginal benefit, defined by the district's relative preference between distance and integration.

Consider the desegregation demand equation implicitly defined by the policy rule in equation (5):

$$I_j - I_j^o = \gamma_j + \beta h_j'(D_j - D_j^o) + \epsilon_j. \tag{6}$$

School boundary desegregation takes the role of quantity consumed, and the integration-distance rate of transformation is equivalent to per-unit price. The parameter β is equivalent to the elasticity of demand for desegregation policy across school districts; γ_j is a district-specific demand shifter that is independent of prices; and ϵ_j is an idiosyncratic component.

Equation (6) provides an empirical framework for testing several hypotheses regarding school boundary setting behavior. Rejecting the null hypothesis that $\beta = 0$ implies that demand for school boundary desegregation is not perfectly inelastic. This would mean that, all else equal, school districts implement school boundaries that are more desegregated when the commuting cost of doing so is lower. Moreover, controlling for price sensitivity, demand shifters γ_j capture fixed differences in district willingness to depart from commuting efficiency to improve racial integration (or correlated aspects). Demand shifters can be modeled as a function of observable district characteristics:

$$\gamma_j = \kappa_o + X_j'\pi + a_j. \tag{7}$$

Estimates of π inform which district observables X_j are associated with higher (or lower) effective preferences for desegregated school boundaries.

5.1 The Cost of School Boundary Desegregation

One challenge to the estimation of (7) is measurement of the commuting cost of desegregating boundaries. District jurisdictions vary across multiple dimensions that impact commuting cost. The spatial distribution of the student population by race – the "shape" of residential segregation – can determine the transportation cost of desegregating school boundaries.[19] If minorities tend to live in neighborhoods that are spatially disconnected from white neighborhoods, the cost associated with school boundary desegregation will be higher than for a jurisdiction in which racially segregated neighborhoods are in close proximity to each other. Additionally, other characteristics, such as the shape of the jurisdiction, its population density, the existence of natural barriers, and the number and location of schools will also influence the rate at which boundaries that sacrifice the minimum distance criterion attain higher levels of integration.

I develop a novel methodology to estimate the price of school boundary desegregation directly from census block data. To fix ideas, suppose that district integration technology is given by

$$h_j'(D - D_j^o) = \psi_j + \kappa_1(D - D_j^o). \tag{8}$$

The first order term is a slope parameter ψ_j that is heterogenous, but higher order terms are governed by parameters that are homogeneous across districts.[20] With this parametrization, there are two sources of district heterogeneity in the per unit price of integration $h_j'(D_j - D_j^o)$ observed at chosen boundaries. Variation in ψ_j is not directly determined by district preferences; some districts are harder to integrate due to exogenous factors like the spatial configuration of residential segregation patterns. Variance in the higher order term is endogenous to the choice of boundaries, and hence it is correlated with district preferences. I am interested in measuring

[19]For example, the geographic pattern of segregation in the city of Baltimore has often been referred to as the "black butterfly", referring the apparent shape that predominantly black neighborhoods make from an aerial view of the metropolis (Brown 2016).

[20]The quadratic assumption is not crucial, I could instead have written a full Taylor expansion of $h_j(D - D^o)$. As long as heterogeneity only enters the linear term, the argument holds.

the first component.

The parametrization in equation (8) also implies that $h'_j(0) = \psi_j$. In other words, a sufficient statistic for the plausibly exogenous portion of desegregation prices can be extracted by estimating the rate of transformation near the neighborhood schools benchmark. The intuition for this is straightforward. Starting from the minimum travel cost set of boundaries, the rate at which extra commuting distance can be transformed into integration is entirely governed by fixed features of the district's jurisdiction. However, as districts depart from the neighborhood schools benchmark to achieve greater racial equity, excess distance $D_j - D_j^o$ grows and decreasing marginal returns kick in. Away from neighborhood schools, differences in $h'_j(D - D_j^o)$ are determined by both ψ_j and district preferences.

I develop an algorithm exploiting census block data to compute an estimate of $h'_j(0)$, the price of desegregation evaluated at neighborhood schools boundaries. The basic idea is to gradually amend a neighborhood schools map with the aim of improving school integration, where "amending" is defined as reassigning a block of residences from one school to another. The algorithm asks: which reassignment would produce the largest increase in school integration? I find and implement that reassignment, generating a marginally different set of school boundaries that are slightly more integrated, but also slightly more expensive – i.e. a new point (D', I') with $D' > D^o$ and $I' > I^o$. The algorithm can then be applied to the (D', I') boundaries, reassigning a single block and producing a new point (D'', I'') with $D'' > D'$ and $I'' > I'$, and so on. The gradient in integration-distance space generated by this routine is an approximation of ψ_j. See Appendix C for a detailed description of this simulation procedure.

Panel (1) of Figure 6 plots the simulation output for 700 districts in the sample. The vertical axis denotes school integration I, while the horizontal axis denotes distance to school per student D in kilometers. Each locus of points represents a different district's estimated integration-distance budget. District budgets originate at the baseline neighborhood schools assignment (D_j^o, I_j^o). One striking feature highlighted here is that school districts vary widely regarding budget origins. For example, Houston ISD in Texas has very low neighborhood integration compared to Tucson USD in Arizona. Even though Houston can obtain higher levels of integration for a much lower commuting cost than Tucson, it would take a large and costly departure from neighborhoods schools for Houston to achieve the level of integration that Tucson obtains cheaply. This highlights the need to control for neighborhood integration levels when interpreting existing school boundary integration as a product of districts' school boundary policy.

Panel (2) of Figure 6 shows district budgets after differencing out the neighborhood schools bundle (D^o, I^o). Plotting the simulated budgets in terms of desegregation $I - I^o$ against excess distance $D - D^o$ highlights variation in the rate of transformation across districts. For instance, both Houston ISD and Pittsburgh City Schools have relatively steep budgets (low integration prices). They can increase boundary integration by more than 10 percentage points at the cost of increasing commuting distance per student by less than half a kilometer. In contrast, San Diego USD and Tucson USD obtain a racial integration gain of less than 5 percentage points with a similar increase in distance. These districts have relatively flat budgets (a high price of integration). There are also plenty of districts in the middle of this spectrum. Charlotte-

Mecklenburg Schools, East Baton Rouge Parish, and Springfield Public Schools are examples of districts facing an approximately median level of desegregation prices.

What drives district differences in the price of school boundary desegregation? Figure 7 builds intuition by focusing on two districts in the sample. The top panel shows the census block geography of two school districts, Henrico County Public Schools, Virginia (left); and Little Rock School District, Arkansas (right). The bottom panel of the figure plots the estimated budget for both of these districts. The budgets originate at approximately the same point, meaning that neighborhood schools produce similar levels of racial integration and commuting distance in these districts. However, they differ considerably in desegregation costs. In order to achieve similar gains in racial integration, policymakers in Henrico would need to increase average travel distance by about twice as much as local leaders in Little Rock would.

The price discrepancy between Little Rock and Henrico is driven by differences in the spatial distribution of racial minorities that are in part driven by the jurisdictions' shape. Although both have similar levels of residential segregation, they differ considerably in the geographic proximity of racial enclaves. Little Rock's predominantly minority blocks are located in the southern part of the jurisdiction, separated by a long strip from whiter neighborhoods in the north. Students residing in the edge of the district's racial boundary could be transported to schools on the other side with little excess travel, improving integration. In contrast, Henrico has a bizarre shape, contributing to a racial distribution over space made up of a central minority neighborhood connected by a narrow path to two white enclaves in the edges of the jurisdiction. Desegregating schools located in the center of Henrico's northern white enclave would entail transporting students from the minority enclave a far distance, passing several other schools on the way and increasing average travel distance by a large amount. Thus, compared to Little Rock, school desegregation is more expensive in Henrico's public school system.

For the purpose of conducting a statistical analysis using these simulated, district-specific, desegregation budgets, I operationalize the estimate of the price of school boundary desegregation by computing the start-to-end-point slope of district budgets,

$$\hat{\psi}_j = -\frac{I_j^{end} - I_j^o}{D_j^{end} - D_j^o}, \tag{9}$$

where (I_j^{end}, D_j^{end}) is the integration-distance pair achieved in the last iteration of the algorithm, and (I_j^o, D_j^o) is the initial, neighborhood schools point.[21] $\hat{\psi}_j$ is interpreted as the marginal commuting cost of desegregating schools by manipulating school boundaries, with higher values corresponding to districts that are more expensive to desegregate. I standardize $\hat{\psi}_j$, scaling to the unit of a standard deviation in the cross-sectional distribution of desegregation cost.

Table 3 presents a descriptive analysis of the covariance of $\hat{\psi}_j$ with district characteristics. The R^2 in the model in Column (1) shows that about 63% the variance in desegregation cost can be explained by district differences in neighborhood school levels of integration and com-

[21] There are several ways to operationalize the output of the district budget simulations to obtain a measure of desegregation cost. In Table E3 of the appendix, I show that results are robust to different parametrizations of $\hat{\psi}_j$, by taking the slope at different parts of each simulated budget.

muting distance (as highlighted in Figure 6), as well as in district size and a quadratic in racial composition. The coefficient on neighborhood integration is positive and large, implying that it is very costly to increase the integration of already integrated districts. The coefficient on neighborhood schools travel distance is also positive, implying that it is increasingly costly to desegregate jurisdictions that face higher baseline travel costs. Log total population also raises desegregation cost, since more students need to change schools to move the needle on integration in more populous districts. The convex shape delineated by the (imprecisely) estimated quadratic on fraction minority suggests that desegregation may be cheaper in more diverse districts, controlling for neighborhood segregation.

Column (2) adds a measure of the "bizarreness" of the shape of the district's geographic jurisdiction to the model. The measure is borrowed from the congressional gerrymandering literature (Chambers and Miller 2010), which has developed methods for measuring the extent to which districts depart from "regularity" (See Figure E.6 in the appendix). District bizarreness is based on the ratio of the area of its shape relative to the area of the shape's convex hull. Higher values of this index correspond to the convex hull's area being larger than the shape's area, which is common to bizarre district shapes. Figure 6 in the appendix shows examples of districts and their convex hull ranked by quantiles of bizarreness.[22] Column (2) shows that, controlling for a range of factors, districts that are shaped bizarrely tend to be associated with higher desegregation costs. This is reminiscent of the maps in Figure 7. Henrico's bizarre shape connects the white and minority sections of the district only by a narrow path. Because district jurisdictions are set historically – most were created in the early 20th century, with a few new district incorporations every decade (Goldin and Katz 2003) – district bizarreness is a candidate instrument for desegregation cost.[23]

Columns (3) through (5) add more district characteristics and geographic controls to the model, highlighting other correlates of desegregation cost. Notably, I introduce flexible controls for log income differences between white and minority households. Controlling for minority income levels (and other factors), higher white income levels are associated with a lower commuting cost of desegregation. At the same time, holding constant white incomes, higher minority income is linked to higher desegregation commuting costs. These patterns are consistent with both negative gap effects and negative white income effects on the cost of desegregation. Because larger racial gaps in income are associated with lower commuting cost, these patterns are also consistent with a theory in which spatial barriers to racial segregation are less common in communities that have larger socioeconomic gaps between racial groups.

Further, districts with a higher private to public school ratio tend to have lower desegregation cost, suggesting that the presence of a large private school sector is correlated with the spatial distribution of residential segregation. Once we add regional controls and state fixed

[22]The formula for the bizarreness index is $b_j \equiv 1 - \frac{Area(S_j)}{Area(Convexhull(S_j))}$, where S_j is a matrix containing the latitude/longitude coordinates – the polygon – that make up the district's geographic jurisdiction. b_j is scaled to have mean zero and standard deviation one in the analysis sample. See Figure E.6 in the appendix.

[23]Table 3 reports the F statistic of the first stage in an instrumental variables model using bizarreness as an instrument for desegregation cost. These range between 15.52 and 19.92 depending on controls, indicating that weak IV issues are not of primary concern in these models.

effects, other significant correlates of cost emerge, such as the share of students in poverty (as measured by free lunch status) and the share of the adult population with a college education. Desegregation costs are also lower in the Northeast and Midwest, relative to the South. I thus control for these factors in models of the determinants on boundary desegregation, presented in the next section.

5.2 The Demand for School Boundary Desegregation

Does the commuting cost of integrating schools influence district policymakers' decision to implement desegregated school boundaries? Table 4 presents estimates of equation (6), the demand for school boundary desegregation as a function of cost. The models in column (1) control for the baseline set of covariates: neighborhood levels of racial integration and commuting distance, district size, and a quadratic in racial composition, which drive much of the observed variation in both desegregation cost and school segregation. Column (2) adds controls for socioeconomic characteristics: log median household income, free lunch share, and adult share with a college education, as a way of assessing whether demand estimates are driven by income effects. Column (3) adds control variables proxying for preferences for desegregated schools: desegregation order indicators, a racial animus index, and the relative importance of charter and private schools (see Table 5 for a detailed description of these). Lastly, column (4) adds state fixed effects, ensuring that estimates are not driven by between state comparisons that may conflate differences in policy and other factors.

Panel A presents OLS estimates, showing a stable negative correlation between actualized boundary desegregation and desegregation cost. The magnitude of the coefficient on cost is approximately invariant to the addition of other controls. It shows that a one standard deviation increase in cost is associated with about a 0.7 percentage point reduction in desegregation, or about 20% of a standard deviation in the observed distribution of desegregation. These results suggest that districts facing lower prices are more likely to have desegregated school boundaries, as one would expect if district policymakers exhibit demand for desegregation. However, one may be worried that these estimates are biased by simultaneity concerns. If desegregation cost is correlated with underlying preferences for school integration, then OLS estimates will generate biased demand estimates.

To address this concern, Panel B presents reduced form (RF) estimates for a demand model using district bizarreness as an instrument for desegregation cost. As mentioned above, in the vast majority of cases the geographic jurisdiction of school districts was determined during the early 20th century, well before the 1954 *Brown* decision (Hoxby 2000, Goldin and Katz 2003). Thus, conditional on demographics and neighborhood segregation, the shape of a school district's jurisdiction is unlikely to be correlated with current policymaker preferences over school integration. After all, sentiments regarding racial diversity have evolved considerably over the last century, and so have the views of today's school boards on racial equity. What has remained largely fixed since the last 6 decades are district jurisdictions and spatial patterns of residential segregation (Rothstein 2017). While it would be incorrect to assume that district shapes are as good as randomly assigned to districts even when controlling for powerful controls, it is reasonable to claim that district bizarreness is excludable from the demand equation at hand, impacting boundary setting decisions only through the cost margin.[24]

The estimates in Panel B suggest that there is a significant reduced form relationship between district shape bizarreness and school boundary desegregation. The magnitude and precision of the estimates are robust to the battery of controls, with the exception of the addition of state effects, which knocks down the coefficient by a third and reduces precision to the 10% significance level. Reduced precision is to be expected, since multiple states in the data contain only a few districts meeting the sample criteria. Estimates suggest that a one standard deviation increase in the bizarreness of the district's jurisdiction leads to about a 0.2 percentage point reduction in desegregation, or 6% of a standard deviation of the desegregation distribution. Panel C presents the 2SLS estimates, essentially scaling the RF estimates by a first stage coefficient of about 0.07.[25] The magnitude of the 2SLS estimates is about four times larger than the OLS estimates, remaining negative and statistically significant. This is consistent with the price of desegregation being negatively correlated with unobserved preferences for segregation. This makes sense intuitively, localities whose geography facilitates racial integration and face low desegregation costs may be more tolerant to racial diversity and more likely to elect school boards concerned with racial equity in schooling. Nonetheless, we cannot rule out that OLS estimates are also attenuated by measurement error in the cost index. The IV estimates suggest that a one standard deviation increase in the cost of desegregating school boundaries is associated with about a 3 percentage point increase in school boundary integration, close to a standard deviation in the national distribution of desegregation.

In sum, the results in Table 4 provide compelling evidence of the existence of district demand for school desegregation. This has an important implication for policy. If the equitability of locally set school boundaries is sensitive to costs, this implies that federal or state government interventions that reduce the cost dimension of desegregation – such as student transportation subsidies – may improve equity in public school systems. For example, there has been recent interest in doing away with Section 426 of the 1974 General Education Provisions Act, which prohibits the use of federal education funds for "the transportation of students or teachers to overcome a racial imbalance in any school or school system or to carry out a plan of racial desegregation" (Gaudiano 2019). My results suggest that this change in the law may indeed result in more equitable school assignments across school districts.

Are there other district characteristics that impact the demand for school boundary desegregation? Controlling for cost, do certain types of districts display a higher effective preference for integrated schools? An initial place to look is the shrinking number of school districts that remain under judicial desegregation orders. To this end, I have gathered data on judicial de-

[24]In appendix Table 2 I show that, conditional on covariates, district bizarreness is uncorrelated with my main proxies for district preferences for integration: indicators for being, or having been, under a court desegregation order, and an index of racial intolerance from white district residents. It is also largely uncorrelated with other district characteristics in the analysis data.

[25]See Table 3. The first stage coefficient estimates suggest that a 1 SD increase in the bizarreness of a district's jurisdiction leads to a .07 standard deviation rise in desegregation cost, controlling for other factors.

segregation orders from the Office of Civil Rights and from Reardon, Grewal, Kalogrides and Greenberg (2012). Importantly, this publicly available data contains information about the current status of desegregation orders, allowing me to separately identify the effect of *being* under federal oversight versus one for *having been* under oversight, but not any longer.[26]

Column (1) of Table 5 presents the result. All specifications in this table control for desegregation cost and for demographic characteristics. The coefficient on the active court order indicator is positive and and precisely estimated. This suggests that active judicial orders shift the demand fo desegregation outward – they lead to higher levels of desegregation regardless of cost. The effect size is about half a standard deviation in the national distribution of desegregation. This is in line with previous research establishing that judicial orders force districts to enact policy efforts to integrate schools (Clotfelter 2004, Johnson 2015), raising their "effective preference" for integration as revealed by their school assignment policies. Furthermore, the fact that the school boundary desegregation index is correlated with court orders implies that school boundaries are a policy lever that is actively used to fulfill such judicial mandates. This has an important implication: higher levels of government oversight impact localities' school assignment decisions.

In contrast, the coefficient on the released desegregation order indicator is very small in magnitude and not statistically different from zero. This suggests that districts whose desegregation order has been lifted behave no differently than districts that have never faced a desegregation order. Assuming that the effect of court orders was similar for these districts while they were active, this result is consistent with localities reverting to neighborhood schools plans after the end of judicial oversight. This finding is also supported by previous literature providing evidence of a causal effect of release from judicial oversight on school district re-segregation (Lutz 2011, Reardon et al. 2012). Thus, an additional implication of this result is that the influence of desegregation court orders over local school assignment policy is unlikely to remain when such orders are rescinded. Oversight may need to be permanent in order to generate lasting effects on equitable school assignment policy.

Another potentially important shifter of demand for desegregation policy is the level of racial animus in a district's jurisdiction. An ugly chapter in the history of school desegregation is the furious and often violent resistance of whites to school integration efforts (Johnson 2019). Qualitative evidence suggests that this type of white animosity to school integration continues to exist today (Siegel-Hawley 2013). But today racial animus could have negative or positive effects on the demand for desegregated boundaries. On the one hand, racially intolerant white parents may elect (or otherwise lobby) school boards to perpetuate patterns of residential segregation in school boundaries (DeRoche 2020). On the other, it may be the case that district leaderships interpret white racial animus as a sign of urgent need and potential value of school integration, inducing them to pursue larger desegregation efforts (SCOTUS 2007). Both of these theories have qualitative backing. The current empirical framework allows us to take these competing hypotheses to the data.

[26] 166 districts in my sample were once under judicial order but have since been released, while 99 districts in the data continue to be under judicial supervision.

I gather survey data on racial intolerance from the National Opinion Research Center 's General Social Survey (GSS), waves 1998-2016. The GSS is a national survey intended to gather data on contemporary American society in order to monitor and explain trends and constants in attitudes, behaviors, and attributes. Using the restricted-use files (requiring IRB approval), I obtain information on respondents' census tract of residence and school district. I collect responses to seven GSS survey questions regarding racial intolerance, restricting the sample to white respondents. This allows me to observe responses to racial intolerance questions for 402 districts in the sample.

To compute an index of white racial intolerance, I follow the procedure of Card, Rothstein, and Mas (2008). For each question, I compute an indicator for an intolerant response. I estimate a linear probability model for each indicator, including school district fixed effects and controlling for gender, age, education, a socioeconomic status index, as well as survey year indicators. I extract the estimated school district effects from these models and standardize each set to have mean zero and standard deviation one. The GSS racial intolerance index is the simple average of these standardized school district effects. See Appendix D for a detailed description of the survey questions and procedure used to to construct this index.[27]

Column (2) of Table 5 presents estimates of the effect of white racial intolerance on the demand for school boundary desegregation.[28] The coefficient is negative and precisely estimated, indicating that greater levels of racial intolerance among whites are associated with lower demand for desegregation and closer adherence to neighborhood schools plans. These results are consistent with local white residents with negative views on integration influencing local policymakers' school assignment policy decisions. An alarming implication of this result is that white racial intolerance continues to be a barrier to school desegregation efforts, 65 years after the landmark *Brown* decision.

In Column (3) of Table 5, I test whether differences in socioeconomic status by race, educational attainment, or the presence of school choice are indirect drivers of districts' desegregation efforts. Controlling for other factors, among them commuting cost, differences in income by race are not predictive of desegregation policy. Juxtaposed with the results in Table 3, this suggests that the impact of racial income inequality on desegregation efforts operates via the cost margin – more unequal jurisdictions are actually easier to desegregate (in terms of commute) and this is what matters do school boundary desegregation.

Further, if private or charter schools are a potentially attractive outside option relative to traditional public schools, districts may feel less empowered to enact controversial school assignments aimed at alleviating racal inequality. The coefficients on these variables are small and indistinguishable from zero, suggesting that school choice does not impact school boundary

[27] Recent research on racial animus has leveraged Google Trends data on internet queries to measure the geography of racial animus (**?**). Unfortunately, Google Trends geographic data (measured at the "market area" level, which tend to be roughly the size of US states) is not sufficiently granular to observe variation in animus between school districts.

[28] I use the pooled sample of 1,486 districts and include an indicator for having a non-missing GSS racial intolerance index as a control. The main results hold when restricting the sample to the 402 districts with non-missing GSS information. Tables are available upon request.

setting markedly. This is also the case for variables related to the fraction of the student body receiving free or reduced price meals. An exception is the fraction of the adult population with a bachelor's degree. While not entirely robust across specifications, my estimates suggest that a more educated local population is associated with a higher demand for desegregated boundaries, controlling for a range of factors. The magnitude of this estimate suggests that a 50 percentage point increase in the share of adults with a college degree leads to about the same increase in desegregation policy as a 1 SD reduction in white intolerance toward racial minorities.

Columns (4) through (6) test whether the results presented above are sensitive to controlling for additional covariates, state fixed effects, or to estimating demand using district bizarreness as an instrument for commuting cost. Across these specifications, the estimated coefficients on the desegregation order indicators and white racial intolerance are largely unchanged.[29] Estimates are less precise in the IV model, but the coefficients remain statistically significant at at least the five percent level. These patterns indicate that results regarding desegregation orders and white racial intolerance are not likely to be driven by district observable characteristics and are robust to the use of a different source of cost variation for demand estimation.[30]

These constitute the main results of the paper. School boundary policy is responsive to concerns for racial equity, but only a few districts are willing to bear the cost of desegregating their school system. Desegregation attempts are sensitive to the costs associated with transporting students to their assigned school, suggesting transportation subsidies would induce greater attempts at integrating schools. Court desegregation orders have a contemporaneous positive effect on school boundary desegregation, regardless of the cost of doing so. However, this effect disappears when judicial oversight is lifted. Importantly, white animus against interaction with minorities is associated with lower desegregation efforts, highlighting the continuing role of white resistance as a barrier to racial inequity in American public schools. Altogether, this study demonstrates that school attendance boundaries are endogenous to school districts' relative taste for educational equity.

6 Discussion – Robustness to Endogenous Residential Sorting

An important consequence of school attendance boundary policy is endogenous residential sorting. There is evidence that home prices jump discontinuously near opposite sides of school boundaries (Black 1999), suggesting that home prices are causally linked to school boundaries via perceived measures of school quality like average test scores. The existence of this mechanism implies that school boundaries have a causal effect on neighborhood segregation patterns. Because a key assumption in this paper is to take neighborhood segregation as given when evaluating school boundaries, it may seem that a causal link between school boundaries and

[29] The controls used in the regression estimates in Table 5 are entered linearly. In appendix Table E2, I show that results are robust to alternate parametrizations of the controls, including quartic polynomials and quantile indicators.

[30] Table E5 in the appendix presents robustness tests of the IV model, showing that these results hold as we vary both the covariates and the definition of school boundary desegregation.

neighborhood segregation would threaten the validity of the analysis. I argue that this is not likely to be the case, for two main reasons.

First, Tiebout models that predict residential sorting equilibrium across school boundaries typically abstract from frictions in sorting dynamics. At the same time, studies on the dynamics of residential segregation usually focus on long-run changes (Cutler et al. 1999, Card, Mas and Rothstein 2008). The focus on long-run dynamics is for good reason. Because of the scale of residential change that must take place to generate meaningful shifts in neighborhood segregation, demographic change across the geography of a school district is a gradual evolutionary process that spans decades. The causal effect of school boundaries on neighborhood segregation thus takes place in long-run housing market equilibrium. But school boundary changes tend to happen frequently, often due to the construction of new schools or to rectify imbalances in school enrollment and capacity.[31] I measure residential demographics in 2010 to evaluate 2013 school boundary maps, which alleviates bias due to endogenous sorting, specially in cases in which the maps were updated between 2010 and 2013, approximately 41% of the sample.[32] Nonetheless, this logic also implies that my analysis could be more sensitive to cases in which school boundaries have not changed for extended periods of time. In Table E8 of the Appendix I show that the main results hold when splitting the sample based on recent changes to school boundaries.[33]

Second, I demonstrate that – in a well-known natural experiment involving dramatic school boundary changes – the causal effect of boundary changes on changes in residential demographics has been modest at best. Charlotte-Mecklenburg Schools (CMS) in North Carolina once held an influential desegregation busing policy. CMS was the plaintiff in a 1971 pivotal decision which held that busing was an appropriate remedy for school segregation.[34] In compliance, CMS enacted a heavily altered school boundary map which involved busing students to distant schools. CMS's influential desegregation plan remained in place for almost three decades until a series of lawsuits were brought to challenge it. In 1999, a lower federal court decision ordered the district to cease using race as a factor in school assignments. CMS complied and implemented a neighborhood schools plan in 2002.

The effect of this sudden policy change has been studied extensively to estimate the effects of school segregation on student outcomes (Kane et al. 2003, Tannenbaum 2015, Weinstein 2016). I contribute to this literature by estimating the effect of this dramatic change in school boundaries on residential demographics. An extended discussion of the data, empirical framework, and results is presented in the Appendix. The research design and identifying assumptions in my analysis are largely parallel to Billings, Deming and Rockoff (2014). I estimate the effect of

[31] In my sample of 1,486 districts, 435 (41%) added new schools or closed schools between the period 2010 – 2013 (restricting attention to traditional public schools).

[32] While difficult to confirm directly, it is likely the case that school districts that added or subtracted schools recently had to make changes to their school attendance boundary map.

[33] The magnitude of the point estimates is stable and roughly invariant to the sample. A few of the estimates lose statistical precision, as is to be expected in smaller samples. For instance, there are only 34 districts with active desegregation orders in the boundary change sample.

[34] Swann v. Charlotte-Mecklenburg Bd. of Educ., 402 U.S. 1 (1971)

changes in the racial composition of school boundaries by comparing census blocks in the same neighborhood that were assigned to the same school prior to the boundary change but were then reassigned to different boundaries in 2002. The outcome of interest is residential racial composition in 2010, controlling flexibly for racial composition in 2000.

I find that increases in the minority share of in-boundary residents driven by school boundary changes has a statistically significant white flight effect that is of relatively modest magnitude. My preferred estimates suggest that a 1 percentage point increase in the minority share of school boundaries leads to a 0.15 percentage point increase in the minority share of residences. This suggests that white households have about an 85% residential compliance rate with school boundary changes that lead to an increase in exposure to minorities. Said in a different way, over a decade one would expect about 15% of whites to move away due to school boundary changes. In addition, I find no evidence that these school boundary changes had discernible impacts on real estate prices. This result is in line with the existing empirical literature on the effect of racial segregation on property prices, which has generated similar null results (Kruse 2005, Card et al. 2008, Tannenbaum 2015). Taken together, I interpret these results as evidence that sorting equilibrium in the housing market is not highly sensitive to school boundary changes in the short to medium run. This finding provides additional assurance that the main analysis is not particularly threatened by household sorting reoptimization across school boundary lines.

7 Conclusion

The racial integration of U.S. public schools has been a controversial topic in policy for over half a century. The federal government is in retreat from its efforts to influence the hand of local jurisdictions to alleviate racial imbalances in public education. Today, decisions affecting school integration are largely left to local policymakers. Understanding how these officials make choices that affect racial equity in their jurisdictions is thus of key importance in this debate.

This paper developed and implemented a novel empirical framework for interpreting local school zoning choices. I used this framework to examine what school boundary desegregation reveals about local governments' preferences for school diversity. The key findings of this revealed preference analysis are the following: (i) districts are more likely to desegregate school boundaries if desegregation can be achieved at a lower commuting cost; (ii) active desegregation orders are associated with more intense integrative school boundary desegregation, but this link is not present for districts that have been released from judicial oversight; and (iii) intolerant racial attitudes on the part of local white residents are negatively associated with school boundary desegregation. Taken together, the evidence suggests that school boundary manipulation is a remarkably responsive area of local education policy which reflects the influence of both local cost and preference factors, with important implications for the racial equity in the country's thousands of school systems.

This study has established that school attendance boundary policy is not set in stone. Instead, it is endogenous to institutions' relative valuation of the multidimensional impacts that school boundaries has on the distribution of school characteristics. School boundaries reveal information regarding these relative preferences. I have developed new tools for stakeholders to monitor these policy decisions at a local level. Future research on this topic should further our understanding of the impact that school zone desegregation has on student outcomes, and of the hyper-local political economy that determine these important policies. Further, the tools developed here can be applied to tackle related questions that are beyond the scope of this study, including the impact of school district political lines on metropolitan area school segregation.

References

Abdulkadiroglu, Atila, Parag A. Pathak, and Alvin E. Roth (2009) "Strategy-Proofness versus Efficiency in Matching with Indifferences: Redesigning the NYC High School Match," *American Economic Review*, Vol. 99, No. 5, pp. 1954–1978, URL: `https://ideas.repec.org/a/aea/aecrev/v99y2009i5p1954-78.html`.

Abdulkadiroglu, Atila, Parag A. Pathak, Jonathan Schellenberg, and Christopher R. Walters (2017) "Do Parents Value School Effectiveness?," NBER Working Papers 23912, National Bureau of Economic Research, Inc, URL: `https://ideas.repec.org/p/nbr/nberwo/23912.html`.

Alesina, Alberto, Reza Baqir, and Caroline Hoxby (2004) "Political Jurisdictions in Heterogeneous Communities," *Journal of Political Economy*, Vol. 112, No. 2, pp. 348–396, URL: `https://ideas.repec.org/a/ucp/jpolec/v112y2004i2p348-396.html`.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan (2007) "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, Vol. 115, No. 4, pp. 588–638, URL: `https://ideas.repec.org/a/ucp/jpolec/v115y2007i4p588-638.html`.

Billings, Stephen B., David J. Deming, and Jonah Rockoff (2014) "School Segregation, Educational Attainment, and Crime: Evidence from the End of Busing in Charlotte-Mecklenburg," *The Quarterly Journal of Economics*, Vol. 129, No. 1, pp. 435–476.

Black, Sandra E. (1999) "Do Better Schools Matter? Parental Valuation of Elementary Education," *The Quarterly Journal of Economics*, Vol. 114, No. 2, pp. 577–599, URL: `https://ideas.repec.org/a/oup/qjecon/v114y1999i2p577-599..html`.

Brown, Arlene and Karen Knight (2005) "School Boundary and Student Assignment Procedures in Large, Urban, Public School Systems," *Education and Urban Society*, Vol. 37, No. 4, pp. 398–418.

Brown, Lawrence (2016) "Two Baltimores: The White L vs. the Black Butterfly," *The Baltimore Sun*.

Card, David and Laura Giuliano (2015) "Can Universal Screening Increase the Representation of Low Income and Minority Students in Gifted Education?," NBER Working Papers 21519, National Bureau of Economic Research, Inc, URL: `https://ideas.repec.org/p/nbr/nberwo/21519.html`.

——— (2016) "Can Tracking Raise the Test Scores of High-Ability Minority Students?," *American Economic Review*, Vol. 106, No. 10, pp. 2783–2816, URL: https://ideas.repec.org/a/aea/aecrev/v106y2016i10p2783-2816.html.

Card, David, Alexandre Mas, and Jesse Rothstein (2008) "Tipping and the Dynamics of Segregation," *The Quarterly Journal of Economics*, Vol. 123, No. 1, pp. 177–218, URL: https://ideas.repec.org/a/oup/qjecon/v123y2008i1p177-218..html.

Card, David and Jesse Rothstein (2007) "Racial Segregation and the Black-White Test Score Gap," *Journal of Public Economics*, Vol. 91, No. 11, pp. 2158–2184.

Caro, F., T. Shirabe, M. Guignard, and A. Weintraub (2004) "School redistricting: embedding GIS tools with integer programming," *Journal of the Operational Research Society*, Vol. 55, No. 8, pp. 836–849.

Cascio, Elizabeth, Nora Gordon, Ethan Lewis, and Sarah Reber (2008) "From Brown to busing," *Journal of Urban Economics*, Vol. 64, No. 2, pp. 296–325, URL: https://ideas.repec.org/a/eee/juecon/v64y2008i2p296-325.html.

Chambers, Christopher P. and Alan D. Miller (2010) "A measure of bizarreness," *Quarterly Journal of Political Science*, No. 5, pp. 27–44.

Chen, Jowei (2017) "The Impact of Political Geography on Wisconsin Redistricting: An Analysis of Wisconsin's Act 43 Assembly Districting Plan," *Election Law Journal*, Vol. 16, No. 4.

Chen, Jowei and David Cottrell (2016) "Evaluating partisan gains from Congressional gerrymandering: Using computer simulations to estimate the effect of gerrymandering in the U.S. House," *Electoral Studies*, Vol. 44, pp. 329–340.

Chen, Jowei and Jonathan Rodden (2013) "Unintentional Gerrymandering: Political Geography and Electoral Bias in Legislatures," *Quarterly Journal of Political Science*, Vol. 8, No. 3, pp. 239–269, URL: https://EconPapers.repec.org/RePEc:now:jlqjps:100.00012033.

Clotfelter, Charles T. (2004) *After Brown The Rise and Retreat of School Desegregation*: Princeton University Press.

Coleman, J. S., E. Q. Campbell, C. J. Hobson, J. McPartland, A. M. Mood, F. D. Weinfeld, and R. L. York (1966) "Equality of Educational Opportunity," *Washington, DC: U.S. Department of Health, Education, and Welfare, Office of Education.*

Cutler, David M., Edward L. Glaeser, and Jacob L. Vigdor (1999) "The Rise and Decline of the American Ghetto," *Journal of Political Economy*, Vol. 107, No. 3, pp. 455–506, URL: https://ideas.repec.org/a/ucp/jpolec/v107y1999i3p455-506.html.

DeRoche, Tim (2020) *A Fine Line: How Most American Kids Are Kept Out of the Best Public Schools*, Los Angeles, California: Redtail Press.

Dur, Umut M., Scott Duke Kominers, Parag A. Pathak, and Tayfun Sonmez (2013) "The Demise of Walk Zones in Boston: Priorities vs. Precedence in School Choice," NBER Working

Papers 18981, National Bureau of Economic Research, Inc, URL: https://ideas.repec.org/p/nbr/nberwo/18981.html.

Ellison, Glenn and Parag A. Pathak (2016) “The Efficiency of Race-Neutral Alternatives to Race-Based Affirmative Action: Evidence from Chicago’s Exam Schools,” NBER Working Papers 22589, National Bureau of Economic Research, Inc, URL: https://ideas.repec.org/p/nbr/nberwo/22589.html.

Friedman, John N. and Richard T. Holden (2008) “Optimal Gerrymandering: Sometimes Pack, But Never Crack,” *American Economic Review*, Vol. 98, No. 1, pp. 113–144.

Gaudiano, Nicole (2019) “Anti-busing law dating from the 1970s eyed for elimination,” *Politico*.

Goldin, Claudia and Lawrence F. Katz (2003) “The "Virtues" of the Past: Education in the First Hundred Years of the New Republic,” NBER Working Papers 9958, National Bureau of Economic Research, Inc.

Hannah-Jones, Nikole (2016) “Choosing a School for My Daughter in a Segregated City,” *New York Times Magazine*.

Hanushek, Eric A. and Steven G. Rivkin (2006) “School Quality and the Black-White Achievement Gap,” NBER Working Papers 12651, National Bureau of Economic Research, Inc, URL: https://ideas.repec.org/p/nbr/nberwo/12651.html.

Hoxby, Caroline M. (2000) “Does Competition among Public Schools Benefit Students and Taxpayers?,” *American Economic Review*, Vol. 90, No. 5, pp. 1209–1238, URL: https://ideas.repec.org/a/aea/aecrev/v90y2000i5p1209-1238.html.

Jackson, C. Kirabo (2009) “Student Demographics, Teacher Sorting, and Teacher Quality: Evidence from the End of School Desegregation,” *Journal of Labor Economics*, Vol. 27, No. 2, pp. 213–256, URL: https://ideas.repec.org/a/ucp/jlabec/v27y2009i2p213-256.html.

Johnson, Rucker C. (2015) “Long-run Impacts of School Desegregation & School Quality on Adult Attainments,” NBER Working Papers 16664, National Bureau of Economic Research, Inc, URL: https://ideas.repec.org/p/nbr/nberwo/16664.html.

——— (2019) *Children of the Dream: Why School Integration Works*: Basic Books.

Kane, Thomas J., Douglas O. Staiger, and Stephanie K. Riegg (2005) “School Quality, Neighborhoods and Housing Prices: The Impacts of school Desegregation,” NBER Working Papers 11347, National Bureau of Economic Research, Inc, URL: https://ideas.repec.org/p/nbr/nberwo/11347.html.

Kane, Thomas J., Douglas Staiger, and Gavin Samms (2003) “School Accountability Ratings and Housing Values,” *Brookings-Wharton Papers on Urban Affairs*, pp. 83–137.

Kruse, K.M. (2005) *White Flight: Atlanta and the Making of Modern Conservatism*, Politics and society in twentieth-century America: Princeton University Press, URL: https://books.google.com/books?id=c5763Zgu4_oC.

Lareau, Annette, Elliot Weininger, and Amanda Cox (2018) "Parental Challenges to Organizational Authority in an Elite School District: The Role of Cultural, Social, and Symbolic Capital," *Teachers College Record*, Vol. 120, No. 1.

Lee, Barrett A., Sean F. Reardon, Glenn Firebaugh, Chad R. Farrell, Stephen A. Matthews, and David O'Sullivan (2008) "Beyond the Census Tract: Patterns and Determinants of Racial Segregation at Multiple Geographic Scales," *American Sociological Review*, Vol. 73, No. 5, pp. 766–791.

Lutz, Byron (2011) "The End of Court-Ordered Desegregation," *American Economic Journal: Economic Policy*, Vol. 3, No. 2, pp. 130–168, URL: `https://ideas.repec.org/a/aea/aejpol/v3y2011i2p130-68.html`.

Orfield, Gary and Susan Eaton (1997) *Dismantling Desegregation: The Quiet Reversal of Brown V. Board of Education*: The New Press.

Pathak, Parag (2011) "The Mechanism Design Approach to Student Assignment," *Annual Review of Economics*, Vol. 3, No. 1, pp. 513–536, URL: `https://EconPapers.repec.org/RePEc:anr:reveco:v:3:y:2011:p:513-536`.

Reardon, Sean F., Elena Tej Grewal, Demetra Kalogrides, and Erica Greenberg (2012) "Brown Fades: The End of Court?Ordered School Desegregation and the Resegregation of American Public Schools," *Journal of Policy Analysis and Management*, Vol. 31, No. 4, pp. 876–904, URL: `https://EconPapers.repec.org/RePEc:wly:jpamgt:v:31:y:2012:i:4:p:876-904`.

Reardon, Sean and Ann Owens (2014) "60 Years After Brown: Trends and Consequences of School Segregation," *Annual Review of Sociology*, Vol. 40, No. 199-218.

Reber, Sarah (2005) "Court Ordered Desegregation: Successes and Failures Integrating American Schools since Brown versus Board of Education," *Journal of Human Resources*, Vol. 40, No. 3, URL: `https://EconPapers.repec.org/RePEc:uwp:jhriss:v:40:y:2005:i:2:p559-590`.

Richards, Meredith P. (2014) "The Gerrymandering of School Attendance Zones and the Segregation of Public Schools: A Geospatial Analysis," *American Educational Research Journal*, Vol. 51, No. 6, pp. 1119–1157.

Rivkin, Steven and Finis Welch (2006) *Has School Desegregation Improved Academic and Economic Outcomes for Blacks?*, Vol. 2 of Handbook of the Economics of Education, Chap. 17, pp. 1019–1049: Elsevier, URL: `https://ideas.repec.org/h/eee/educhp/2-17.html`.

Rothstein, Richard (2017) *The Color of Law: A Forgotten History of How Our Government Segregated America*: New York; London: Liveright Publishing Corporation.

Samuels, Christina A. (2011) "School Boundary Debate Divides Minnesota Suburb," *Education Week*, Vol. 31, No. 6, p. 1.

——— (2019) "A Losing Fight to Keep Schools Desegregated," *Education Week*, Vol. 39, No. 1, pp. 16–17.

Saporito, Salvatore and David Van Riper (2016) "Do Irregularly Shaped School Attendance Zones Contribute to Racial Segregation or Integration?" *Social Currents*, Vol. 3, No. 1, pp. 64–83.

Saporito, Salvatore and Deenesh Sohoni (2006) "Coloring Outside the Lines: Racial Segregation in Public Schools and Their Attendance Boundaries," *Sociologoy of Education*, Vol. 79, pp. 81–105.

Schlenker, Charles (2017) "Unit Five Enters Emotional Minefield of Redistricting."

SCOTUS (2007) *Parents Involved in Community Schools v. Seattle School District No. 1*, No. 05-908: Supreme Court of the US.

Siegel-Hawley, Genevieve (2013) "Educational Gerrymandering? Race and Attendance Boundaries in a Demographically Changing Suburb," *Harvard Education Review*, Vol. 83, No. 4, p. 580.

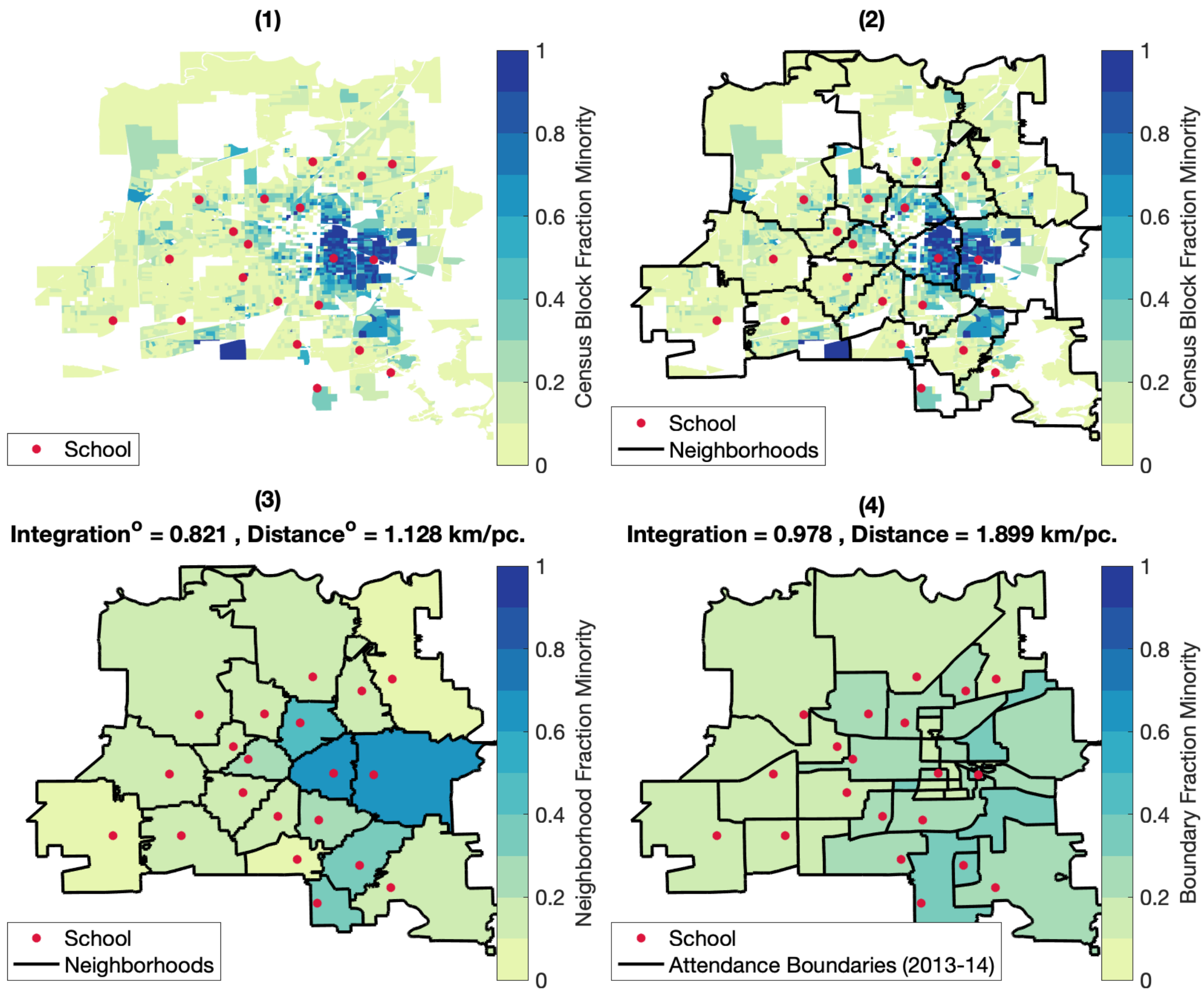
Sohoni, Deenesh and Salvatore Saporito (2009) "Using GIS to Explore Racial Segregation between Schools and Their Corresponding Attendance Areas," *American Journal of Education*, Vol. 115, No. 4, pp. 569–600.

Tannenbaum, Daniel (2015) "Does School Quality Affect Neighborhood Development? Evidence from a redistricting reform.," *Working Paper.*

Weinstein, Jeffrey (2016) "The Impact of School Racial Compositions on Neighborhood Racial Compositions: Ecidence from School Redistricting," *Economic Inquiry.*

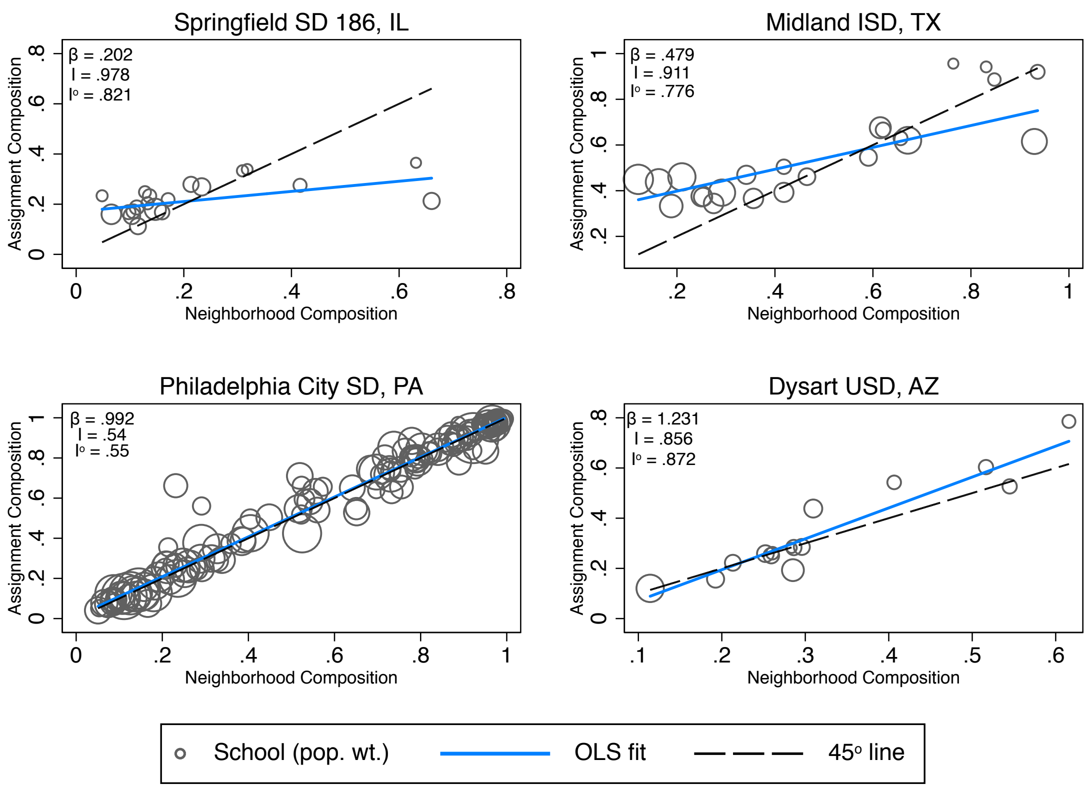
Welch, Finis and Audrey Light (1987) "New Evidence on School Desegregation," *Unicon Resarch Corp., Commission on Civil Rights, Washington, D.C.*

Figure 1: School Boundary Desegregation – Springfield School District No. 186, IL.



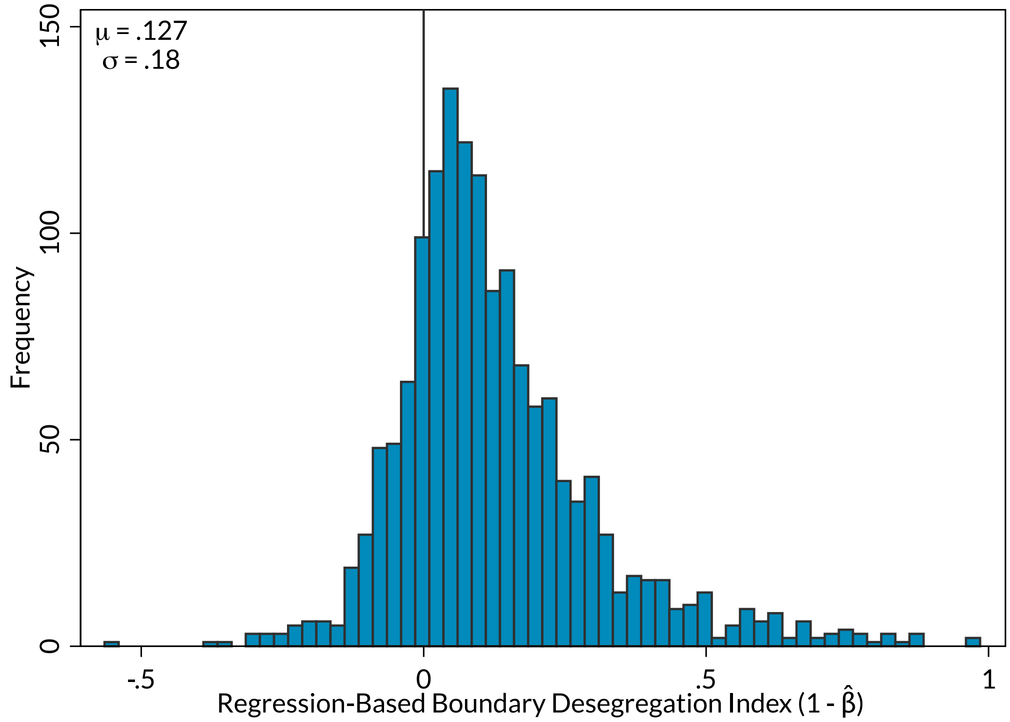
Note: Panel (1) shows a map of the 2010 racial composition of residential census blocks, where light shades denote a low residential fraction black or Hispanic. Red circles denote the location of elementary schools in this district. Panel (2) shows *school neighborhoods*, a minimum travel distance school assignment for Springfield's census blocks. Panel (3) shows the distribution of neighborhood racial composition, where I^o is the level of school racial integration of neighborhoods and D^o is travel distance to school per student in kilometers. Integration is defined as one minus the variance ratio segregation index for black o Hispanic students. Panel (4) shows Springfield's 2013-14 elementary *school attendance boundaries*, and their resulting distribution of school assignment racial composition. These boundaries are highly discontiguous (due to a busing scheme) that results in higher integration I and higher distance per student D, relative to neighborhoods. Springfield Public Schools District has had an active desegregation plan since 1976 (McPherson v. School Dist. No. 186, Springfield Ill.)

Figure 2: School Boundary vs Neighborhood Racial Composition – Selected Districts



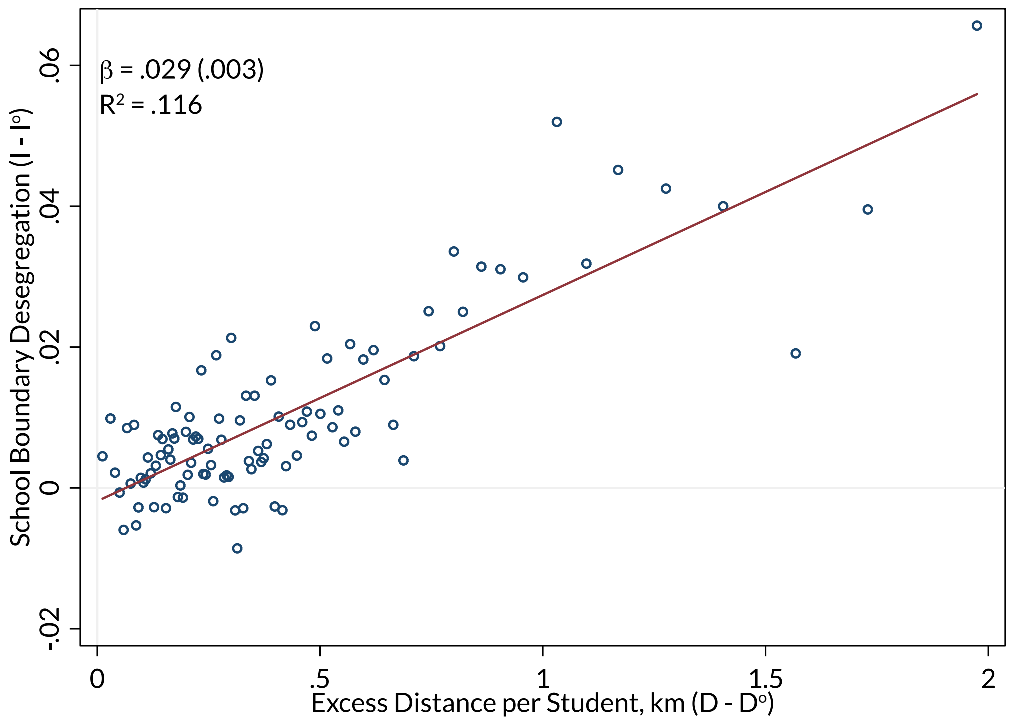
Note: Weighted scatter plots of the racial composition of 2013-14 school boundaries (school *assignments*) against the composition of *neighborhoods* for individual school districts. School observations are weighted by population. I report the OLS regression and the 45 degree line, as well as the OLS slope coefficient, it's robust standard error, and the level of racial integration of neighborhoods, I^o, and assignments, I. Integration is defined as one minus the variance ratio segregation index for black o Hispanic students.

Figure 3: The Distribution of School Boundary Desegregation Across Districts in 2013-14



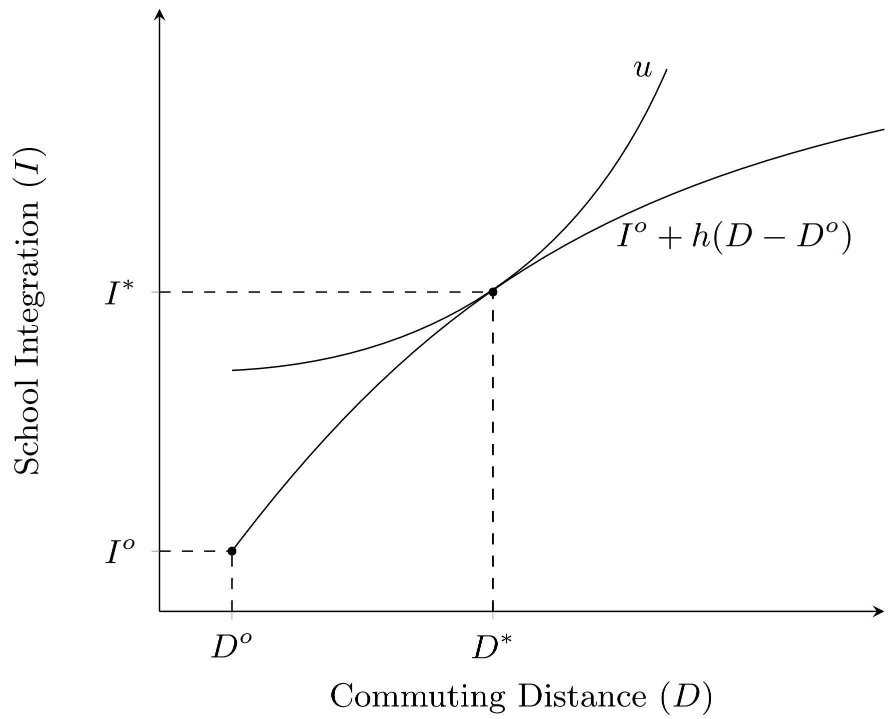
Note: Histogram of school boundary desegregation $(1-\hat{\beta})$, based on the OLS coefficient $\hat{\beta}$ of a within-district regression of school boundary racial composition (the residential fraction black or hispanic) on the composition of school neighborhoods.

Figure 4: Desegregation and Excess Travel Distance in School Boundaries



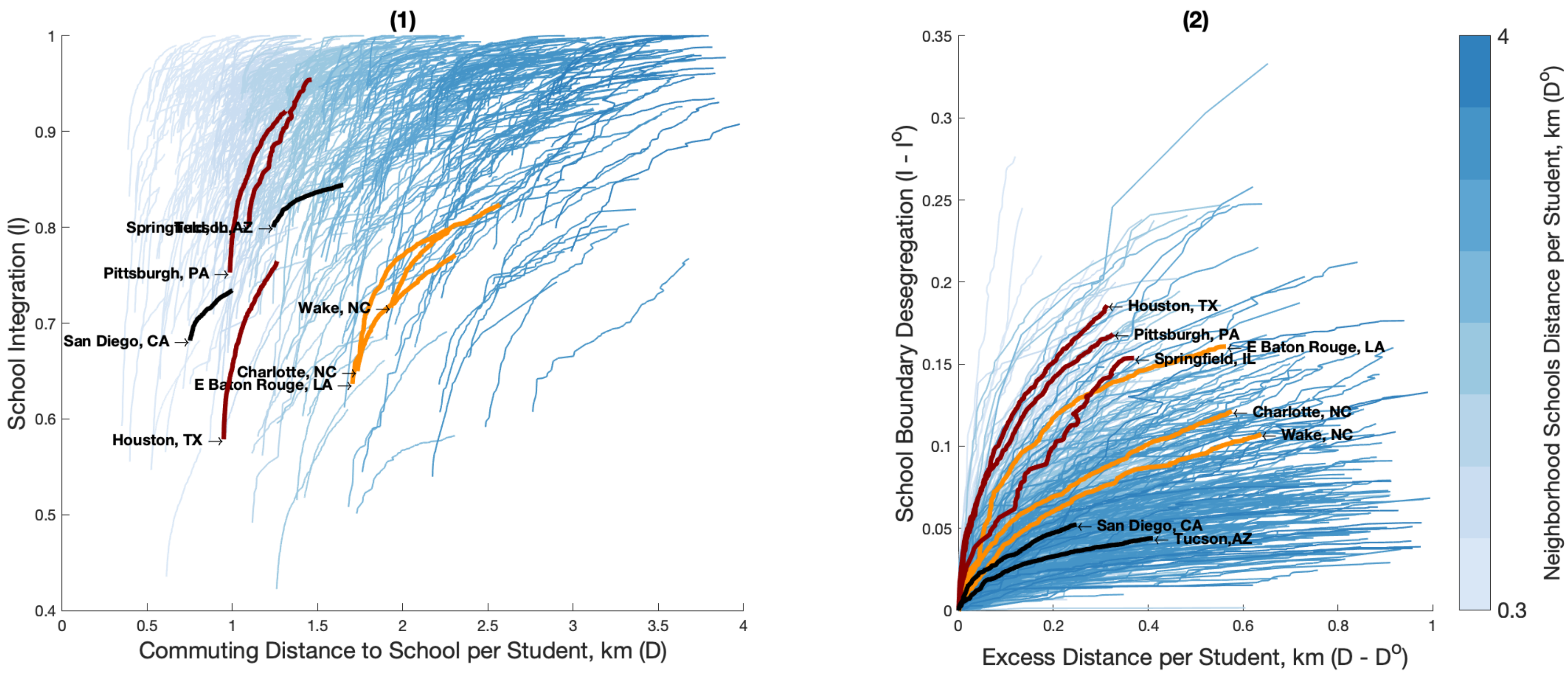
Note: Figure plots the mean level of school boundary desegregation across one hundred quantiles of excess distance per student in 2013-14 boundaries. See Section 3 for the detailed description of construction of these variables. I report the weighted OLS line for this scatter, as well as the OLS slope coefficient, its robust standard error (in parenthesis), and the model's R-squared.

Figure 5: A School District's Optimal Choice of School Boundaries in Integration-Distance Space



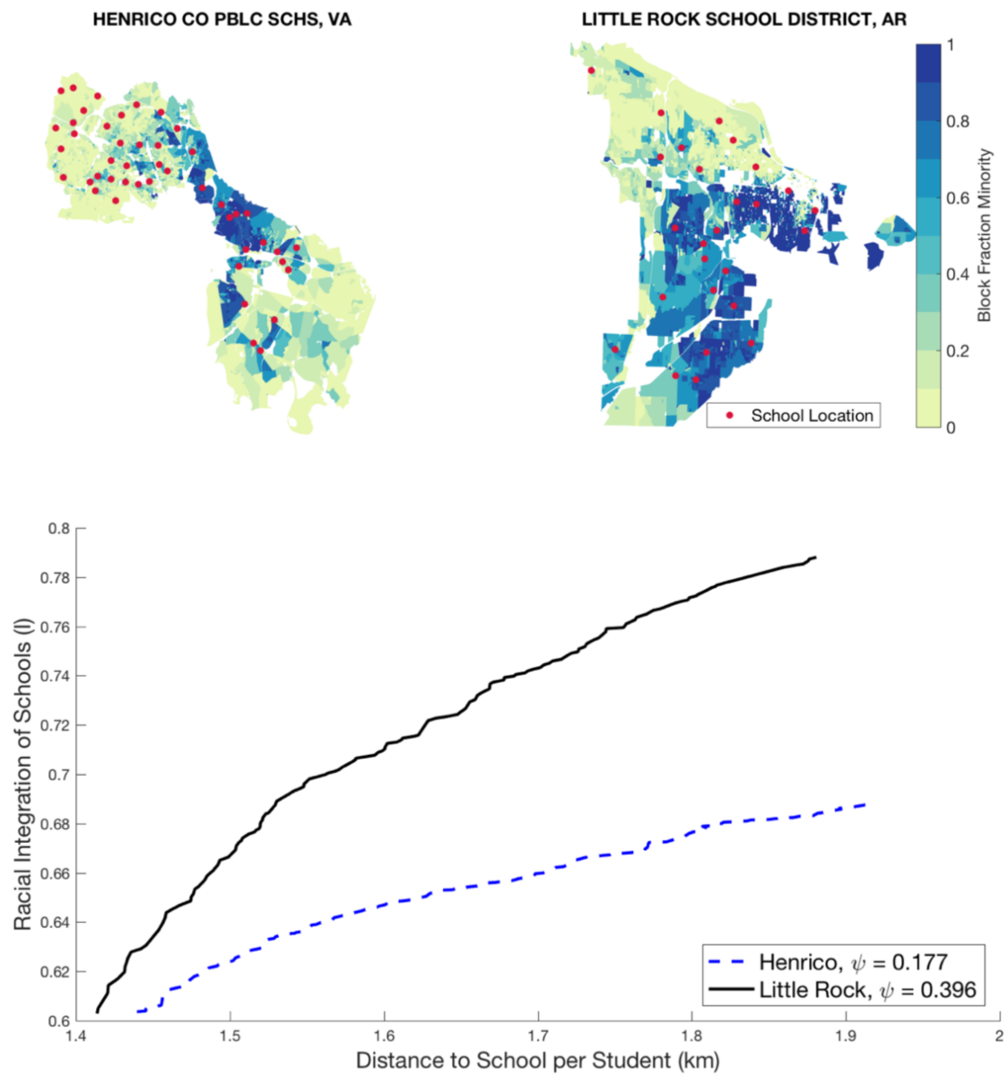
Note: Illustration of school attendance boundary choice model developed in Section 4. The horizontal axis denotes aggregate distance travelled to school in the district, while the vertical axis measures the level of SAB racial integration. Districts have a heterogenous origin (D^o, I^o), where D^o is lowest travel distance feasible given the geography of the jurisdiction and the location of schools. The district faces an integration-distance technology ("bufget") that is governed by I^o and $h(D - D^o)$, where $h(D - D^o)$ is the maximum increase in integration that can be achieved for an increase in distance $D - D^o$. The district has preferences over (D, I) bundles, represented by indifference curve u. The district's optimal SAB choice, (D^*, I^*), satisfies the condition $\frac{\partial h}{\partial D} = -\frac{\partial u/\partial D}{\partial u/\partial I}$.

Figure 6: Simulated Budget Between Racial Integration and Commuting Distance for 700 School Districts



Note: This figure plots 700 simulated school district budgets (production frontiers) between school integration and school commuting distance. Simulations are based on a school boundary optimization algorithm applied to school location and census block racial composition data, see Appendix C. In Panel (1), the vertical axis measures school racial integration at the district level (I) and the horizontal axis measures distance travelled to school per student in the district (D). Each separate locus of points is a distinct district's approximate integration-distance schedule, which originate at minimum cost bundle (D^o, I^o) corresponding to neighborhood schools. Panel (2) shows a similar plot after differencing out neighborhood levels, resulting in a plot of desegregation $(I - I^o)$ on excess distance $(D - D^o)$, highlighting differences in the marginal cost of desegregation. In boldface, the budget of the following school districts: Houston ISD, TX; Pittsburgh City Schools, PA; Springfield Public Schools, IL; East Baton Rouge Parish, LA; Charlotte Mecklenburg Schools, NC; Wake County Schools, NC; San Diego USD, CA; and Tucson USD, AZ.

Figure 7: Differences in Districts' Cost of Desegregation – Henrico County Public Schools, VA and Little Rock School District, AR



Note: Top panel shows racial composition census block maps of these school districts' jurisdictions. Red circles denote elementary school locations. Bottom panel shows the simulated integration-commuting distance budget (production frontier) for each district. Simulations are based on a school boundary optimization algorithm applied to school location and census block racial composition data, see Appendix C.

Table 1: Summary Statistics of School District Estimation Sample

	Mean	SD	P25	P50	P75
School Boundaries and Integration					
School boundary integration (I)	0.923	0.087	0.896	0.955	0.984
Neighborhood integration (I^o)	0.913	0.093	0.875	0.945	0.981
Boundary desegregation ($I - I^o$)	0.010	0.032	-0.003	0.003	0.013
Boundary-neighborhood comp. OLS ($1 - \hat{\beta}$)	0.127	0.180	0.016	0.092	0.203
School enrollment integration	0.906	0.102	0.866	0.944	0.978
Home-School Commute Distance					
Boundaries, km per capita (D)	2.46	1.53	1.33	2.03	3.13
Neighborhoods, km per capita (D^o)	2.04	1.35	1.09	1.60	2.50
Excess travel distance ($D - D^o$)	0.42	0.37	0.17	0.31	0.53
Commuting cost of desegregation	-0.00	1.00	-0.30	0.32	0.67
District Characteristics					
Number of elementary schools	14.66	19.79	6.00	9.00	15.00
Total population	102,896	167,169	36,565	57,656	105,506
Population 5 to 9 years old	6,954	10,654	2,457	3,894	7,231
Fraction black or hispanic	0.27	0.22	0.10	0.20	0.39
Fraction black or hispanic (5 to 9 yrs.)	0.35	0.25	0.14	0.28	0.51
Median household income (2014 USD)	58,955	22,354	42,989	53,158	70,272
White Median household income	63,359	21,929	47,754	58,298	74,777
Minority Median household income	46,268	19,553	32,634	41,760	55,921
Adult fraction with college	0.59	0.14	0.50	0.59	0.69
Student fraction FRPL	0.53	0.24	0.35	0.56	0.72
Bizarreness of jurisdiction shape	-0.00	1.00	-0.63	-0.10	0.49
Court desegregation order in effect	0.06	0.24	0.00	0.00	0.00
Court desegregation order released	0.11	0.31	0.00	0.00	0.00
White racial intolerance index (GSS)	-0.04	0.50	-0.31	-0.05	0.27
Private to public school ratio	0.50	0.39	0.23	0.42	0.67
Charter to public school ratio	0.12	0.22	0.00	0.00	0.17
Region, Northeast	0.13	0.34	0.00	0.00	0.00
Region, South	0.36	0.48	0.00	0.00	1.00
Region, Midwest	0.24	0.43	0.00	0.00	0.00
Region, West	0.27	0.44	0.00	0.00	1.00
N	1,486				

Note: Summary of the distribution of school district variables used in the analysis. Integration is defined as one minus the variance ratio index of segregation for black or Hispanic students. Boundary desegregation is defined as the difference in integration between 2013-14 school boundaries (I) and neighborhood integration (I^o). An alternative desegregation index, the boundary-neighborhood composition OLS slope, is based on a regression of the racial composition of a school's assignment on its neighborhood composition, see Figure 2. Commuting distance from homes to schools is defined by the euclidean distance between census block centroids and schools, aggregated to the district level using population weights. See Section 5.1 for the definition of the commuting cost of desegregation. Bizarreness of district jurisdiction shapes is measured based on the ratio of the area of a jurisdiction to the area of its convex hull. See Appendix D for the definition the white racial intolerance index.

Table 2: School Boundary Desegregation and District Racial Gaps in School Characteristics

Gaps in School Chars.	Realized School Segregation		Teacher Experience Gap		GT Participation Gap	
	(1)	(2)	(3)	(4)	(5)	(6)
Boundary Desegregation	-0.858***	-0.824***	0.092***	0.092***	-0.840***	-0.735***
	(0.064)	(0.061)	(0.017)	(0.019)	(0.125)	(0.129)
Covariates		✓		✓		✓
Mean	.094		-.006		.052	
SD	.102		.02		.118	
R^2	0.78	0.79	0.09	0.10	0.20	0.24
N	1,486	1,486	1,486	1,486	1,486	1,486
Gaps in Outcomes	Grade Repetition Gap		Achievement Gap			
	(1) (%)	(2) (%)	(3) Math (sd)	(4) Math (sd)	(5) ELA (sd)	(6) ELA (sd)
Boundary Desegregation	0.050	0.044	0.355*	0.386**	0.662***	0.622***
	(0.037)	(0.037)	(0.210)	(0.194)	(0.202)	(0.184)
Covariates		✓		✓		✓
Mean	-.009		.576		.571	
SD	.037		.226		.226	
R^2	0.08	0.10	0.25	0.32	0.17	0.34
N	1,486	1,486	1,408	1,408	1,409	1,409

Note: Robust standard errors reported in parenthesis. In all specifications, the dependent variable is a district level racial gap, defined as $\bar{Y}_j^{nm} - \bar{Y}_j^{m}$, where $\bar{Y}_j^{r}$ is the district average of the outcome for students in racial group $r = nm, m$, non-minorities and minorities (black or Hispanic). In panel A, Columns (1) and (2) correspond to the gap in average school enrollment racial composition (fraction black or Hispanic), which is equivalent to the variance ratio index of segregation in school enrollment. Columns (3) and (4) report estimates for the gap in the fraction of school teachers in their first or second year in the profession. Columns (5) and (6) correspond to gaps in student exposure to the "gifted and talented" (GT) school program. In panel B, Columns (1) and (2) show results for gaps in student grade retention rates, the fraction of students held back a grade. Then columns (3)-(6) use the racial achievement gap, as measured by Stanford's SEDA. All models control for neighborhood segregation levels. Additional covariates include log population, log median household income, population fraction minority, and US region fixed effects.

Table 3: Correlates of the Cost of School Boundary Desegregation

	Desegregation Cost				
	(1)	(2)	(3)	(4)	(5)
Neighborhood integration (I^o)	7.6296***	7.6701***	7.3074***	7.2306***	7.1287***
	(0.6317)	(0.6272)	(0.6975)	(0.6872)	(0.7366)
Neighborhood distance (D^o)	0.2456***	0.2534***	0.2366***	0.2121***	0.2058***
	(0.0130)	(0.0136)	(0.0148)	(0.0146)	(0.0159)
ln(Total population)	0.2189***	0.2258***	0.2249***	0.1846***	0.1556***
	(0.0296)	(0.0300)	(0.0329)	(0.0329)	(0.0339)
Number of schools administered	-0.0027	-0.0029	-0.0033*	-0.0030*	-0.0023
	(0.0019)	(0.0019)	(0.0017)	(0.0017)	(0.0018)
Fraction minority	-0.6355	-0.6582	-0.5280	-0.7786	-0.8854*
	(0.4192)	(0.4165)	(0.5010)	(0.4844)	(0.5302)
Fraction minority sq.	0.2596	0.2725	0.2134	0.4208	0.6089
	(0.4546)	(0.4526)	(0.4908)	(0.4720)	(0.4830)
Bizarreness of jurisdiction shape		0.0701***	0.0738***	0.0646***	0.0689***
		(0.0167)	(0.0163)	(0.0162)	(0.0174)
White log median HH income			-0.3073***	-0.2937***	-0.3161***
			(0.1090)	(0.1090)	(0.1211)
Minority log median HH income			0.2011***	0.1915***	0.2179***
			(0.0692)	(0.0689)	(0.0701)
Adult fraction with bachelor's			-0.4182**	-0.4623**	-0.5446**
			(0.2122)	(0.2021)	(0.2125)
Student fraction FRPL			-0.5676***	-0.6103***	-0.7641***
			(0.1709)	(0.1731)	(0.2088)
Court desegregation order in effect			0.0955	0.0879	-0.0231
			(0.0841)	(0.0810)	(0.0878)
Court desegregation order released			0.0979	0.0862	0.0405
			(0.0786)	(0.0745)	(0.0780)
Racial intolerance of whites (GSS)			-0.0100	-0.0131	-0.0440
			(0.1324)	(0.1326)	(0.1333)
Private to public school ratio			-0.1569***	-0.1126**	-0.1117**
			(0.0429)	(0.0446)	(0.0456)
Charter to public school ratio			0.1419	0.1479*	0.1156
			(0.0890)	(0.0883)	(0.0997)
Northeast				-0.2177***	
				(0.0731)	
South				0.0249	
				(0.0457)	
Midwest				-0.0983**	
				(0.0402)	
First Stage F-stat		17.73	20.48	15.95	15.67
State FE					✓
R^2	0.63	0.64	0.65	0.66	0.67
N	1,486	1,486	1,479	1,479	1,476

Note: Robust standard errors reported in parenthesis. OLS models of the cost of school boundary desegregation as a function of district characteristics. The cost of desegregation is derived from the simulated budget constraints described in Appendix C. Cost is scaled to have mean of zero and standard deviation of one.

Table 4: The Demand for School Boundary Desegregation

Panel A: OLS Models	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Desegregation Cost	-0.00692*** (0.00198)	-0.00699*** (0.00196)	-0.00706*** (0.00185)	-0.00686*** (0.00188)
Demographic Controls	✓	✓	✓	✓
Socioeconomic Controls		✓	✓	✓
Preference Controls			✓	✓
State FE				✓
N	1,486	1,479	1,479	1,479
Panel B: Reduced Form Models	(1) RF	(2) RF	(3) RF	(4) RF
Bizarreness of jurisdiction shape	-0.00235** (0.00101)	-0.00253** (0.00100)	-0.00253*** (0.000980)	-0.00172* (0.000973)
Demographic Controls	✓	✓	✓	✓
Socioeconomic Controls		✓	✓	✓
Preference Controls			✓	✓
State FE				✓
N	1,486	1,479	1,479	1,479
Panel C: 2SLS Models	(1) IV	(2) IV	(3) IV	(4) IV
Desegregation Cost	-0.0335** (0.0140)	-0.0359** (0.0140)	-0.0355*** (0.0133)	-0.0253* (0.0134)
Demographic Controls	✓	✓	✓	✓
Socioeconomic Controls		✓	✓	✓
Preference Controls			✓	✓
State FE				✓
N	1,486	1,479	1,479	1,479

Note: Robust standard errors reported in parenthesis. Reports OLS estimates of school boundary desegregation $(I - I^o)$ regressed on the estimated commuting cost of desegregation. Column (1) includes controls for neighborhood levels of integration and commuting distance. Column (2) adds the following covariates: log population, population fraction minority, and log median household income. Columns (3) and (4) use the same covariates, and report instrumental variable estimates of this equation using the bizarreness of districts' jurisdiction shapes as an instrument for desegregation cost. The F-statistic of the first stage of the IV model (a regression of desegregation cost on district bizarreness plus covariates) is reported.

Table 5: Shifters of the Demand for School Boundary Desegregation

	School Boundary Desegregation ($I - I^o$)					
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV
Desegregation cost	-0.00693***	-0.00693***	-0.00643***	-0.00666***	-0.0327**	-0.0243*
	(0.00195)	(0.00188)	(0.00186)	(0.00189)	(0.0146)	(0.0132)
Court desegregation order in effect	0.0149***		0.0145***	0.0138***	0.0166***	0.0131***
	(0.00477)		(0.00476)	(0.00491)	(0.00531)	(0.00501)
Court desegregation order released	-0.000184		-0.000515	-0.00185	0.00180	-0.00117
	(0.00360)		(0.00360)	(0.00369)	(0.00414)	(0.00389)
Racial intolerance of whites (GSS)		-0.0105***	-0.00936**	-0.0102**	-0.01000**	-0.0112**
		(0.00374)	(0.00382)	(0.00415)	(0.00470)	(0.00440)
Private to public school ratio			-0.00146	-0.00225	-0.00427	-0.00411
			(0.00334)	(0.00358)	(0.00421)	(0.00414)
Charter to public school ratio			0.000872	-0.00159	0.00464	0.000491
			(0.00300)	(0.00345)	(0.00421)	(0.00394)
White log median HH income			-0.00164	-0.000124	-0.00975	-0.00612
			(0.00570)	(0.00648)	(0.00727)	(0.00785)
Minority log median HH income			-0.00494	-0.00541	-0.000217	-0.00174
			(0.00371)	(0.00375)	(0.00453)	(0.00455)
Adult fraction with bachelor's			0.0197*	0.0233**	0.00799	0.0140
			(0.0108)	(0.0114)	(0.0133)	(0.0131)
Student fraction FRPL			-0.00733	-0.00659	-0.0233*	-0.0200
			(0.00753)	(0.00848)	(0.0122)	(0.0132)
ln(Total population)	-0.00314**	-0.00307**	-0.00203	-0.00258	0.00260	0.0000814
	(0.00140)	(0.00149)	(0.00157)	(0.00164)	(0.00294)	(0.00246)
Fraction minority	0.00984	0.0132	0.0370**	0.0460***	0.0158	0.0303
	(0.0124)	(0.0125)	(0.0149)	(0.0174)	(0.0227)	(0.0225)
Fraction minority sq.	-0.0129	-0.0152	-0.0281**	-0.0321**	-0.0166	-0.0214
	(0.0122)	(0.0124)	(0.0135)	(0.0149)	(0.0195)	(0.0187)
Neighborhood integration (I^o)	-0.0801***	-0.0885***	-0.0728***	-0.0670***	0.116	0.0581
	(0.0238)	(0.0238)	(0.0238)	(0.0236)	(0.104)	(0.0926)
Neighborhood distance (D^o)	0.00161**	0.00235***	0.00298***	0.00326***	0.00828***	0.00675**
	(0.000719)	(0.000668)	(0.000903)	(0.00100)	(0.00305)	(0.00282)
Northeast			0.00623**		-0.000285	
			(0.00288)		(0.00472)	
South			0.000225		0.000746	
			(0.00219)		(0.00253)	
Midwest			0.00514***		0.00200	
			(0.00192)		(0.00275)	
State FE				✓		✓
N	1,486	1,486	1,479	1,479	1,479	1,479

Note: Robust standard errors reported in parenthesis. Dependent variable in all models is school boundary desegregation. See Appendix C for the definition and estimation detials of desegregation cost. Indicators for desegregation orders and their status are obtained from the Department of Education Office of Civil Rights and from Reardon et al. (2012). White racial intolerance is measured using General Social Survey data, as in Card et al. (2008), see Appendix D. Ratios of the number of private schools to the number of publics in the district are obtained using the NCES 2013 Private School Survey. See Table 4 for details on the instrumental variables estimates in Column (5).

A Data Appendix

I make use of the National Center of Education Statistics' (NCES) Student Attendance Boundary Survey (SABS) as the primary data source for this study. This survey was the first attempt to collect data on school attendance boundaries of all districts in the U.S.[35] The SABS data were collected over a web-based self-reporting system, through e-mail, and mailed paper maps. The creators then harmonized these different data types into GIS shape files, which greatly facilitates a systematic analysis. The universe of school districts is defined as those included in the Census Bureau's SY 2013-14 School District Review Program and the Common Core of Data, specifically those that are denominated as a regular school district and has at least one school open during the school year. This frame resulted in more than 5,000 school districts eligible to participate in SABS. The survey collected data on attendance boundaries for all K-12 grade levels.

I measure the spatial distribution of racial composition in school district geography using census block-level race by age tabulations from the 2010 Census in combination with the 2010 census block GIS shape files produced by TIGER/Line. Total population, age, gender, and race are the only variables that the census makes available to the public at the census block level, but this suffices to measure segregation at a remarkably fine spatial level. In urban settings, census blocks' area correspond to city blocks, while in rural areas they have larger size.

By laying the SABS geographic data over the census block mapping of a LEA jurisdiction, I can assign each block to a given school in the district, whose location is know from GPS coordinates present in the Common Core of Data.[36] The resulting crosswalk between census blocks and schools is the policy which I study in this paper, a policy which the district chose deliberately. This crosswalk is the key object determining the mapping between many interesting economic and social outcomes. I study the relationship between neighborhood racial segregation and school segregation generated by this mapping, motivated by the literature on the effects of segregation and the historical relevance of race in U.S. socioeconomic patterns.

I choose to focus on elementary schools for a few reasons.[37] First, elementary schools are smaller a hence generally more numerous within each district; this means that the district has more leeway in designing attendance zones for these schools than for higher grades. Second, a majority of districts operate a feeder system between schools, meaning that lower level schools feed into upper level schools systematically. Hence, middle school attendance boundaries can be roughly thought of as the union of a few elementary school zones. Finally, as elementary schools are the lowest rung of public education, they are the first point at which children engage in social interaction outside of the home, making them the first place in which school segregation

[35]This also means that there is limited panel data for SAZs with the exception of pilot and SABINS.

[36]Specifically, the assignment of blocks to SAZs is done by computing the block centroid and asking whether this point is inside the polygon defined by the SAZ. This may lead to errors in assignment. These are likely very limited, but also correlated with how close is to SAZ boundary, which should keep in mind when thinking of spatial RDs

[37]It should be noted that the term 'elementary school' is used to refer to schools that serve different sets of grade levels, but generally up to fifth or sixth grade

takes place.

The main dataset used in this study is the School Attendance Boundary Survey (SABS) for SY 2013-2014, the Department of Education's first attempt at characterizing the school attendance boundaries of every large school district in the country. Using GIS software, I link this spatial data to 2010 census block geography, for which I can observe population by race. This allows me to compute the racial composition of school assignments with great accuracy. Figure 1 depicts the main unit of analysis, a school district divided into elementary school attendance boundaries laid over the 2010 distribution of race.

The SABS included a total of 33,638 attendance boundaries administered by 4,731 school districts. Given that I focus on the boundary-drawing problem and its relation to school segregation, I make a number of sample restrictions which discard cases in which this problem is degenerate. Table A.1 provides a gradual depiction of how sample restrictions change the distribution of SABs in the analysis sample. The first column in Table A.1 reports mean characteristics for all attendance boundaries in the sample. The average SAB has a total population of about 9,600 residents, 618 of which are aged 5 to 9 years, with an enrollment to population ratio (for grades K-4) of 84%, and an average student distance to school of about 2.75 kilometers. Column (2) shows how the sample changes when I drop de facto school districts (i.e. districts that serve a single school for each grade level) and those that exclusively use nonresidential assignments.

The majority of districts dropped here are rural, but this restriction also gets rid of the largest district in the country, New York City Schools. This is reflected in the mean SAB characteristics, with a decrease in both average population and distance to school. Further sample restrictions, such as discarding small districts that serve less than 2000 students or administer fewer than 5 schools (column (3) in Table 1), or dropping of un-diverse districts with more than 97% or less than 3% minority (column (4) of Table 1), do not seem to significantly affect the mean characteristics of SABs or districts in the sample. The final analysis sample contains 23,823 attendance boundaries. The SABS data also reflects some of the complexities associated with student assignment rules.[38]. Some districts enact 'choice zones' which assign some residences to multiple schools which create overlapping SABs (I call this feature 'multiple assignment'); 13% of SABs in the sample have this feature. Discontiguous SABs reflect student busing schemes and generate 'satellite SABS'; 12% in the sample have this. Moreover, districts some times have some schools open to enrollment (no assigned residences); only about 2% of schools in the analysis sample.[39]

In addition to data on SABs and the residential distribution of race, I use several other sources to measure attributes of school districts (and sometimes schools), including: desegregation court orders, median household incomes, education attainment of adults, school district finance, qualitative measures of school quality, racial gaps in student achievement, real estate

[38]Not all complexities are depicted the data, however. For instance, some districts operate magnet and other special schools which do not make use of a typical address-based attendance boundary system, these schools are not present in SABS. I discuss the implications of this restriction in the data appendix.

[39]I assign open enrollment schools the mean characteristics of the district. Please see Section 2.5 for a discussion of the implications of this imputations for the current analysis.

values and characteristics, and others. The data sources are the U.S. Census, the National Center for Education Statistics, and the Office of Civil Rights of the Department of Education.

B Definition of Minimum Distance SABs

SABs that minimize travel distance to school are a convenient counterfactual for existing zoning choices. Such a design is a "neighborhood schools" assignment scheme in the strict sense – the set of residences assigned to a school is precisely those that are not closer to any other school. Neighborhoods are thus simply defined areas of closest proximity to schools, creating a perfect partition of the jurisdiction into a number of polygons equal to the number of schools. In mathematics such partition of a space given a finite set of points (school locations) is called the Voronoi mapping. Drawing these zones requires a straightforward optimization procedure based on the distance matrix between census blocks and schools – each element of this matrix measuring the distance between a census block centroid and a school location.

In Figure 1, panels (2) and (4), the reader can see a comparison between Springfield's actual school attendance boundaries and the minimum travel distance counterfactuals. By definition, the benchmark map has a lower mean distance to school per pupil than the actual map. I assume that a district's minimum travel distance mapping with respect to it's school locations is a feasible and reasonable counterfactual SAB assignment scheme.[40]

Voronoi maps are theoretically well-defined no matter which distance metric is used. I choose euclidean distance both for ease of exposition and elegance. However, the empirical results presented in the rest of the paper do not rely heavily on this assumption. Providing evidence for this claim, I study an example in which Voronoi maps are constructed by combining real road networks and Dijkstra's algorithm. I take census block geography of Fresno, CA. I obtain the "Roads" shapefile from the U.S. Census TIGER/Line, a map denoting all roads. Using this rich data, I construct the road network of the city, with road intersection representing nodes, and the roads themselves denoting network connections.

Using the road network, I construct the distance matrix between all census block centroids in Fresno and all of its elementary schools. The rows of this matrix correspond to unique city blocks, while each column corresponds to a unique school. Each element of this matrix is the minimum road network distance to each school, computed using Dijkstra's algorithm, which finds the minimum distance path between any two points in a network. In my case, the two points is the closest road intersection to a census block and elementary schools and the network is the roads. Having constructed the distance matrix, I can quickly find the minimum road network distance zones, by assigning blocks to their closest school, in terms of road network distance.

Equipped with both minimum euclidean distance school assignments and minimum road

[40]Richards (2014) was the first, to my knowledge, to introduce the use of minimum travel distance maps as counterfactual SAB schemes. The idea of using counterfactual maps to assess to the extent of boundary manipulation is also present in the political science literature on congressional gerrymandering, see (Chen 2013).

network distance (henceforth, RND) assignments, I can empirically assess the degree of bias due to the euclidean distance assumption. Appendix Figure 1 plots a census block level histogram of the euclidean proximity ranking of schools, with school assignments corresponding to minimum road network distance. The vast majority of blocks are assigned to the same school regardless of which distance metric is used. About 500 blocks, or 13% of blocks in the city, obtain a different assignment with minimum RND criteria. The majority are linked to the second closest school in terms of euclidean distance, with very few exceptions.

Discrepancies between euclidean and RND Voronoi assignments may lead to systematic difference in the distribution of racial composition across SABs, potentially biasing my estimates of desegregation policy. To test this, appendix Figure 2 plots the racial composition of existing SABs against the composition of both the euclidean Voronoi and RND Voronoi zones. I plot the OLS fit for each relationship. The plot shows that , while there is indeed some variation in the racial composition of minimum distance zones across the euclidean and RND metrics, the resulting relationship with real 2013-14 SABs is almost exactly the same. Therefore, I would estimate almost exactly the same level of desegregation policy regardless of which counterfactual is being used. Considering the minimum RND zones are much more cumbersome to deal with (specially when dealing with hundreds of districts across the country), I opt for the euclidean metric instead for the main analysis.

A related but separate potential critique of the minimum distance SAB counterfactuals is that they are unrealistic, as they ignore concerns for school capacity. Indeed, by simply assigning residences to the school they are closest to, it may be the case the resulting assigned population of each school may violate capacity constraints. While the spatial distribution of school locations is correlated with population density – schools are located closer to each other in densely populated districts, and Voronoi zones will therefore be smaller in denser districts by definition – this may be a potential source of bias. Still, in order for this to be the case a necessary condition is that SAB racial composition vary systematically with capacity constraint adjustments to minimum distance school assignments.

To partially alleviate this concern, Appendix Figure 3 plots a histogram of total population across all SABs in the data for existing 2013-14 zoning as well as for my euclidean minimum distance (Voronoi) counterfactuals. There is common support in both of these distributions, with very similar moments. If anything, it appears like Voronoi zones tend have lower population than actual SABs, as suggested by the relative excess mass in the left tail of the distribution. I interpret this as evidence that Voronoi zones do not systematically violate school capacity. I further assume that any capacity discrepancies could be adjusted without systematic variation in the distribution of school racial compositions.

Another interesting aspect of the distribution of the decomposition SAB integration is how it varies across space. Figure 4 displays two heat maps of mainland U.S. at the school district level. The small polygons correspond to the jurisdictions of the governing school districts in my sample. The heat coloring measures eight quantile categories in the cross-sectional distribution of each variable. The map in the top shows the spatial distribution of the neighborhood segregation component I^o of SAB integration. One notable pattern is that the south's school districts – typically defined along county lines for these states – have some of the most segregated neighborhoods. School districts in the urban centers of the west, specially in California, are also more residentially segregated than the median district in the sample.

The bottom map in Figure 4 corresponds to the spatial distribution of SAB desegregation policy component $I - I^o$. There is ample policy heterogeneity across space even within states. SAB desegregation is remarkably absent in residentially segregated California with the exception of a few districts. The majority of school districts that enact above median desegregation policy are located in the south. This makes sense given that the south was the focus of the desegregation movement of the 1960s and 70s, and it is also the region where the majority of districts that remain under judicial supervision are located (I formally test the link between court orders and policy in Section 6).

C The School Attendance Boundary Optimization Algorithm

This section details the algorithm used to estimate the rate at which school boundary optimization can generate racial integration in school assignments at the cost of greater commuting distance, conditional on residential racial segregation patterns. In Section 5.1, I summarized the procedure intuitively as the gradual amendment of minimum travel distance SABs with the aim of improving school integration. To state precisely what is meant by this, I introduce additional notation.

Let $s = 1, ..., N_j^S$ index each primary school administered by district j, with N_j^S denoting the total number of primary schools belonging to this district. Additionally, let $b = 1, ..., N_j^B$ index residential blocks located within district j's jurisdiction, where N_j^B denotes the total number of residential blocks in the district. A school attendance boundary map can be represented by a $N_j^B \times N_j^S$ binary matrix $\mathbf{A_j}$, such that an element of this matrix $a_{bs} = 1$ if residential block b is assigned to primary school s and is zero otherwise. Similarly, one can define a distance matrix $\mathbf{D_j}$ with elements d_{bs} which measure the distance in kilometers between residential block b and the location of school s.

The minimum aggregate travel assignment, denoted $\mathbf{A_j^o}$ has elements defined as

$$a_{bs}^o = 1\Big(s = \underset{s' \in \{1,...,N_j^S\}}{\text{argmin}} (d_{bs'})\Big), \tag{10}$$

where $1(\cdot)$ denotes the indicator function. This simply means that each residential block is assigned to the nearest school. Once we have knowledge of $\mathbf{A_j^o}$, the level of racial integration generated by this assignment is straightforward to compute, given by

$$I_j^o = g(\mathbf{A_j^o}; \mathbf{p_j}, \mathbf{m_j}). \tag{11}$$

Here, $\mathbf{p_j}$ is a $N_j^B \times 1$ vector of residential block population counts and $\mathbf{m_j}$ is a vector of equal dimension collecting residential block minority shares. The function $g(\cdot)$ represents the aggregation school assignment populations in the relevant manner to compute a racial integration index.

SAB optimization consists of the gradual perturbation of $\mathbf{A_j^o}$. A perturbation is defined as the reassignment of some b from one school to another, which simply consists of setting $a_{bs} = 0$ and picking some s' to set $a_{bs'} = 1$. Define the finite set of all district assignments that differ from $\mathbf{A_j^o}$ by exactly one perturbation as $\mathcal{R}(\mathbf{A_j^o})$. The task is to find

$$\mathbf{A_j^1} = \underset{\mathbf{A} \in \mathcal{R}(\mathbf{A_j^o})}{\operatorname{argmax}} \; g(\mathbf{A}; \mathbf{p_j}, \mathbf{m_j}). \tag{12}$$

The school attendance boundaries defined by $\mathbf{A_j^1}$ generate the greatest increase in racial integration that is feasible when allowing a single block to be reassigned relative to its benchmark assignment in $\mathbf{A_j^o}$. It is then possible to iterate the optimization procedure by defining

$$\mathbf{A_j^k} = \underset{\mathbf{A} \in \mathcal{R}(\mathbf{A_j^{k-1}})}{\operatorname{argmax}} \; g(\mathbf{A}; \mathbf{p_j}, \mathbf{m_j}). \tag{13}$$

Suppose that K iterations of this procedure are performed. This would result in a sequence $\mathbf{A_j^o}, \mathbf{A_j^1}, ..., \mathbf{A_j^K}$ of SAB assignment matrices, with a corresponding sequence of increasing integration levels $I_j^o, I_j^1 ..., I_j^K$ and aggregate distance levels $D_j^o, D_j^1 ..., D_j^K$.

The goal of this exercise is to estimate the rate of transformation between travel distance and school racial integration, an object derived from their production possibility frontier. Therefore, it is necessary to constrain the procedure outlined above such that it finds optimal school reassignments (in the sense of equation (4)) constrained to arbitrarily small increases in travel distance. Provided that this setting does not lend itself naturally to convex optimization methods used widely in economics, I take an alternative approach.

I restrict the set of possible reassignments to residential blocks located right at the boundary of the SAB polygon. Reassignments can only be done to a neighboring school, guaranteeing the increase in aggregate distance generated to be minimal. An added benefit of this approach is that SAB polygons are also guaranteed to retain contiguity for the fist few iterations. Formally, this restriction implies that optimization search is restricted to a subset $\mathcal{C}(\mathbf{A_j^o}) \subseteq \mathcal{R}(\mathbf{A_j^o})$, where $\mathcal{C}(\mathbf{A_j^o})$ is the set of SAB assignments that differ from $\mathbf{A_j^o}$ by exactly one perturbation at the edge of a SAB. This restricted procedure is identical to (4) except with $\mathbf{A} \in \mathcal{C}(\mathbf{A_j^{k-1}})$.

The optimization algorithm is applied to each district j in the sample. Once aggregate distance has increased by 30% relative to minimum distance or if integration-improving reassignments can no longer be found, the algorithm stops. The resulting sequences of integration and distance levels are used to generate the estimate of the rate of transformation that is used in the main analysis.

A potential objection to the algorithm is that it won't perform well for higher values of $D - D^o$. Starting from D^o, the algorithm tries to find the value $h_j(\varepsilon)$ for small $\varepsilon > 0$. But it isn't guaranteed to be successful for larger values of $D - D^o$, as for these one might want to consider school boundary alternatives that aren't local perturbations (e.g. busing a group of students across town). Such alternatives involve discrete jumps in distance cost, which may be worthwhile if they achieve enough of an improvement in I. For instance, consider a district with

SABs that are three narrow strips – one white, one mixed, and one black. It might make sense to swap some students between the white and black strips, jumping over the mixed one in the middle. The "gradient descent" generated by my algorithm won't find reassignments requiring such discrete jumps. Hence, we may expect that these approximations overestimate the cost of desegregation, specially far away from the neighborhood schools benchmark. This is acceptable given that I am considering perturbations local to $h_j(0)$. Furthermore, this type of algorithm is becoming of wide use in the congressional gerrymandering literature in political science (Chen and Rodden 2013, Chen and Cottrell 2016, Chen 2017).

D Construction of GSS white racial intolerance index

The National Opinion Research Center's General Social Survey (GSS) is a national survey intended to gather data on contemporary American society in order to monitor and explain trends and constants in attitudes, behaviors, and attributes. Starting in 1998, all waves of the GSS include census tract codes for respondents' residence. The survey collects respondents' race and also asks a number of questions related to intolerance toward different racial groups. Using the the 1998-2016 waves of the GSS, I exploit this information to construct a school district level index of the racial intolerance of local white residents.

I use the following GSS questions to define the index

1. On the average Blacks have worse jobs, income, and housing than white people. Do you think these differences are . . .
    (a) Mainly due to discrimination?
    (b) Because most Blacks have less in-born ability to learn?
    (c) Because most Blacks don't have the chance for education that it takes to rise out of poverty?
    (d) Because most Blacks just don't have the motivation or will power to pull themselves up out of poverty?
2. Suppose there is a community-wide vote on the general housing issue. There are two possible laws to vote on. Which law would you vote for?
    A. One law says that a homeowner can decide for himself whom to sell his house to, even if he prefers not to sell to Blacks.
    B. The second law says that a homeowner cannot refuse to sell to someone because of their race or color.
3. Some people think that Blacks have been discriminated against for so long that the government has a special obligation to help improve their living standards. Others believe that the government should not be giving special treatment to Blacks. Where would you place yourself on this scale, or haven't you made up your mind on this?

4. The second set of characteristics asks if people in the group tend to be hard-working or if they tend to be lazy. Where would you rate Blacks in general on this scale?'
5. Do people in these groups tend to be unintelligent or tend to be intelligent? Where would you rate Blacks in general on this scale?
6. What about living in a neighborhood where half of your neighbors were Blacks? Would you be very in favor of it happening, somewhat in favor, neither in favor nor opposed to it happening, somewhat opposed, or very opposed to it happening?
7. What about having a close relative marry a Black person? Would you be very in favor of it happening, somewhat in favor, neither in favor nor opposed to it happening, somewhat opposed, or very opposed to it happening?

I follow the procedure of Card, Rothstein, and Mas (2008) to extract a racial animus index from these survey questions. For each question, I compute an indicator for an intolerant response. I estimate a linear probability model for each indicator, using only white GSS respondents who can be assigned to a NCES school district id. The models include school district fixed effects and controls for gender, age, education, a socioeconomic status index, and survey year indicators. I extract the school district effects and standardize each set to have mean zero and standard deviation one. The GSS Racial Animus Index is the simple average of these standardized school district effects.

E The Effect of SAB Racial Composition on Residential White Flight

One implicit assumption held constant throughout the analysis is that residential racial sorting patterns are fixed with respect to school boundary changes. This assumption allows me to hold 2010 census block geography constant when comparing racial compositions across different sets of SABs within a jurisdiction. Holding residential patterns constant is a strong assumption, however. If residential sorting responds drastically and immediately after changes in school boundaries take place, this would potentially invalidate the results of this study. I now turn to a sensitivity analysis regarding this assumption.

Previous work has established that increases exposure to minority populations systematically led to white flight in localities across the country, including school districts (Clotfelter 2004; Kruse 2005; Reber, 2005; Card, Rothstein and Mas, 2008; Boustan, 2010; Boustan and Margo, 2013). Many of these studies focus on historical events of national importance, such as the era of desegregation orders or the Great Migration. In order to check the robustness of my analysis to endogenous resorting effects, I need to estimate this white flight effect at a more granular spatial level, for the nuanced changes in the composition of schools generated by SAB changes. The 2002 abrupt end of a desegregation order in Charlotte-Mecklenburg Schools (CMS) in North Carolina presents an almost ideal scenario to estimate the effect of SAB changes on a district's spatial distribution of race.

Historically, CMS administered one of the most influential school desegregation plans in the country. They were the plaintiff in the 1971 Supreme Court Case *Swann v. Charlotte–Mecklenburg Board of Education* – a pivotal decision which held that busing was an appropriate remedy for the problem of racial imbalance in schools given existing residential segregation. The decision had enormous implications, as it placed the burden on school districts to end de facto school segregation. In compliance, CMS enacted a heavily manipulated SAB map which involved busing students to distant schools. The plan then served as a model for other school districts that desegregated in similar fashion.

CMS's influential desegregation plan remained in place for almost three decades until a series of lawsuits were brought to challenge it. In 1999, a lower federal court decision declared CMS as a "unitary" school system and ordered the district to cease using race as a factor in school assignments. CMS complied with this order and implemented a neighborhood schools plan in SY 2002–03. The effect of this dramatic policy shift has been studied extensively to estimate the effects of school segregation on student outcomes (Kane and Staiger, 2003; Billings et al., 2014; Tannenbaum, 2015; Weinstein, 2016). I intend to contribute to this literature by estimating the effect of this policy shock on the racial composition of residences. To this end, I have acquired school attendance boundary map data for CMS elementary schools for the school years 2000 through 2010.

E.1 Descriptives

The end of desegregation busing in Charlotte brought about abrupt changes in school boundaries, generating exogenous changes in the racial composition of school assignments. Figure 9 illustrates these changes with two school boundary heat maps of CMS for the SY 2000-01 (left panel) and SY 2010-11 (right panel). The heat color corresponds to the racial composition of SABs using the 2000 census. Visually, it is clear that boundaries in 2000 were more racially integrated than in 2010. In 2000, boundaries were highly discontiguous and some of them stretched from the outskirts of the county (the suburbs) all the way the high-minority inner part of city. In contrast, 2010 boundaries look much more like the minimum-travel distance school boundaries first proposed in Figure 1 – they reflect a "neighborhood schools" assignment plan.

Figure 10 further illustrates the dynamics of SAB desegregation brought about by rezoning. The top panel shows a scatter plot similar to those in Figure 2. The horizontal axis measures the racial composition of neighborhoods – as defined by my counterfactual – and the vertical axis measures the composition of actual school assignments. The figure shows that 2000 boundaries attenuated neighborhood segregation considerably. However, by 2010 the boundaries almost perfectly replicate residential segregation in school assignments.

The bottom panel in Figure 10 shows the time trend of desegregation policy in CMS for each school year in the period 2000-2010. The end of busing in CMS brought about a dramatic drop in SAB desegregation. They went from an impressive 0.18 level of SAB desegregation in 2000 to almost an exact zero in 2010. The pattern also demonstrates that there were no changes in desegregation policy in the years between 2002 and 2010. In addition, the plot shows the trend in excess student distance to school. Encouragingly, the end of busing in Charlotte was also accompanied by a dramatic drop in transportation costs. During the busing days, distance travelled to school per student was 1.53 km. This number dropped to 0.34 km per student after the enactment of the 2002 neighborhood schools plan, reducing aggregate travel distance by 77.8%.

I want to estimate whether these policy changes led to a white flight effect. I exploit variation in SAB composition generated by this policy shock to estimate the causal effect it has on the composition of residences.[41] Denote pre-policy period observations by $t = 0$ (SY 2000-01), and post-period observations by $t = 1$ (SY 2010-11). I construct M_{st}, the fraction minority of residents in a given SAB s in school year t, using 2000 census block geography. The bottom panel of Figure 9 presents a block level histogram of the school composition shock, ΔM_s, generated by SAB reassignment. There is considerable support in both negative and positive values of the shock. This is the variation in treatment.

To measure the outcome of interest, I construct a novel longitudinal dataset of racial composition of census blocks for the 2000 and 2010 decennial census. Table 6 and Figure 11 summarize the resulting dataset. Figure 11 establishes the existence of strong mean reversion in the racial composition of residences. The top panel of Figure 11 shows a map of census block geography of CMS. The heat structure in this map corresponds to changes in the fraction minority of residents, with purple tones denoting increases (positive values), and orange tones denoting decreases (negative values). It is notable from this figure that the suburbs of Charlotte received large influxes of minorities during this period, while the center of the city saw decreases in the fraction of minority residences. These visual patterns suggest that Mecklenburg county underwent enormous demographic change between 2000 and 2010, with whites returning to the central area of the city, and minorities becoming more represented in its outskirts. One would not want to attribute all of these dynamics to school reassignments, motivating the use of lagged outcomes as controls in the regressions.

The bottom panel in Figure 11 shows a binned scatter plot of the decennial change in block racial composition against baseline racial composition in 2000. There is a clear pattern of mean reversion in the data: higher baseline levels predict increasingly negative changes. Notably, census blocks that were almost 100% white in 2000 gained 10 percentage points in fraction minority, while those that were almost 100% minority, gained a similar fraction of whites. I present a quadratic fit for this scatter, which does a good job at explaining the observed variation. Given these patterns, I use a quadratic control for baseline composition in the regressions.

Table 6 provides additional summary of the data, showing the average population of census blocks in 2000 and 2010. The average block in 2000 was 31% minority, and increased to 41% by 2010. In addition, I have constructed average block property prices and appraisal values, using data from Mecklenburg County cadastre. The mean residential property price fell from $159,532

[41] Weinstein (2016) explores a similar research question. He uses school district administrative data to estimate the effect of SAB reassignments on residential composition. His analysis is enabled by the presence of student addresses in district records. My focus on data from residential census blocks, however, alleviates the attrition concerns that are present in his analysis. He reaches similar conclusions and the estimates are of similar magnitude to mine.

in 2000, to $138,690 in 2010. The bottom panel in Table 8 reports summary demographics at the SAB level. Importantly, SAB demographics are computed using 2000 census geography regardless of the school year. Thus, the variation in SAB demographics presented in Table 8 is driven solely by changes in SABs and not by residential changes. In 2000 CMS administered 67 schools, with an average 43% fraction minority. The number of schools went up to 91 in 2010, with the average composition of schools left unchanged.

E.2 Identification Strategy

The natural experiment that I am interested in studying can be illustrated with a simple example. Suppose that a given block of homes is reassigned from a school boundary that is 10% minority to one that is 40% minority. These homes face a change in SAB composition $\Delta M = 0.30$. I am interested in estimating whether the racial composition of this block of homes changes because of this reassignment. In other words, how many (if any) of the white inhabitants in this block would move away because they prefer schools that have a lower minority population? A first step toward assessing this residential resorting effect is looking at Δy – the change in the block's racial composition y. Nonetheless, we wouldn't want to attribute all of the variation in Δy to school reassignment, as it may be the case that the composition of these residences were changing for other causes that happen to be correlated with ΔM (e.g. neighborhood gentrification) – we would need to control for these confounders.

The patterns described above suggest that there are two obstacles to the identification of the causal effect of SAB composition. First, the fact that CMS had a desegregation plan in the pre period means that there is dependence between pre-period SAB composition and the baseline composition of residences. Indeed, CMS policymakers literally selected neighborhoods based on their composition when drawing pre-period SABs in order to desegregate schools. Second, the mean reversion pattern illustrated in Figure 11 are also correlated with the treatment. Figure 11 shows an influx of whites to the central part of the city, which used to be a high fraction minority area of the city in 2000. It was also from precisely this area of the city that a large fraction of minority students were bused out to faraway schools during the integration era. Thus, without making proper adjustments, the gentrification pattern in central Charlotte would lead to spurious correlation between the treatment and changes in the composition of residences.

Estimating the causal relationship between changes in residential composition and changes in SAB composition requires that we control flexibly for these confounding factors. I use the following regression specification:

$$y_{ijs1} = \gamma_{js0} + \beta M_{s1} + g(y_{ijs0}) + \epsilon_{ijs1} \tag{14}$$

where i denotes census blocks, j denotes neighborhoods (census tracts), and s indexes SAB; y_{ijs1} is a block's racial composition in the post-period, the outcome of interest; γ_{js0} are pre-period SAB by neighborhood fixed effects; $g(y_{ijs0})$ is a quadratic function of pre-period outcomes. I am interested in β, the coefficient on post-period SAB composition, M_{s1}.[42] OLS estimates of

[42] Billings, Deming, and Rockoff (2014), estimate similar models on student outcomes, finding large negative

(11) capture the causal effect of school composition if the following identification assumption holds

$$E\Big[\epsilon_{ijs1} M_{s1} \;\Big|\; \gamma_{js0}, g(y_{ijs0})\Big] = 0. \tag{15}$$

Once I control for fine-grained spatial fixed effects and a quadratic function of baseline block composition, unobserved determinants of post block composition are uncorrelated with post SAB composition. In other words, I assume that conditional on baseline racial composition, new SAB boundaries are as good as randomly drawn within small residential neighborhoods which used to have the same school assignment in the pre-period.

Notice that β can be interpreted as one minus the rate of compliance of white households with changes in SABs. Indeed, if we conceptualize SAB reassignment as the instrument in a two-equation system in which the endogenous variable is the composition of school enrollments, $1-\beta$ is the coefficient in the first stage regression. The intuition is that β measures the fraction of whites that move residences in response to an increase in SAB minority composition. If whites sort away completely when faced with any increases in minority composition in assignment, we would expect $\beta = 1$. On the other hand, if whites do not respond at all to increases in the minority composition of their school assignments, we would get $\beta = 0$.

E.3 Results

Panel A of Table 7 presents estimates of equation (11). The model in column (1) is a simple specification which controls for confounders using a linear term of pre-period SAB composition and a quadratic function of pre-period block composition (as motivated by Figure 9). The estimated effect in this model – $\hat{\beta} = 0.153$ – is highly statistically significant and it implies that whites have an 84.7% residential with compliance rate with increases in SAB composition. In other words, a 25 percentage point increase in the minority composition of a SAB leads to a $0.25 \times 0.153 \times 100 = 3.83$ percentage point increase in the fraction minority of residences, or a 11.6% increase relative to the average fraction minority of a Charlotte, NC census block. Columns (2) through (4) control more flexibly for the confounders, using within-neighborhood estimates of these effects. The strictest specification, in column (4), controls for old SAB by tract fixed effects (which are very fine-grained spatial controls) and gives an estimated effect of $\hat{\beta} = 0.143$, similar to the first specification.

In theory, SAB changes may change households willingness to pay for their residences. As resorting happens, demand for neighborhoods with high minority SABs may go down which would tend to push prices down. Hence, we expect the coefficient on M_{s1} to be negative in these specifications. Table 7 Panel B tests for this effect using log property prices as the outcome. Since not all census blocks in Mecklenburg County had property sales, the number of observations in these regression is lower. None of these estimates are statistically significant – although, as we introduce additional controls the point estimates become increasingly negative. I interpret this as evidence that the end if integrated schools in CMS did not have a significant effect on local housing markets. This result is in line with the existing empirical literature on the effect

effects .

of racial segregation on property prices, which has generated similar null results (Kruse 2005, Card et al. 2008, Tannennbaum 2015).

I close the analysis with a brief inspection of the demographic mechanisms generating my causal estimates. Two broad demographic patterns affected Charlotte between 2000–2010, immigration and gentrification. The combination of these generates an aggregate relationship between composition change and baseline composition akin to mean reversion, as can be seen in the bottom panel of Figure 9. The regression model in equation model (11) tells us that the treatment effect can be thought of as deviations from this mean reversion trend. Figure 10 provides a a visual illustration of the dynamics at play. Here, I plot the average change in block composition within deciles of baseline block composition for three different groups: (1) Blocks that had a change in SAB composition of less than -0.1, that is, blocks that got a whiter reassignment (negative treatment); (2) Blocks that saw SAB composition changes between -0.1 and 0.1 (a neutral 'control' treatment); and (3) blocks that got an increase in minority assignment of more than 10 percentage points, 0.1 (positive treatment).[43] Neighborhood fixed effects have been partialed out from these variables – hence, they are to be interpreted as deviations from mean neighborhood compositions.

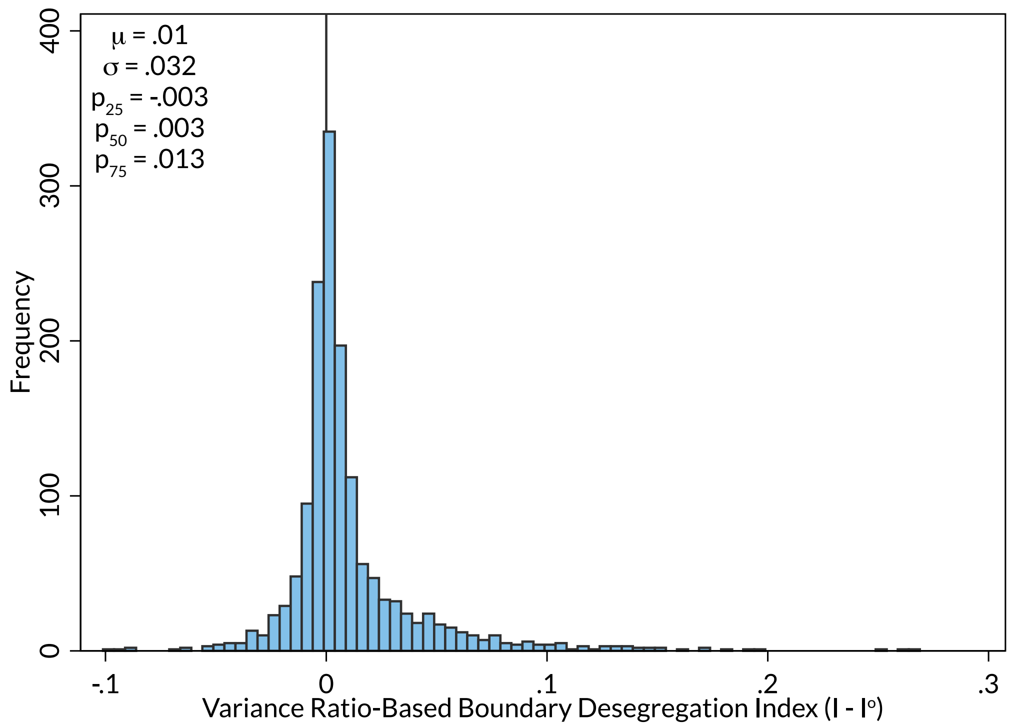
Figure 10 shows that households that resorted in light of boundary changes tended to looked different from the rest of their neighbors. The gray line – corresponding to the comparison group ($-0.1 < \Delta M < 0.1$) – trends down, and both the positive and negative treatment groups follow it in approximately parallel fashion, but with key deviations at the extremes. Second, the red line (increase in SAB composition, $\Delta M > 0.1$) is always above of the black line (decrease in SAB composition, $\Delta M < 0.1$). This means that, within all deciles of baseline composition, an increase in SAB composition leads to at least a weakly higher change in block composition. Hence, the pattern of these differences suggest that white flight is present across the board, although some of these differences are not statistically significant. Second, my white flight estimates are generated by two extremes of the distribution: the exit of whites from blocks that where whiter than the neighborhood average in the positive treatment group, and the arrival of whites to blocks that were less white than average in the negative treatment group. These patterns suggest that complier blocks in this natural experiment were those that looked different from the rest of their neighborhood. White households in minority neighborhoods exited once given a higher minority assignment, while minority household in white neighborhoods exited (at a higher rate). More detailed investigation into this mechanism would useful to policymakers, something that I leave for future research.

In summary: my estimates suggest that white households have an 85% residential compliance rate with SAB racial composition over a decade. In other words, one would predict to lose 3.8 percentage points of the fraction white in a neighborhood if it faced a 25 percentage point increase in the minority fraction of students assigned to a school. While this effect is significant, it is modest. It implies that the main analysis in this study is robust to endogenous residential sorting, especially considering the relative frequency of SAB changes. Moreover, I find that

[43]The threshold of 0.1 for the partition of the support of the treatment variable is arbitrary, it is motivated by the approximately multi-modal distribution of the treatment variable observed in the bottom panel of Figure 7.

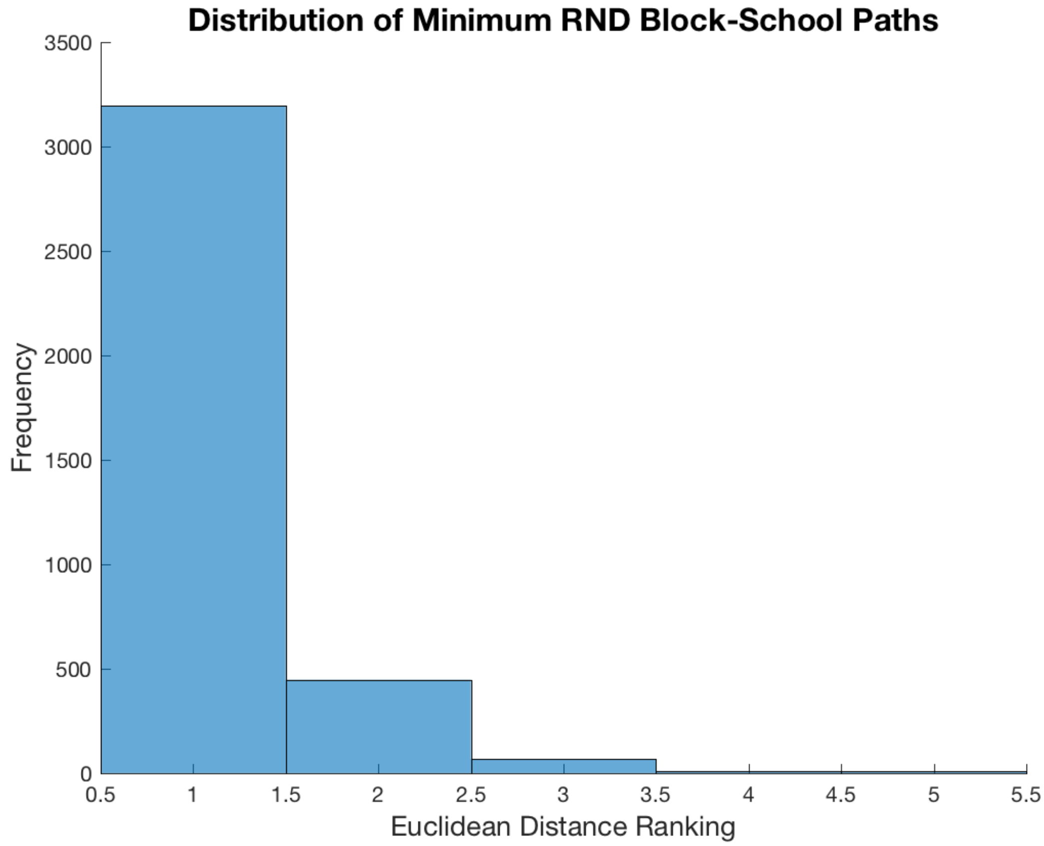
housing markets are not adversely affected by increases in school minority assignments, at least through the price mechanism. Taken together, I interpret these results as evidence that sorting equilibrium in the housing market is not particularly sensitive to SAB changes, at least in the short to medium run.

Figure E.1: The Distribution of School Boundary Desegregation Across Districts (Segregation Index-Based)



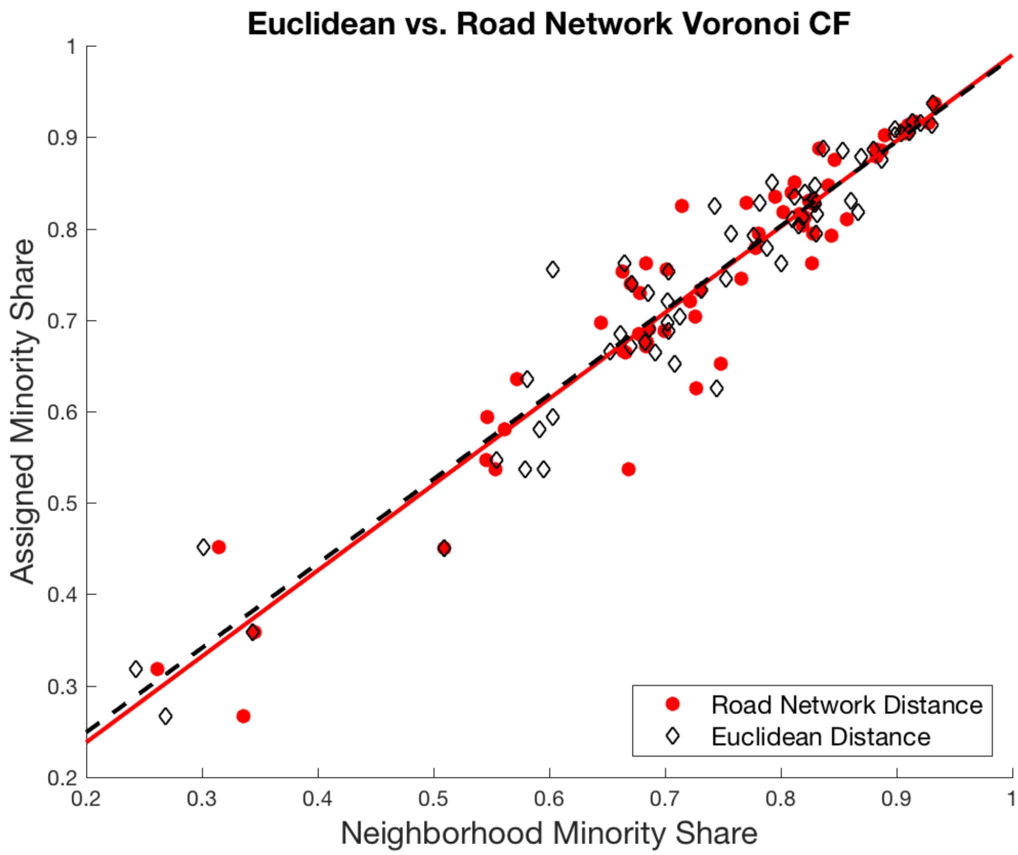
Note: Figure shows a histogram of school boundary desegregation ($I - I^o$), based on the difference in integration between school boundaries and neighborhoods. Integration is defined by the variance ratio index of segregation for black and Hispanic students.

Figure E.2: euclidean Distance Ranking of Schools in Minimum Road Network Distance School Zones



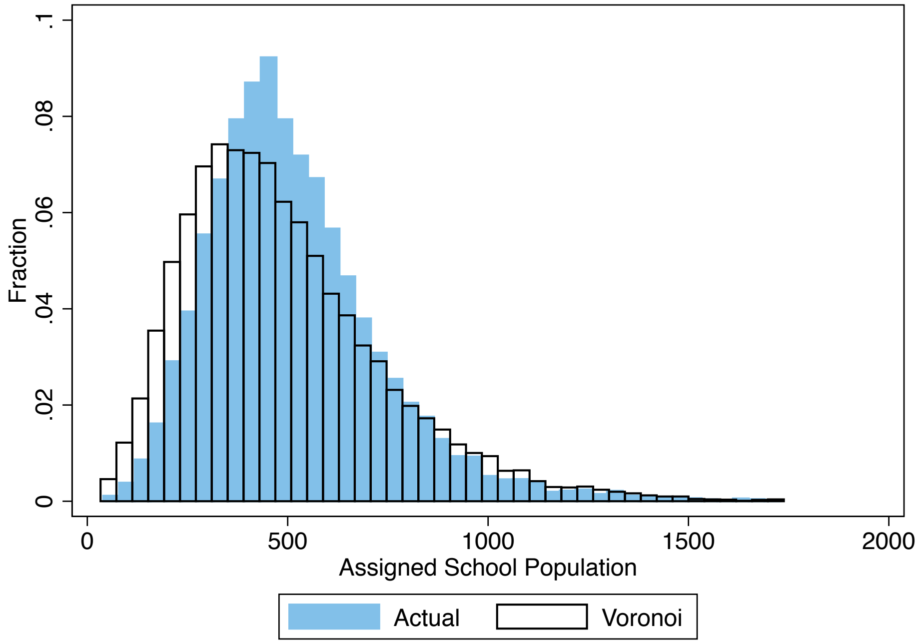
Note: Figure presents census block level histogram of Fresno Unified School District with minimum road network distance (RND) school assignments. The horizontal axis measures the euclidean distance ranking of the school assigned to each block using minimum RND criteria. Lower ranking correspond to shorter distances. euclidean ranking equal to 1 means that closest school in terms of euclidean distance is the same as the closest school using RND.

Figure E.3: Bivariate relationship between racial composition of minimum euclidean distance zones against racial composition of minimum road network distance zones.



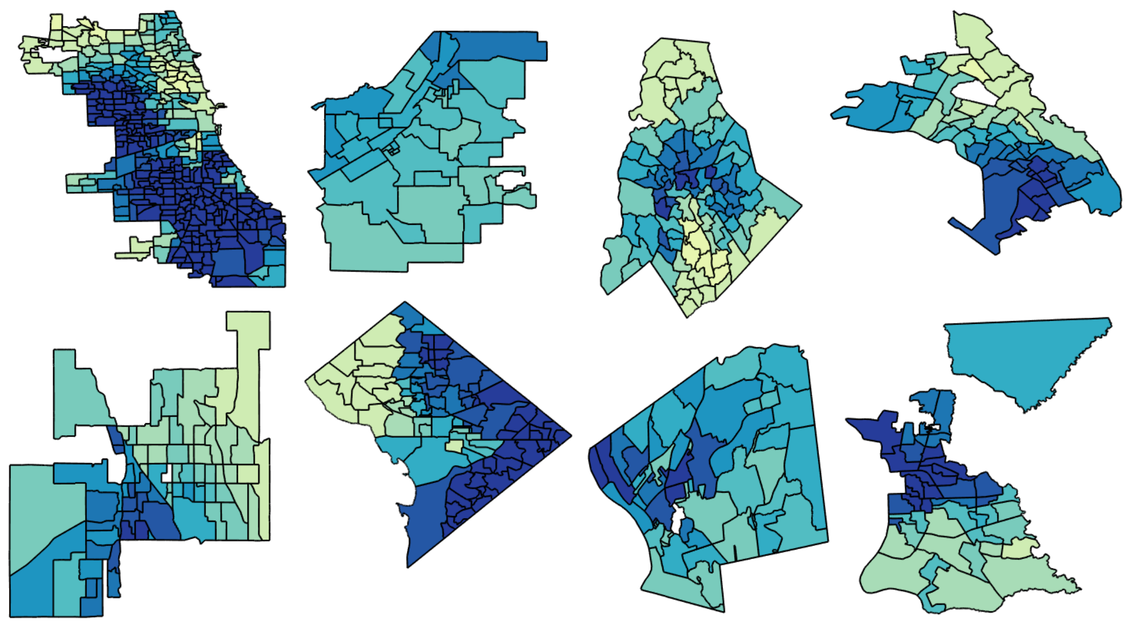
Note: Scatter plot summarizes two bivariate relationships of the racial composition of Fresno USD's school attendance boundaries (SABs). In red circles, I plot the racial composition (fraction black or hispanic) of a school's existing 2013-14 SAB against counterfactual racial composition based on minimum road network distance (RND) zoning. In black diamonds, I present a similar plot, with counterfactuals defined using the minimum euclidean distance instead.

Figure E.4: Total Population of SABs, SY 2013-14 and euclidean Voronoi Counterfactuals



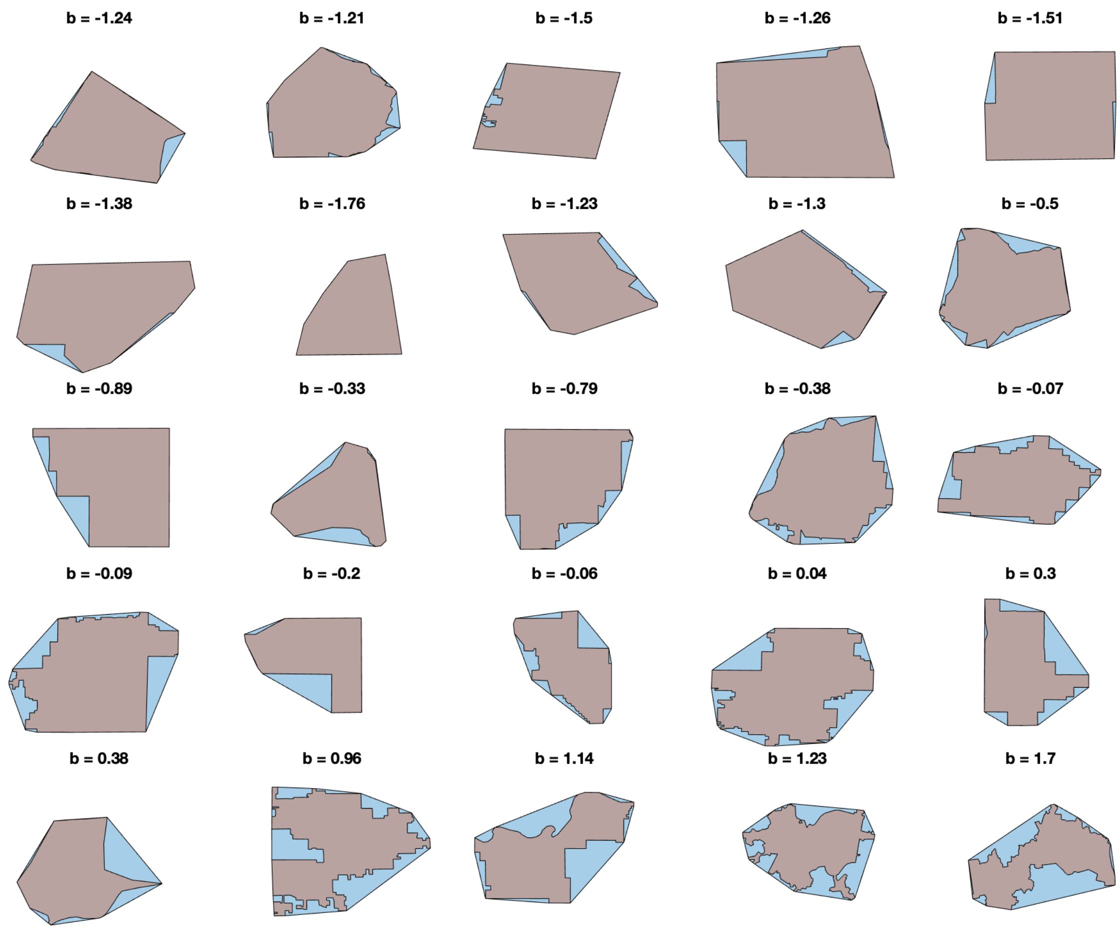
Note: Figure plots histogram of total 2010 census population in actual existing 2013-14 school attendance boundaries (SABs) and in euclidean Voronoi counterfactual SABs.

Figure E.5: Eight School District Zoning Observations



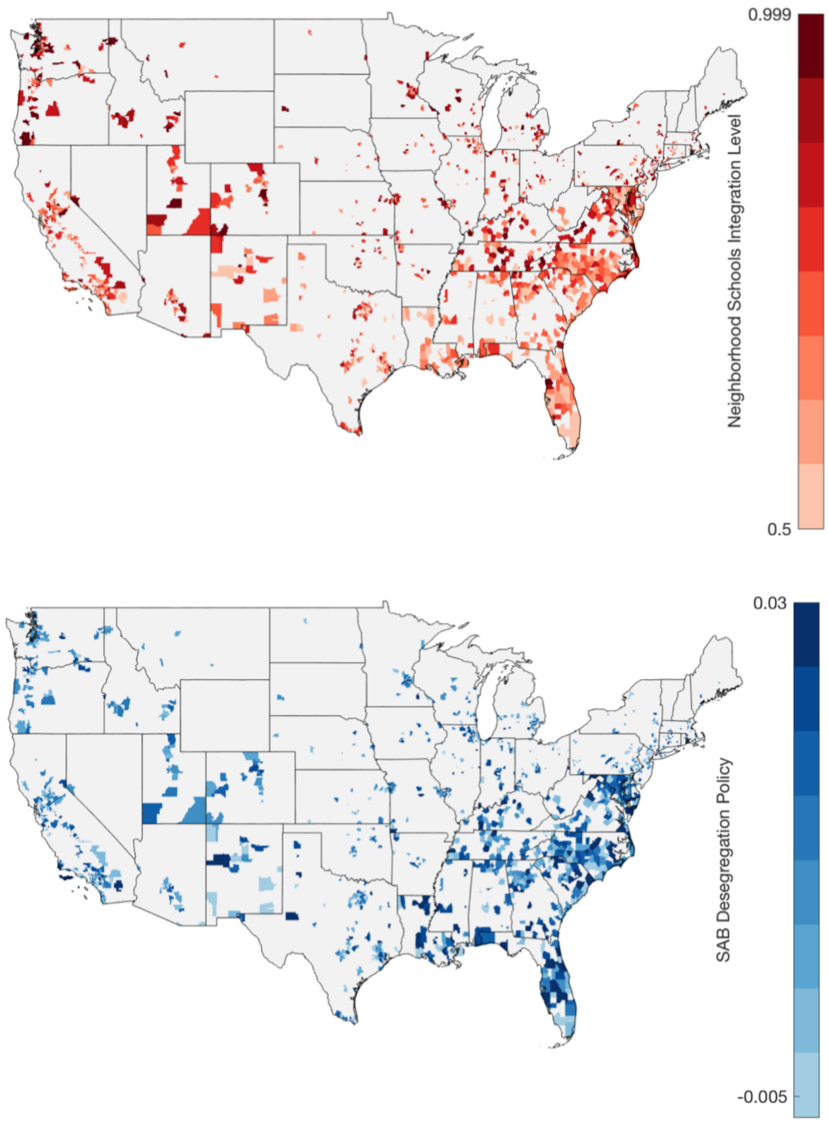
Note: Figure plots the jurisdiction and 2013-14 school attendance boundaries (SABs) of eight school district observations in the analysis dataset (in order from top left across columns) : City of Chicago SD 299, IL ; Riverside USD, CA; Charlotte-Mecklenburg Schools, NC; Oakland USD, CA; Tucson USD,AZ; DC Public Schools, DC; Springfield SD, MA; East Baton Rouge Schools, LA. The analysis dataset contains approximately 1,500 of these maps. The heat coloring denotes the racial composition (fraction black or hispanic) of each SAB – lighter colors denoting low fraction minority.

Figure E.6: School District Jurisdiction Bizarreness



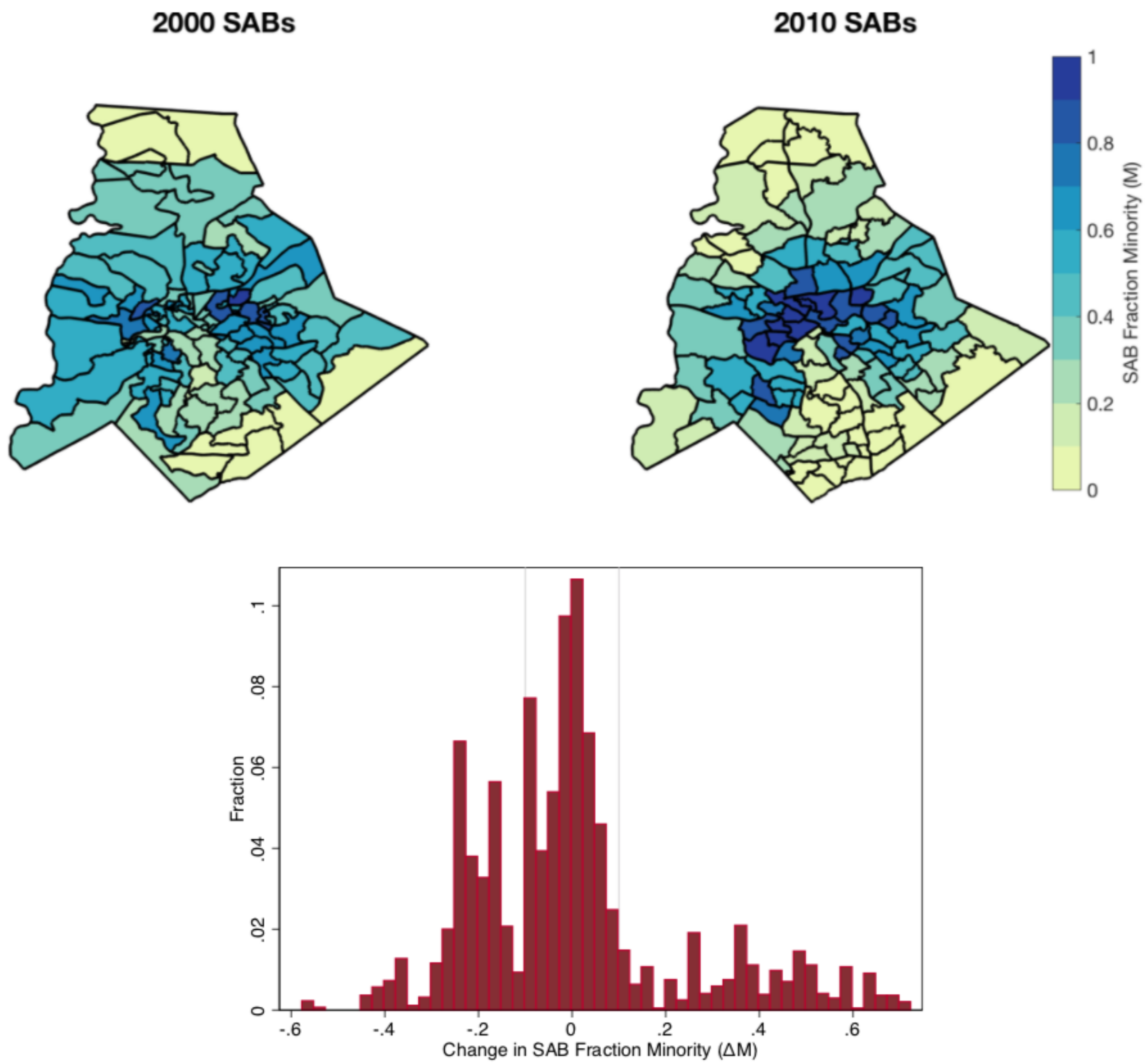
Note: Figure plots the jurisdiction of 25 school districts and the convex hull of the jurisdiction's shape. It reports the bizarreness index b of the jurisdiction, defined as one minus the ratio of the area of the district to the area of its convex hull, and standardized to have mean zero and standard deviation 1. Rows are ordered by five quantiles of the distribution of district bizarreness. Top rows correspond to low bizarreness, and bottom rows to high bizarreness.

Figure E.7: Spatial Distribution of Neighborhood Schools Integration and SAB Desegregation Policy, SY 2013-14 SABs



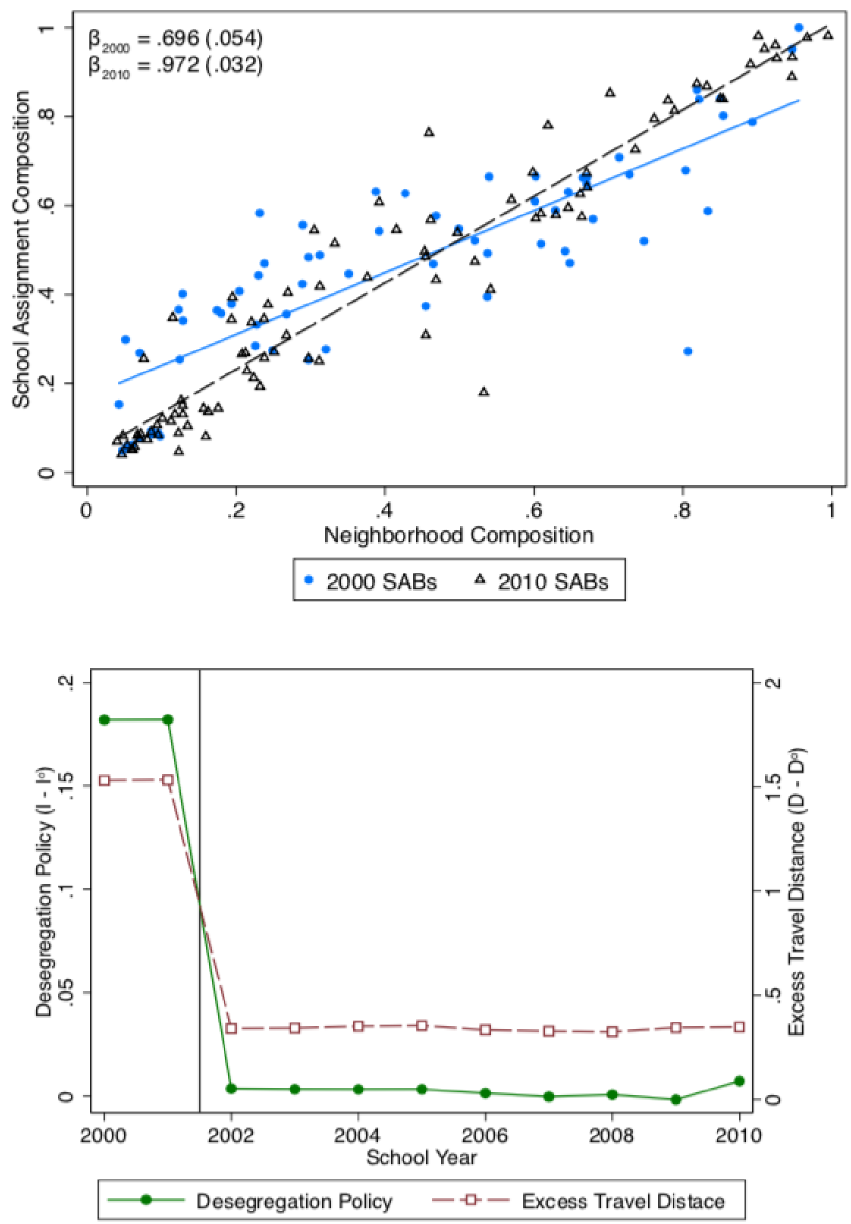
Note: The figure plots heat maps of mainland U.S. at the school district level. The red heat coloring in the top panel denotes eight quantiles neighborhood integration (I^o). I^o is computed at the school district level as SAB integration that would be achieved under a minimum distance counterfactual SABs detailed in Section 3.1. Darker red tones denote higher levels of racial integration. The blue heat coloring in the bottom map corresponds to eight quantiles of SAB desegregation policy ($I - I^o$) – the difference in integration between SY 2013-14 SABs and neighborhood schools counterfactual SABs.

Figure E.8: Distribution of SAB Racial Composition Changes. Charlotte, NC, 2000 and 2010.



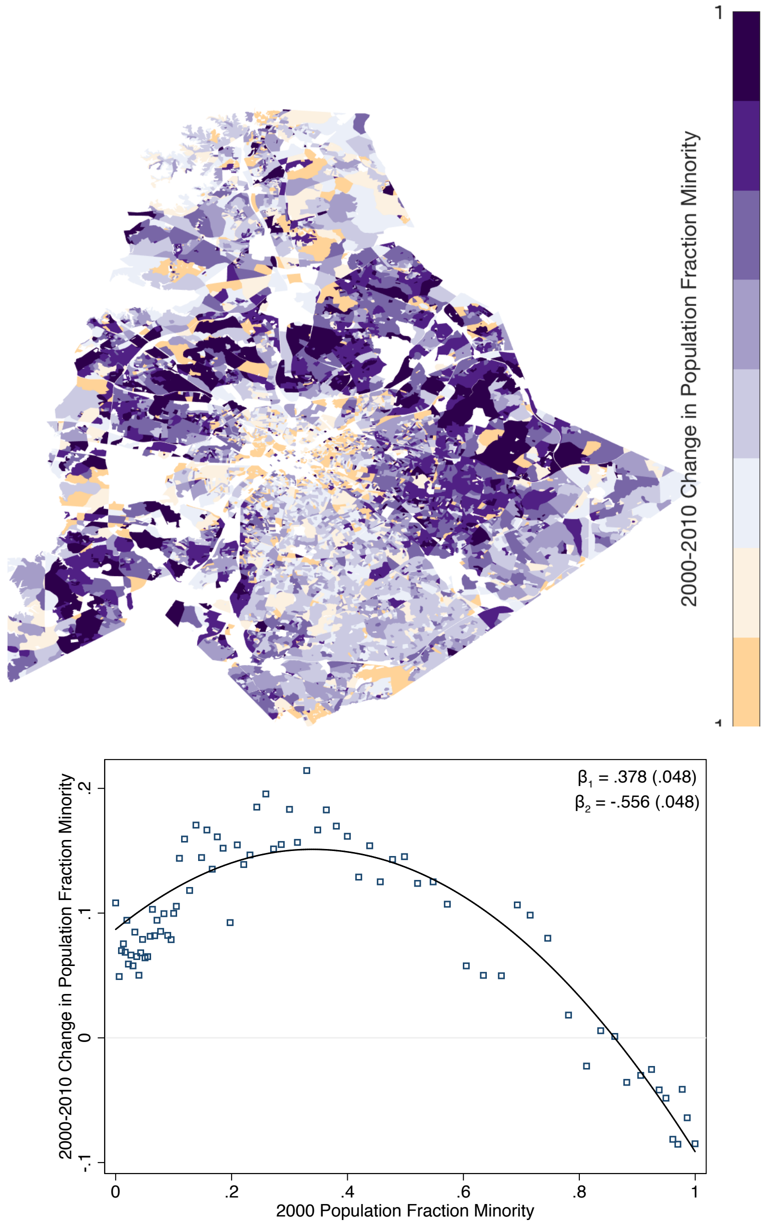
Note: Top left panel shows a heat map of the composition of Charlotte's school attendance boundaries (SABs) in SY 2000-01 under 2000 census block geography. Top right panel shows a similar heat map for SY 2010-11 SABs using 2000 census geography. Light colors denote low fraction minority school assignments, and vice versa. The bottom panel shows a histogram of the distribution of the change in the racial composition of SABs caused by these boundary changes. This is the distribution of treatment 'dosages' across the population in the district.

Figure E.9: Time Trend of SAB Desegregation and Excess Travel Distance in Charlotte, NC.



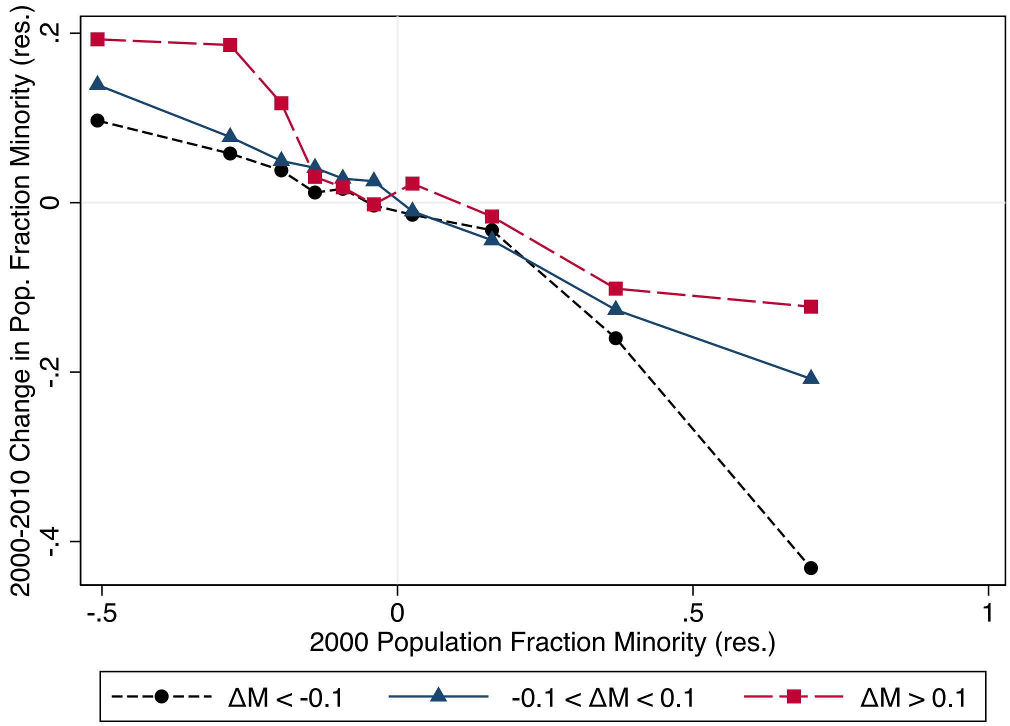
Note: Top panel shows scatters of school assignment composition against neighborhood composition in CMS school district. Blue circles correspond to SY 2000-01 and black triangles for SY 2010-11. In 2001 CMS had a desegregation plan in place. In 2010 CMS implemented a neighborhood schools plan. I report $(1-\hat{\beta})$, where $\hat{\beta}$ is the OLS coefficient of these relationships. Racial composition is computed using 2000 census block data. The bottom panel reports SAB desegregation levels for each school year in 2000-2010. It also plots excess distance travelled to school per student in kilometers. See Section 3 for definitions.

Figure E.10: Distribution of 2000-2010 Change in Racial Composition of Census Blocks, Charlotte, NC



Note: Top panel shows heat map of Charlotte census blocks. Darkening purple color denotes higher values of positive changes in racial composition, i.e. increases in minority population. Orange coloring denotes negative change, or increases white population. Bottom panel shows the bivariate relationship between changes and initial levels, i.e. Δm_b agains m_{2000}. It plots a quadratic OLS fit for this relationship. Coefficients reported in top right.

Figure E.11: Mechanisms of Residential Resorting on the Basis of Race caused by School Composition Shocks



Note: Figure plots the mean 2000-2010 change in racial composition within ten quantiles of baseline (2000) racial composition for three groups in the sample. Both variables have been residualized with respect to baseline SAB-by-census tract fixed effects, so they are to be interpreted as deviations from the mean in the neighborhood, with zero representing no deviation from neighborhood mean. The three groups are defined by the magnitude of the change in school attendance boundary (SAB) composition generated by school reassignments, holding 2000 census geography constant. The three groups are: negative treatment ($\Delta M < -0.1$), neutral treatment ($-0.1 < \Delta M < 0.1$), and positive treatment ($\Delta M > 0.1$).

Table E.1: SABS Summary Statistics – Sample Restriction Cascade.

	(1)	(2)	(3)	(4)
Panel A: Demographics of SAB Assignments				
Total Population	9637.15	8056.22	8332.30	8431.63
Fraction Minority	0.31	0.32	0.35	0.36
Population 5 to 9 years old	618.23	551.04	570.70	578.11
Fraction Minority	0.38	0.39	0.43	0.44
Enrollment K4	392.47	399.72	411.18	415.76
Fraction Minority	0.42	0.43	0.47	0.48
Enrollment/Population Ratio	0.84	0.87	0.87	0.87
Panel B: Characteristics of SABs				
Distance to School per Student (km)	2.75	2.56	2.27	2.20
Open Enrollment School	0.05	0.02	0.02	0.02
Multiple Assignment SAB	0.14	0.14	0.13	0.13
Satellite SAB	0.12	0.12	0.12	0.12
SAB Bizarreness	0.21	0.21	0.22	0.22
Title I Eligible School	0.79	0.77	0.76	0.76
Panel C: Characteristics of School Districts				
Total Population	392874.21	343789.17	400068.53	411689.83
Fraction Minority	0.30	0.31	0.33	0.34
Adult Fraction with College	0.48	0.50	0.50	0.50
Median Household Income	56951.59	58252.85	58247.70	58541.62
Median Property Value	197244.27	201729.07	201474.55	203315.80
Total Revenue per Pupil	12358.65	12152.69	11943.70	11940.70
N schools	33638	28853	24588	23823
N school districts (LEAs)	4731	3138	1715	1607
Defacto School Districts	✓			
Non-Residential Assignment Districts	✓			
Small Districts	✓	✓		
Undiverse Districts	✓	✓	✓	

Note: This table reports mean characteristics of school attendance boundaries (SAB) in school districts included in the SY 2013-2014 School Attendance Boundary Survey (SABS), produced by NCES. Panel A summarizes the 2010 demographics of census blocks assigned to schools via attendance boundaries using GIS software. Fraction minority is the fraction of residents from the minority group (blacks and hispanics). Enrollment counts for are from the Common Core of Data. Panel B reports geographical characteristics of SABs. Distance to school per student is measured as the population-weighted mean euclidean distance between census block centroids and school locations. Open enrollment schools do not use student residence as a factor in student assignments. Multiple Assignment SABs refers to instances in which boundaries overlap, such that residences can be assigned to more than one school. Satellite SABs refers to discontiguous attendance zones, such that separate distant neighborhoods can be assigned to the same school, generating SABS composed of several polygons. SAB bizarreness is computed as the ratio of SAB surface area to that of its convex hull (see Chambers and Miller 2010). Panel C reports characteristics of school districts from 2010 census block group geography, matched with GIS software. Columns show increasingly restrictive samples. Defacto school districts that administer only one school for each school grade, such that SABs are degenerate, taking on the entire school district boundary. Non-residential assignment districts are those that don't use student residences in any school assignments. Small districts are defined as those with less than 5 schools or less than 2000 total population. Undiverse districts are those with less 3% fraction minority, and those with more than 97% fraction minority.

Table E.2: Middle and High School Summary Statistics, by School District

Middle Schools	Mean	SD	P25	P50	P75
School Boundaries and Integration					
Boundary desegregation ($I - I^o$)	0.009	0.030	-0.002	0.001	0.013
School boundary integration (I)	0.957	0.070	0.948	0.987	0.997
School enrollment integration	0.948	0.078	0.934	0.982	0.996
Home-School Commute Distance					
Neighborhoods, km per capita (D^o)	3.638	2.044	2.248	3.017	4.484
Boundaries, km per capita (D)	4.180	2.294	2.577	3.604	5.293
District Characteristics					
Number of elementary schools	4.832	5.551	2	3	5
Total population	113,704	209,650	39,932	63,844	114,178
Fraction black or hispanic	0.275	0.224	0.097	0.205	0.384
Median household income	59,272	23,260	43,749	54,585	71,555
Adult fraction with college	0.500	0.149	0.397	0.487	0.597
Student fraction FRPL	0.502	0.237	0.311	0.510	0.684
Court desegregation order in effect	0.070	0.255	0.000	0.000	0.000
Court desegregation order released	0.121	0.326	0.000	0.000	0.000
White racial intolerance index (GSS)	-0.018	0.475	-0.300	-0.048	0.274
Region, Northeast	0.099	0.299	0.000	0.000	0.000
Region, South	0.402	0.491	0.000	0.000	1.000
Region, Midwest	0.218	0.413	0.000	0.000	0.000
Region, West	0.280	0.449	0.000	0.000	1.000
Observations	1,250				
High Schools	Mean	SD	P25	P50	P75
School Boundaries and Integration					
Boundary desegregation ($I - I^o$)	0.012	0.037	-0.002	0.002	0.015
School boundary integration (I)	0.952	0.071	0.937	0.983	0.996
School enrollment integration	0.942	0.079	0.918	0.974	0.995
Home-School Commute Distance					
Neighborhoods, km per capita (D^o)	4.530	2.292	2.855	3.821	5.604
Boundaries, km per capita (D)	5.083	2.494	3.261	4.385	6.390
District Characteristics					
Number of elementary schools	4.698	6.850	2.000	3.000	5.000
Total population	159,025	277,491	56,337	92,769	163,666
Fraction black or hispanic	0.286	0.214	0.111	0.229	0.408
Median household income	56,375	21,875	42,071	52,435	68,813
Adult fraction with college	0.488	0.146	0.388	0.478	0.584
Student fraction FRPL	0.452	0.215	0.291	0.444	0.595
Court desegregation order in effect	0.095	0.293	0.000	0.000	0.000
Court desegregation order released	0.153	0.360	0.000	0.000	0.000
White racial intolerance index (GSS)	-0.008	0.546	-0.308	-0.057	0.284
Region, Northeast	0.064	0.246	0.000	0.000	0.000
Region, South	0.452	0.498	0.000	0.000	1.000
Region, Midwest	0.191	0.393	0.000	0.000	0.000
Region, West	0.293	0.455	0.000	0.000	1.000
Observations	792				

Note: Sample is restricted to districts serving at least two schools in a given grad level.

Table E.3: Correlates of School District Jurisdiction Bizarreness

	School District Jurisdiction Bizarreness				
	(1)	(2)	(3)	(4)	(5)
Neighborhood integration (I^o)	-0.577	-0.346	-0.414	-0.622	-0.543
	(0.428)	(0.456)	(0.453)	(0.454)	(0.443)
Neighborhood distance (D^o)	-0.111***	-0.133***	-0.127***	-0.164***	-0.116***
	(0.0172)	(0.0206)	(0.0211)	(0.0258)	(0.0286)
ln(Total population)	-0.0995**	-0.0631	-0.0608	-0.132**	-0.0685
	(0.0503)	(0.0512)	(0.0552)	(0.0589)	(0.0631)
Number of schools administered	0.00211	0.00154	0.00139	0.00200	0.00305*
	(0.00180)	(0.00189)	(0.00200)	(0.00206)	(0.00179)
Fraction minority	0.324	0.237	0.222	-0.392	-0.129
	(0.417)	(0.471)	(0.479)	(0.497)	(0.533)
Fraction minority sq.	-0.184	-0.239	-0.239	0.267	-0.0184
	(0.429)	(0.441)	(0.445)	(0.456)	(0.466)
White log median HH income		-0.243	-0.228	-0.226	-0.348*
		(0.175)	(0.178)	(0.174)	(0.180)
Minority log median HH income		-0.134	-0.143	-0.183	-0.142
		(0.122)	(0.124)	(0.123)	(0.125)
Adult fraction with bachelor's		0.327	0.266	0.262	0.264
		(0.366)	(0.394)	(0.390)	(0.396)
Student fraction FRPL		0.115	0.146	0.0678	0.0233
		(0.224)	(0.230)	(0.227)	(0.256)
Court desegregation order in effect			-0.132	-0.118	-0.248**
			(0.131)	(0.129)	(0.122)
Court desegregation order released			0.0153	0.0304	-0.0243
			(0.0971)	(0.0989)	(0.100)
Racial intolerance of whites (GSS)			-0.189	-0.175	-0.136
			(0.141)	(0.146)	(0.138)
Private to public school ratio			0.0152	0.0906	0.0953
			(0.0653)	(0.0690)	(0.0718)
Charter to public school ratio			-0.0461	-0.0726	0.0306
			(0.114)	(0.116)	(0.141)
Northeast				-0.466***	
				(0.0865)	
South				-0.0794	
				(0.0799)	
State FE					✓
N	0.03	0.04	0.04	0.06	0.16
R^2	1,486	1,479	1,479	1,479	1,476

Note: Robust standard errors reported in parenthesis.

Table E.4: Robustness of Main Results to Covariate Specification

	School Boundary Desegregation ($I - I^o$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Desegregation Cost	-0.003**	-0.003**	-0.003*	-0.003*	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Desegregation order in effect	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Desegregation order released	-0.001	-0.001	0.000	0.000	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Racial intolerance of whites (GSS)	-0.008***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Charter to public school ratio	-0.003	-0.002	-0.001	-0.001	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Private to public school ratio	0.002	0.001	0.002	0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Linear specification	✓	✓				
Quartic polynomial			✓	✓		
Discretized (nq = 4)					✓	✓
US Region effects		✓		✓		✓
N	1,517	1,517	1,517	1,517	1,517	1,517
R^2	0.135	0.137	0.175	0.179	0.158	0.163

Note: Robust standard errors reported in parenthesis. Covariates include neighborhood segregation, mean neighborhood commuting distance to schools, the district fraction black or Hispanic, log population, population density, log median household income, and fraction of the adult population with a bachelor's degree.

Table E.5: Robustness of Main Results to Cost Measure Specification

	Baseline Estimate			Alternate Estimate		
	(1)	(2)	(3)	(4)	(5)	(6)
Desegregation Cost	-0.004***	-0.003**		-0.003**	-0.002*	
	(0.001)	(0.001)		(0.001)	(0.001)	
Deseg. Cost quartile 2			-0.004			-0.002
			(0.003)			(0.002)
Deseg. Cost quartile 3			-0.009***			-0.009***
			(0.003)			(0.003)
Deseg. Cost quartile 4			-0.012***			-0.010***
			(0.003)			(0.003)
Base controls (discretized, nq = 4)	✓			✓		
Full controls (discretized)		✓	✓		✓	✓
US Region effects		✓	✓		✓	✓
N	1,517	1,517	1,517	1,506	1,506	1,517
R^2	0.139	0.191	0.192	0.132	0.186	0.193

Note: Robust standard errors reported in parenthesis. The outcome in these models is the boundary desegregation index. Base controls are neighborhood segregation and mean neighborhood commuting distance to schools. Baseline estimates of desegregation cost are defined as in equation (1). Alternate estimates of desegregation cost The full set of controls include the prior as well as the district fraction black or Hispanic, log population, population density, log median household income, and fraction of the adult population with a bachelor's degree.

Table E.6: Robustness of Main Results to Definition of School Boundary Desegregation Index

	Variance Ratio	Dissimilarity			Regression based Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deseg. Cost quartile 2	-0.004*	-0.002	-0.006	-0.006	0.035**	-0.009	-0.006
	(0.003)	(0.004)	(0.005)	(0.005)	(0.014)	(0.015)	(0.015)
Deseg. Cost quartile 3	-0.009***	-0.019***	-0.020***	-0.019***	0.004	-0.063***	-0.059***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.013)	(0.018)	(0.018)
Deseg. Cost quartile 4	-0.013***	-0.026***	-0.030***	-0.029***	-0.002	-0.098***	-0.095***
	(0.003)	(0.004)	(0.006)	(0.006)	(0.014)	(0.024)	(0.024)
Desegregation order in effect	0.014***	0.026***	0.020***	0.022***	0.041**	0.053***	0.049***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.018)	(0.019)	(0.019)
Desegregation order released	-0.001	0.003	-0.002	0.000	0.002	0.004	0.001
	(0.003)	(0.005)	(0.005)	(0.005)	(0.014)	(0.014)	(0.015)
Racial intolerance of whites (GSS)	-0.008***	-0.010	-0.012**	-0.011**	-0.046**	-0.049**	-0.050***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.019)	(0.019)	(0.019)
Charter to public school ratio	-0.003	-0.013***	-0.004	-0.006	-0.060***	-0.044**	-0.034*
	(0.003)	(0.005)	(0.005)	(0.005)	(0.019)	(0.019)	(0.020)
Private to public school ratio	0.000	0.003	0.001	-0.001	0.012	-0.007	-0.015
	(0.002)	(0.004)	(0.004)	(0.004)	(0.012)	(0.012)	(0.013)
Covariates (discretized)	✓		✓	✓		✓	✓
US Region effects	✓			✓			✓
N	1,517	1,517	1,517	1,517	1,517	1,517	1,517
R^2	0.164	0.071	0.157	0.164	0.023	0.083	0.094

Note: Robust standard errors reported in parenthesis. The variance ratio-based desegregation index is the one used in the main results of the paper. The dissimilarity-based desegregation index is defined as in equation (2), but using the dissimilarity index to measure segregation. The regression-based desegregation index is defined as one minus the OLS slope of a regression of boundary on neighborhood racial composition, as in Figure 2. Covariates include neighborhood segregation, mean neighborhood commuting distance to schools, the district fraction black or Hispanic, log population, population density, log median household income, and fraction of the adult population with a bachelor's degree.

Table E.7: Robustness of Instrumental Variable Desegregation Demand Model

	Variance Ratio		Dissimilarity		Regression based Index	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Desegregation Cost	-0.003**	-0.034**	-0.005*	-0.098*	-0.015**	-0.159
	(0.001)	(0.016)	(0.003)	(0.057)	(0.007)	(0.098)
Desegregation order in effect	0.013***	0.014***	0.021***	0.004	0.054***	0.059**
	(0.004)	(0.005)	(0.007)	(0.014)	(0.020)	(0.023)
Desegregation order released	-0.001	-0.001	0.001	-0.021	0.015	0.017
	(0.003)	(0.004)	(0.005)	(0.015)	(0.016)	(0.019)
Racial intolerance of whites (GSS)	-0.009***	-0.009**	-0.012**	-0.017	-0.042**	-0.046*
	(0.003)	(0.005)	(0.006)	(0.015)	(0.019)	(0.025)
Charter to public school ratio	-0.002	0.003	-0.001	0.008	-0.019	0.007
	(0.003)	(0.005)	(0.005)	(0.012)	(0.020)	(0.029)
Private to public school ratio	0.001	-0.002	0.002	-0.012	-0.003	-0.019
	(0.002)	(0.003)	(0.004)	(0.011)	(0.013)	(0.019)
Covariates	✓	✓	✓	✓	✓	✓
US Region effects	✓	✓	✓	✓	✓	✓
N	1,517	1,517	1,517	1,517	1,517	1,517
First Stage F-stat		10.75		4.185		10.75

Note: Robust standard errors reported in parenthesis. The variance ratio-based desegregation index is the one used in the main results of the paper. The dissimilarity-based desegregation index is defined as in equation (2), but using the dissimilarity index to measure segregation. The regression-based desegregation index is defined as one minus the OLS slope of a regression of boundary on neighborhood racial composition, as in Figure 2. IV models are 2SLS estimates using desegregation cost as the endogenous variable and the bizarreness of district's jurisdiction as the excluded instrument. Covariates include neighborhood segregation, mean neighborhood commuting distance to schools, the district fraction black or Hispanic, log population, population density, log median household income, and fraction of the adult population with a bachelor's degree.

Table E.8: Robustness To Recent Change in Number of Schools

Stable Boundary Sample	School Boundary Desegregation ($I - I^o$)					
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV
Desegregation Cost	-0.00832**	-0.00763**	-0.00763**	-0.00850**	-0.0229	-0.0165
	(0.00324)	(0.00319)	(0.00322)	(0.00338)	(0.0174)	(0.0177)
Court desegregation order in effect	0.0148**		0.0141**	0.0112*	0.0160**	0.0114*
	(0.00578)		(0.00576)	(0.00613)	(0.00653)	(0.00598)
Court desegregation order released	0.00542		0.00517	0.00234	0.00599	0.00232
	(0.00483)		(0.00470)	(0.00452)	(0.00470)	(0.00443)
Racial intolerance of whites (GSS)		-0.0115**	-0.0105**	-0.0104*	-0.00855*	-0.00931*
		(0.00504)	(0.00508)	(0.00531)	(0.00509)	(0.00534)
State FE				✓		✓
N	1,051	1,051	1,051	1,051	1,051	1,051
Boundary Change Sample						
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV
Desegregation Cost	-0.00593***	-0.00654***	-0.00581***	-0.00610***	-0.0480**	-0.0254*
	(0.00203)	(0.00202)	(0.00202)	(0.00208)	(0.0230)	(0.0144)
Court desegregation order in effect	0.0124		0.0121	0.0129	0.00828	0.00866
	(0.00853)		(0.00850)	(0.00809)	(0.0107)	(0.00859)
Court desegregation order released	-0.00672		-0.00846	-0.00758	-0.00596	-0.00739
	(0.00536)		(0.00546)	(0.00609)	(0.00850)	(0.00644)
Racial intolerance of whites (GSS)		-0.00971*	-0.0103*	-0.0109*	-0.0192	-0.0166*
		(0.00513)	(0.00527)	(0.00625)	(0.0141)	(0.00871)
State FE				✓		✓
N	435	435	435	435	435	435

Note: Robust standard errors reported in parenthesis. .

Table E.9: Interaction of SAB Racial Composition Shock with New School Construction

	(1)	(2)	(3)	(4)
Δ SAB Composition (2000 Census)	-0.0666	-0.0668	-0.0897	-0.0215
	(0.176)	(0.175)	(0.168)	(0.206)
New School		0.00142	0.000682	-0.0563
		(0.0516)	(0.0517)	(0.0566)
Δ SAB Comp. × New School			0.0510	-0.00787
			(0.177)	(0.216)
Quadratic in Baseline Composition of Block	✓	✓	✓	✓
Baseline Composition of SAB				
Baseline SAB Fixed Effects	✓	✓	✓	
Census Tract Fixed Effects	✓	✓	✓	
Baseline SAB-by-Census Tract Fixed Effects				✓
N	3460	3460	3460	3451
N census tracts	97	97	97	
N SABs (schools)	68	68	68	
N tract-by-SABs				242
R^2	0.161	0.161	0.161	0.194

Note: Standard errors clustered at the census block group level in all models. The level of observation is a census block in Mecklenburg County, NC. In all models the dependent variable is the logged mean property sales price at the census block level. Hedonics (including: number of bathrooms and bedrooms, square footage, presence of AC and heating, number of floors, etc.) were first partialled out from property prices in a first stage regression at the property (parcel) level, see Appendix. Estimated models are different versions of equation (12) in the text, augmented for treatment effect heterogeneity with respect assignment to new schools. The indicator for New School is defined as school attendance boundaries (SABs) with identifiers that were not present in the 2000 CMS SAB map. Column (1) controls for a quadratic function for baseline (2000) block racial composition and the 2000 (baseline) composition of SAB assignments. Column (2) controls more flexibly for baseline SAB effects by including fixed effects for the 2000 school attendance boundary (zone) of a given block. Column (3) adds census tract fixed effects. Column (4) adds baseline (2000) SAB - by - census tract fixed effects.

Table E.10: Summary Statistics - Mecklenburg County 2000 and 2010 Census Block Geography.

	2000		2010		Change	
	mean	sd	mean	sd	mean	sd
Census Block Demographics and Real Estate						
Block Population	141.10	220.95	175.65	331.67	34.55	210.30
Fraction Minority	0.33	0.35	0.41	0.35	0.08	0.18
ln(Mean Property Sales Price)	11.98	0.71	11.89	0.94	-0.08	0.65
ln(Mean Property Appraisal Value)	11.92	0.70	11.84	0.73	-0.07	0.41
SAB Demographics (2000 Census Constant)						
SAB Population	803.52	254.08	621.20	211.71	-182.32	302.30
Fraction Minority	0.43	0.21	0.43	0.31	0.00	0.23
N	4393.00		4393.00		4393.00	
N schools	67		91		91	

Note: The top panel of this table reports the average and standard deviation of 2000 and 2010 census block population and racial composition for Mecklenburg County, North Carolina. I also report log of mean property sales prices and value appraisals from the Mecklenburg County cadastre and tax office, aggregated to census block geography. The bottom panel reports summary demographic characteristics of school assignments (SABs) to census blocks. Importantly, SAB demographics are 2000 census constant. That is, they are measured under 2000 census geography for both SY 2000 and SY 2010 SABs. This ensures that that variation in SAB composition used in the regressions is generated by SAB changes, and not changes in the underlying residential distribution of race. I restrict the sample to census blocks that had non-zero population in both 2000 and 2010. One measurement difficulty in this exercise is that, at the block level, census geography changes with every decennial census. In order to measure the change in block population, I develop an imputation method using GIS software to link 2000 and 2010 census block geography, see Appendix 3.

Table E.11: The Effect of SAB Racial Composition on the Racial Composition of Residences.

Panel A: Residential Block Composition	(1)	(2)	(3)	(4)
School Boundary Composition	0.153***	0.193***	0.151***	0.143**
	(0.0334)	(0.0283)	(0.0474)	(0.0601)
Quadratic in Baseline Composition of Block	✓	✓	✓	✓
Baseline Composition of SAB	✓			
Baseline SAB Fixed Effects		✓	✓	
Census Tract Fixed Effects			✓	
Baseline SAB-by-Census Tract Fixed Effects				✓
N	4393	4393	4393	4393
N census tracts			141	
N SABs (schools)	90	90	90	
N tract-by-SABs				309
R^2	0.237	0.416	0.519	0.543
Panel B: Mean Property Price	(1)	(2)	(3)	(4)
School Boundary Composition	0.0422	-0.0174	-0.0666	-0.0282
	(0.0812)	(0.0966)	(0.176)	(0.215)
Quadratic in Baseline Composition of Block	✓	✓	✓	✓
Baseline Composition of SAB	✓			
Baseline SAB Fixed Effects		✓	✓	
Census Tract Fixed Effects			✓	
Baseline SAB-by-Census Tract Fixed Effects				✓
N	3460	3460	3460	3451
N census tracts			120	
N SABs (schools)	72	72	72	
N tract-by-SABs				240
R^2	0.0407	0.0938	0.161	0.194

Note: Standard errors (shown in parenthesis) are clustered at the census block group level in all models. The level of observation is a census block in Mecklenburg County, NC. In Panel A, the dependent variable is the 2000-2010 change in block racial composition (i.e. the change in the fraction of residents that are black or hispanic). In Panel B, the dependent variable is the logged mean property sales price at the census block level. Hedonics (including: number of bathrooms and bedrooms, square footage, presence of AC and heating, number of floors, etc.) were first partialled out from property prices in a first stage regression at the property (parcel) level, see Appendix. Estimated models are different versions of equation (12) in the text. Column (1) controls for a quadratic function for baseline (2000) block racial composition and the 2000 (baseline) composition of school attendance boundary (SAB) assignments. Column (2) controls more flexibly for baseline SAB effects by including fixed effects for the 2000 school attendance boundary (zone) of a given block. Column (3) adds census tract fixed effects. Column (4) adds baseline (2000) SAB - by - census tract fixed effects.