

OPEN

## School desegregation by redrawing district boundaries

Tyler Simko

Schools in the United States remain heavily segregated by race and income. Previous work demonstrates districts can promote group diversity within their schools with policies like redrawing attendance zones. Yet, the promise of such policies in many areas is limited by the fact that most school segregation occurs between school districts, and not between schools in the same district. I adapt Markov Chain Monte Carlo algorithms from legislative redistricting to redraw school district boundaries that decrease segregation while maintaining desirable criteria like distance to school and using only existing school facilities. Focusing on New Jersey, where the segregation of Black and Hispanic students from White and Asian students is among the worst in the country, I demonstrate that redrawing school districts could reduce more than 40% of existing segregation in the median New Jersey county, compared to less than 5% for redrawing attendance zones alone. Finally, I show how my proposed methodology can be applied to as few as two districts to reduce segregation in proposed consolidations, when small districts are merged into a larger district.

Students in United States schools remain highly segregated by race and income<sup>1</sup>. These patterns of segregation map on to achievement gaps<sup>2</sup> and funding disparities between rich and poor students, which exacerbate inequalities that can have large impacts on later life outcomes<sup>3–6</sup>. A great deal of social science research has demonstrated that integration can reduce these impacts in certain cases, largely by breaking up areas of concentrated poverty<sup>7–9</sup>. Although integrated schools are by no means a cure-all, as biased practices and segregated friendship groups can still occur in diverse environments<sup>10–13</sup>, integrated schools can nonetheless be an important avenue for fostering positive intergroup relationships and creating more equitable learning environments<sup>8,14–16</sup>.

This widespread school segregation is largely driven by patterns of residential segregation, as the vast majority of public school students attend the school they are geographically assigned to by the “attendance zone” set by their local school district<sup>17–20</sup>. A long history of work in operations research and related fields has demonstrated that attendance zones can be redrawn to reduce racial segregation while meeting relevant local constraints like minimizing student travel time to schools<sup>21–28</sup>. However, such “Within-District” methods are limited by the fact that approximately two-thirds of US school segregation occurs between school districts, and not between schools in the same district<sup>29–31</sup>. This means that methods like redrawing attendance zones that do not alter school district lines may be less effective or even impossible (for districts with a single school per age group) in many of the most segregated areas of the United States, such as the Northeast and Great Lakes Midwest, which often feature small districts<sup>32</sup>. For example, New Jersey has approximately half as many public school students as Florida (1.4 million vs. 2.8 million), but nearly ten times as many school districts (702 vs. 76) because states in the Northeast tend to have schools districts at the municipality (rather than county) level (see, National Center for Education Statistics (NCES) Common Core of Data Tables). While others have suggested that redrawing school district boundaries may be a promising policy to combat segregation, methodological evidence that alternative, realistic boundaries could be drawn is limited<sup>27,33–39</sup>.

In this paper, I evaluate the effectiveness of redrawing school district boundaries for racial/ethnic integration. I adapt geographic simulation algorithms from the legislative redistricting and operations research literatures to create alternative school district boundaries. I employ Markov Chain Monte Carlo (MCMC) algorithms<sup>40</sup> to draw realistic plans that incorporate policy constraints like student travel distance to school and using only existing school facilities. Further, I compare this “Between-District” model to a “Within-District” model that attempts to integrate schools without redrawing existing district lines. I focus on New Jersey, where segregation of Black and Hispanic students from White and Asian students is among the worst in the country, and simulate alternative boundaries that cover the entire state, encompassing 1,273 elementary schools across all 21 counties. Throughout this study, I follow previous work by adopting the terms “Black” and “Hispanic” used by the U.S. Census Bureau and NCES, the sources of race and ethnicity data used in this study<sup>4,27</sup>.

I find evidence that redrawing school district lines could reduce more than 40% of school segregation in the median New Jersey county. These large gains include, but are not limited to, the most intensely segregated areas in

Department of Politics, Princeton University, Princeton, NJ 08544, USA. email: tsimko@princeton.edu

New Jersey—named “apartheid schools”<sup>41</sup>—including Essex, Hudson, Union, Camden, and Monmouth counties. Further, the strong algorithmic constraints ensure these improvements require no new school infrastructure, make minimal changes to school enrollment, and keep students assigned to schools close to their homes. Without redrawing district lines, I find that the “Within-District” model can reduce less than 5% of existing segregation in the median county. Put another way, my results demonstrate that existing school district boundaries drawn at the municipality-level are a major barrier to integration: when limited to redrawing attendance zones within existing district lines, I show that state of the art optimization algorithms reduce existing segregation levels by less than 5% in the median county. These results support claims made in *Latino Action Network v. New Jersey*, an ongoing school segregation case, where plaintiffs allege the state’s “municipally-based system of school districts interacts with longstanding State practices that have fostered and enabled residential segregation to institutionalize school segregation” and propose between-district remedies.

New Jersey’s current political and legal contexts make my results locally relevant, but my findings also have broader relevance for policymakers and academics. First, my results suggest that redrawing district lines can be a successful policy for increasing integration in dense areas with large numbers of school districts, like large areas of the United States and particularly in the Northeast. Second, I contribute a methodological framework to a growing body of recent work in algorithmic redistricting for comparing the efficacy of multiple policies in the same geographic area. While reimagining school district lines may be less likely in other settings, my methodological approach can be adapted to compare the integration efficacy of other policies, like “zones of choice”<sup>42</sup>. Among policy options to weaken the connection between address and school district like inter-district choice, redrawing district boundaries can be thought to represent a “conservative” inter-district approach that maintains a strong geographic constraint. However, in practice the promise of school choice policies can be severely limited by factors like existing residential segregation and the homogeneity of convenient school options available to families.<sup>43–46</sup>

Beyond demonstrating the extent of possibilities for integration by redrawing school district boundaries, I also show that my proposed methodology can successfully integrate school districts experiencing “mergers”—consolidating two or more adjacent districts (while not necessarily closing any individual schools)—a frequent and growing policy discussion in New Jersey and beyond. State and local policymakers discuss district consolidation as a policy option for addressing various issues plaguing small districts like high administrative spending, declining enrollments, high local tax rates, and a lack of program offerings<sup>33,38,47,48</sup>. My proposed methodology can successfully integrate mergers both large (such as all districts within a county) and small, and I show that as few as two adjacent school districts could merge to promote school integration. Mergers may be a particularly promising opportunity for meaningful integration: although school rezoning efforts taken by districts often face political pushback due to parental concerns over issues like property values<sup>49,50</sup>, district consolidations are generally done *voluntarily*. Further, these results are timely and have immediate relevance—in 2022, Governor Phil Murphy signed S3488, a bill providing financial incentives for school districts to consolidate with others around them, which several efforts already under discussion.

### Algorithmic simulations for integration policy evaluation

The central question of this paper asks how much school integration is possible when school district lines are redrawn to promote group racial diversity while maintaining or improving compliance with other desirable criteria. To answer this question, I employ algorithmic integration tools that combine student enrollment and geographic data with structural and probabilistic “constraints” to draw realistic alternative school attendance zones. These constraints ensure that only existing school buildings are used, students remain in their current home and attend a school close to their home, drawn districts remain “compact” to maintain reasonable distances to school, and school capacity (i.e. the number of seats in the building) remains roughly fixed. The details of the data preparation, algorithms, constraints, and validation procedures are described at length in Methods.

### Comparing policy scenarios

I run two algorithmic integration scenarios—from here called the “Within-District” and “Between-District” scenarios—to evaluate the potential efficacy of redrawing school district lines. Both scenarios seek to optimize racial integration, while using the same data described and meeting the same constraints described in Methods. The two scenarios differ exclusively on whether the simulations are allowed to cross existing school district lines. The “Within-District” models redraw attendance zones separately in each district, which serves to keep all current district lines fixed. Alternatively, the “Between-District” models use the same data and constraints, but are allowed to cross district lines.

While the Between-District models offer more flexibility by allowing the algorithm more space to move, there is no guarantee that the models will do so given the constraints. For example, New Jersey’s extremely dense population could conflict with the school capacity constraint described in Methods: although more integration could be possible by moving further outwards, schools may quickly become over-enrolled, limiting the potential integration under the Between-District model. Similarly, there may be a trade-off between racial integration and compactness<sup>21</sup> that limits the increased efficacy of the Between-District model.

For the Within-District scenario, I run the algorithm separately for every school district in my sample. Specifically, the algorithm redraws attendance zones for every school building in each district, but must abide by existing school district lines when doing so. As existing attendance zones are entirely nested within districts (and districts are nested within counties), this scenario redraws attendance zones within each existing school district boundary. If the district operates only one school building, the same map is adopted (as it is already optimal according to all constraints discussed below). This scenario is highly policy relevant, as it represents the best-case outcome for reducing segregation given the status quo administrative system.

In the Between-District scenario, I optimize attendance zone boundaries separately for each county in my sample. I run this scenario at the county level because of New Jersey's unusually powerful county Board of Education, which play important roles in support and oversight for schools in a given county.

This additional administrative layer may exist in part to mitigate some of the inefficiencies involved in running such a larger number of individual small school districts. For this reason, mergers and consolidations are frequently proposed between some or all districts within a county, but are rarely proposed to cross county lines.<sup>47,51</sup>

My Between-District scenario is consistent with several possible alternative administrative designs. For example, integrating across existing district lines within a county corresponds exactly to drawing county-wide or regional school districts, as discussed in Supplementary Information Sects. A.3 and A.4. In this interpretation, policymakers could redraw attendance zones such that students attend integrated schools, but districts would effectively be consolidated at the county level. Alternatively (though perhaps less politically likely), the current number of school districts could be kept the same, and district lines within counties could be re-drawn to mitigate the high levels of residential segregation.

Though both scenarios are relevant, their comparison demonstrates the extent to which existing district lines are a barrier to integration. If both models perform similarly, then redrawing existing school district lines may neither be a necessary step towards achieving large integration gains nor worth the political capital necessary to do so. Alternatively, if the Between-District models are much more effective than the Within-District models, this suggests that redrawing district lines or other less geographically conservative inter-district policies may be worth the effort. Further, knowing the magnitude of differences between policy options would allow policymakers to make more informed decisions about trade-offs.

I note that there are many policy options that could change school district lines beyond redrawing them. For example, policymakers regularly consider options like regional districts or district mergers, as discussed further in Sects. A.4 and A.10. Further, I demonstrate that my proposed methodology can also be used to evaluate other policies to change district lines. For example, I use my same methodology to evaluate the promise of district consolidations. Such "mergers" are often considered in states like New Jersey, in which all school buildings remain the same but the higher-level administrative districts are merged to create a single, larger district.

## Results

Overall, I find consistent evidence that the Between-District consistently outperforms the Within-District model, being about five times *more* effective in the median New Jersey county. This represents a median of 19 vs. 2 percentage point reductions in the dissimilarity index, which translates to approximately 45% vs. 4% reductions in segregation levels. I employ the "Dissimilarity Index" throughout<sup>52</sup> as a measure of segregation, though the proposed methodology can be used alongside any measure of group diversity. I further describe dissimilarity and show robustness to using the entropy index<sup>53</sup> in the Supplementary Information. Further, the constraints ensure that these gains are met while making all maps logically feasible by avoiding large increases in student distance to school, maintaining school capacity, requiring no new infrastructure, and keeping a single school in each attendance zone.

First, I discuss these results within a single county to offer context on how improvements are made given the necessary constraints. Then, I discuss results across all counties, paying particular attention to the heterogeneity in comparative performance between the Within and Between-District models across counties. Finally, I show that redrawing districts does not require state-wide changes to be effective by applying my methodology to district consolidations.

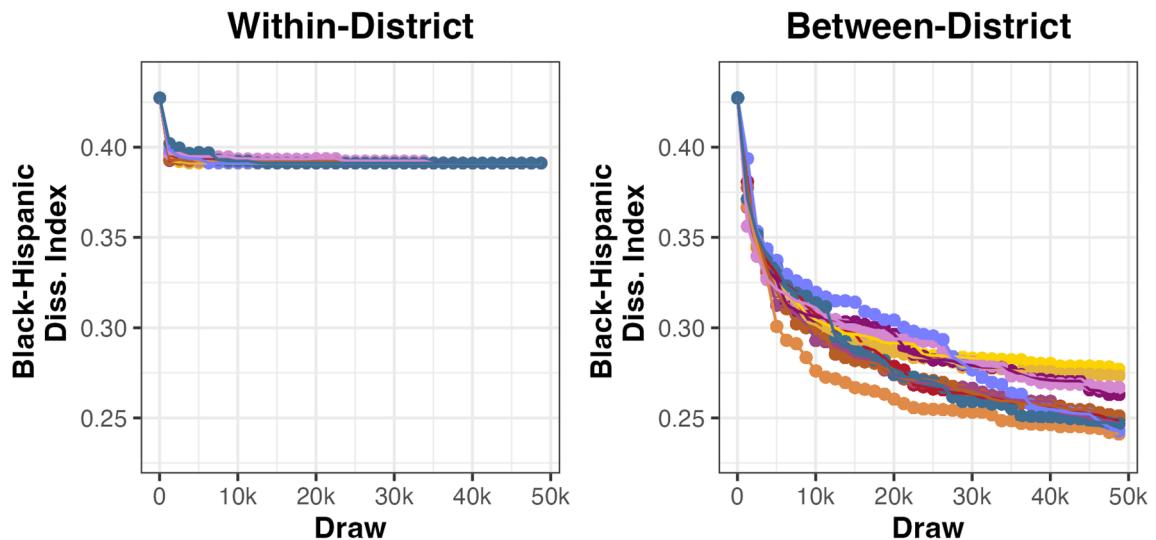
### Illustration: county-specific results

In Morris County, my sample identifies 78 elementary schools across 35 unique districts. Morris serves as a useful initial county to discuss because its school districts are typical of New Jersey overall. First, existing segregation of Black and Hispanic students is high, with a dissimilarity index of 43% that is approximately the median for the state. Second, the schools across Morris are not evenly split between districts, and instead features many small districts with a few large districts. For example, 20 Morris districts (57%) operate only a single elementary school. This institutional fragmentation is likely to lead to segregation across district lines. It certainly does in Morris County, where districts like Dover serve a majority Hispanic population, yet are surrounded by many more suburban districts with low proportions of Black and Hispanic students.

The Morris situation mirrors many across the state, where we might expect the Within-District model to struggle to successfully integrate. By having many single school districts, attendance zone integration within district will be impossible for a majority of districts in the county, and any feasible gains will come from the remainder of districts in the county. Alternatively, the Between-District model may be able to integrate Morris schools by redrawing existing district lines and re-assigning students in neighboring, racially segregated, districts.

Figure 1 confirms this intuition by showing that the Between-District model finds significantly more integration while the Within-District model fails to find substantial opportunity for gains in group diversity. The left panel demonstrates that the Within-District model finds initial progress (displayed via a lower value on the y-axis, as measured by dissimilarity) in approximately the first 1,000 steps of the algorithm (displayed on the x-axis). This occurs by redrawing attendance zones in the 15 Morris districts with more than one school. These initial gains reduce segregation in Morris County by approximately .03 on the dissimilarity index, but the model quickly stalls and makes little further progress for the rest of the draws. This pattern is consistent across all ten independent chains of the algorithm (as indicated by the line colors), demonstrating that the model fails to find progress and is not stuck in a local mode.

Alternatively, the Between-District leverages the additional flexibility of crossing school district boundaries to make much more progress. The right panel of Fig. 1 shows continued progress throughout steps of the



**Fig. 1.** Displays racial integration progress in Morris County for both the Within (redrawing attendance zones alone) and Between-District (redrawing attendance zones and school district boundaries) models. The x-axis represents draws (steps) of the MCMC algorithm described in Methods, the y-axis displays the dissimilarity index for Black and Hispanic students at each step, and the different colored circles and lines represent independent algorithmic chains. The results show that the Between-District model consistently outperforms the Within-District model across all ten independent chains, indicating that redrawing school district lines would be a promising policy for reducing school segregation.

algorithm. Encouragingly, this pattern replicates across all ten independent chains of the algorithm. Further, Supplementary Information Figure 7 shows that these integration gains are possible while meeting the school capacity and compactness constraints.

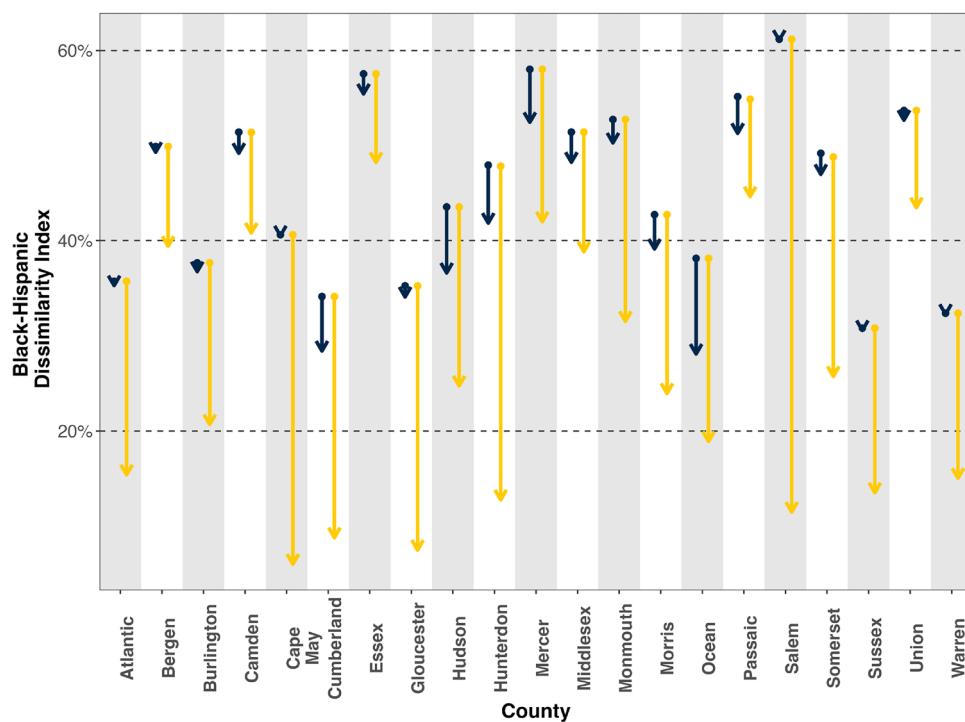
#### Integration is possible across all New Jersey counties

Figure 2 demonstrates that the Between-District scenario (maize) clearly outperforms the Within-District (blue) model in all 21 counties in New Jersey. Within each county, both arrows start (indicated with a point) at the existing Black-Hispanic dissimilarity index in a given county, and end (indicated with arrow head) at the final (50,000th) draw of the model. The consistency of these results across counties is encouraging given the geographic and institutional diversity of the state. My results suggest that redrawing school district boundaries would be an effective way to reduce segregation in counties as distinct as Hudson—an extremely dense, urban area with transit connections to downtown New York City—and Sussex—featuring low-density mixes of farms and forests with light-density suburban homes.

While strong Between-District performance is intuitive given that it offers additional flexibility by crossing existing school district lines, the model still operates under the strong constraints discussed in Methods. These constraints will restrict the model from pursuing further possible integration if it moves too far from the specified criteria described above. For example, New Jersey's high density means that incorporating new students might over-enroll the school, even if doing so would further increase diversity.

These results also allow us to compare the *magnitude* of the difference between the Within and Between-District models. This can be useful both in identifying areas where the Between-District model strongly outperforms (to know when to target the redrawing of district lines) and areas where both models perform similarly (to know where efforts to target redrawing district lines may not be as effective). For example, in Monmouth County I find the Between-District model is approximately eight times more effective than the Within-District model in the median county, reducing segregation by 40% (vs. 4.6%). In Ocean County, the Between-District model outperforms by a smaller factor of approximately 1.91 (50% vs. 26% segregation reduction). These heterogeneities are important because redrawing existing district lines takes more political coordination than Within-District redrawing (which can be done by individual school boards), and understanding when and where redrawing district lines is more effective can help districts to make locally informed decisions. Heterogeneity analyses in Supplementary Information Sect. A.6 find that redrawing attendance zones is most effective in districts with high enrollments. Sect. A.7 also finds that redrawing district boundaries is likely to be most effective in areas with small-to-mid populations and population densities like suburbs, in line with past work.<sup>54</sup>

In three counties—Cape May, Salem, and Warren—all districts in my sample only operate a single elementary school each. This means that Within-District models can make no possible progress at all. Nonetheless, the Between-District model in each of these counties is extremely effective. In Salem County, the Between-District model eliminates over 80% of segregation between schools, and in Cape May County the final dissimilarity index is brought to nearly 0. These large proportional gains are possible in part because these counties have relatively small numbers of Black and Hispanic students. However, these small counties with large numbers of single-school districts are also the most likely to consider inter-district changes like consolidation. My results in

**Between-District** **Within-District**


**Fig. 2.** Displays integration progress for the Within (blue) and Between District (maize) models for all 21 counties in New Jersey. Arrows start (shown with point) at the existing Black-Hispanic dissimilarity index in a given county, and end (shown with arrow head) at the final (50,000th) draw of the model. The results show that the Between-District model consistently outperforms the Within-District model. The magnitude of this overperformance varies dramatically between counties, with heterogeneity discussed in Supplementary Information Sects. A.6 and A.7.

the next section suggest that redrawing district boundaries during consolidations would be extremely effective for reducing segregation.

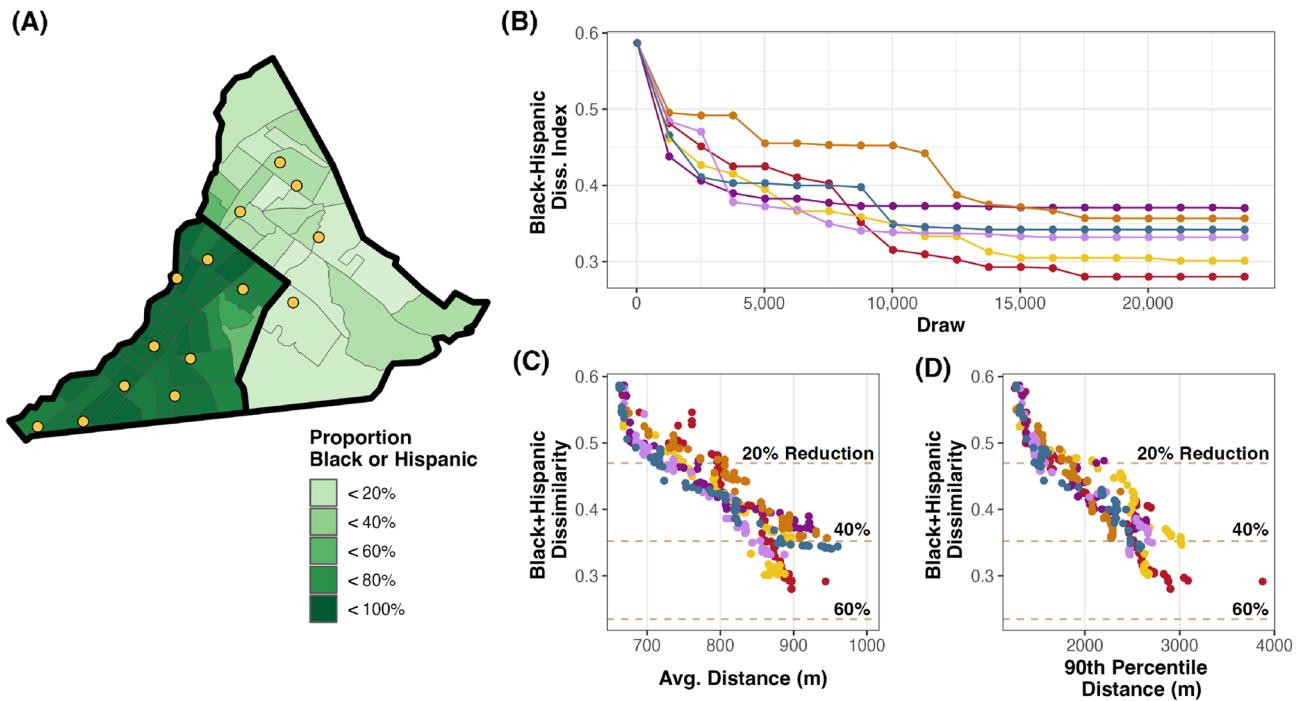
Combined, these results indicate that redrawing district boundaries can be an effective integration strategy across all counties in a diverse state. However, these results do not suggest that Within-District integration can never be a promising strategy. Consistent with previous work<sup>17,27,59</sup>, my results demonstrate that redrawing attendance zones within existing school district boundaries can be an effective policy for reducing segregation in large, racially diverse districts with large numbers of students (heterogeneity is discussed further in Supplementary Information Sect. A.7). Maintaining district lines will still limit possible integration for large areas of New Jersey because of its large number of separate, small districts. While redrawing district lines would allow for further integration, working within a single district may be politically or logically simpler in some cases.

### District consolidations

Changing school district lines could be accomplished through several policy options beyond redrawing district boundaries. In this section, I demonstrate how my proposed methodology can be used to integrate schools during district consolidations. Often called “mergers,” consolidations administratively combine several adjacent school districts (though, without necessarily opening or closing any actual schools). Although policymakers generally offer financial and logistical reasons for district consolidation, here I show that district consolidation can also be an opportunity for integration.

I illustrate the potential of district consolidations for integration with an example merger between Plainfield and Scotch Plains-Fanwood, two districts in Union County. In Supplementary Information Sect. A.10, I describe why similar sizes, budgetary considerations, and high residential segregation make these districts a reasonable choice for demonstrating the potential benefits of consolidation. Here, I use my integration model to simulate redrawing attendance zones within a newly consolidated school district. I run the model using all of the same parameters, constraints, and procedures as those used for my main results.

The results in Fig. 3 indicate that redrawing attendance zones within a newly merged district could eliminate nearly 50% of existing segregation. Panel (B) shows that dissimilarity between the 14 elementary schools in this area falls from .59 to .28 in the best performing chain’s final plan. Panels (C) and (D) show the well-known trade-off between diversity and travel time, as integration generally requires longer travel times when groups are highly residentially segregated and school locations are fixed<sup>41</sup>. These results demonstrate that student distance to school would likely increase under this model, shown for both the average student and at the 90th percentile.



**Fig. 3.** Panel A shows existing racial demographics in Scotch Plains and Plainfield, two school districts in Union County. Black lines designate school districts, shapes are Census block groups, and yellow dots are existing elementary schools. Census data is prepared using<sup>56</sup>. Panel B shows segregation reductions using the same format as Fig. 1, where lines represent the dissimilarity index at each draw and colors indicate independent chains. Panels C and D here show average and 90th percentile student distance (in meters) from school across each draw, where colors also designate chains. Horizontal dashed lines indicate proportional reductions in segregation.

However, these large proportional differences represent relatively modest substantive changes: the maximally integrated districts according to this district increase average distance to school by less than a mile on average, though the 90th percentile distance can increase by one or two miles in the most integrated scenario.

My approach also allows policymakers to evaluate the range of options when pursuing integration and decide which combination best suits their community preferences and goals. For example, local policymakers might wish to opt for a policy near the middle of demonstrated integration possibilities. For example, policymakers could aim to reduce 20 or 30% of the existing segregation between the two communities (rather than the maximum possible of nearly 50%), to achieve meaningful integration across old district lines while making even smaller impacts on distance to school. This is indicated by the horizontal dashed lines, showing what distance increases corresponding to 20, 40, and 60% proportional decreases in segregation levels.

These results suggest that even if a merger were completed for financial or administrative reasons, stakeholders could use the consolidation as an opportunity to update attendance zone boundaries and reduce a large fraction of segregation. This kind of measurable integration criteria could be appended on top of existing consolidation laws (such as New Jersey's S3488), or used in federal desegregation programs such as the Fostering Diverse Schools Demonstration Grants Program (FDS) launched in May 2023.

## Discussion

Millions of students in the United States still attend highly segregated schools. My results show that redrawing school district boundaries can be a highly effective way to reduce segregation in several settings. In New Jersey, a state where the segregation of Black and Hispanic students from White and Asian students is among the worst in the country, I show my proposed methodology can reduce more than 40% of existing segregation in the median county. Strong algorithmic “constraints” ensure that these improvements do not sacrifice goals commonly desired by parents and policymakers like maintaining school enrollment and keeping students close to home. My results speak most directly to New Jersey, but commonalities like large numbers of small school districts can be found in states like California, Illinois, Texas, Missouri, Montana, and Wisconsin<sup>38</sup>.

I further show that my proposed methodology can produce large gains in integration during consolidations between as few as two districts. State and local governments routinely consider consolidation for educational, logistical, and financial reasons. Many such discussions are ongoing in New Jersey, and are likely to continue given recent legislation that incentivizes consolidations. State policymakers could add diversity to the list of considerations by, for example, providing financial incentives to districts who consolidate while redrawing new boundaries to foster integration.

My results also demonstrate the limitations of integration policies that keep school district lines fixed. My results indicate “Within-District” solutions like redrawing attendance zones are unlikely to effectively reduce segregation in fractionalized areas with small districts, even if adopted at scale<sup>57</sup>. In New Jersey, my results suggest that solutions to school segregation must cross district lines to be effective. One primary benefit of this approach is that redrawing district lines can maintain contiguous “neighborhood” schools that are close to home, unlike choice systems or inter-district busing patterns. However, policymakers could also consider other inter-district policies with less emphasis on geography or invest in new facilities, such as regional “controlled choice” plans or inter-district enrollment in themed magnet schools, all of which have been widely adopted in other areas of the country<sup>58-61</sup>.

There is significant room for future work. For example, my models do not directly account for school choice. This is a reasonable decision for New Jersey, which has extremely low levels of school choice. However, school choice both within and between districts is more common in other areas of the country. Future work could directly incorporate school choice into integration models that cross district lines, similar to how existing work has begun to incorporate policies like “zones of choice”<sup>55</sup>. Further, my flexible MCMC approach can be useful when working with state and local partners in real-world settings, as additional custom constraints could be used to match local needs (e.g. avoiding attendance zones that cross some local geographic barrier).

Further, my results integrate school district boundaries at one particular snapshot in time, and do not account for how families could respond and dynamically select schools after integration efforts. For example, progress integrating schools could be partially undone by “white flight” patterns where families move after being rezoned<sup>62,63</sup>. This limitation is primarily driven by a lack of data on how families could respond to changes, and seems to be a particularly promising area for future work. Such work could build on discrete choice models developed primarily for static contexts<sup>64</sup>. Of course, individual policies like redrawing boundaries, opening magnet schools, and inter-district choice need not also be mutually exclusive as they are in my model. Future work should provide further evidence to policymakers by evaluating how such policies can best synergize to improve educational opportunity.

Finally, I have argued this methodological approach can be a valuable way to explore the promise of integration policy. However, I stress that the purpose of the results presented here is *not* to create a single, “optimal” assignment plan that I argue should be adopted in reality. Instead, I have demonstrated a methodology that I argue can be applied to particular local decisions to illuminate policy trade-offs. I argue my approach offers a useful way to compare the potential efficacy of policies that also incorporates realistic constraints. However, the design, goals, and constraints of any particular implementation of algorithmic approaches like mine should be based on community decisions with stakeholders like families, students, staff, and policymakers.

## Methods

My algorithmic models require two primary sources of data: student enrollment and geographic boundaries. First, student data comes from the National Center for Education Statistics (NCES) Common Core of Data for 2021–2022. The NCES centralizes data on student enrollment, district spending, and school characteristics to create a national database of all public elementary and secondary schools. I start by selecting all regular school districts in New Jersey from NCES that are public (non-charter), active school districts as of 2020-2021. A regular school district is not part of administrative arrangements like supervisory unions or operates schools with specialized programs like vocational programs or correctional facilities. From these 512 resulting school districts, I identify 1,273 regular, public (non-charter) schools that were open as of the 2020-21 school year. I download 2021–2022 school-level enrollment data by racial / ethnicity group for each of these schools. I focus on elementary schools primarily because (1) their boundaries are often combined to form the boundaries of the middle and high schools their students attend and (2) younger children may accrue additional benefits from being in diverse educational environments for longer periods of time<sup>8,9,17,27</sup>.

Second, I combine this school-level enrollment data with geographic data and demographics available from the US Census. I start by downloading current school district geographic boundaries<sup>65</sup>. Once district locations are known, I spatially match every school building described in the previous step to a corresponding Census block using<sup>66</sup>. Beyond the enrollment-by-grade-race-ethnicity data I download in the previous step from NCES, there are no publicly available sources linking these enrollment counts to residential locations. Researchers studying geographic school enrollment often use Census data to estimate the number of students of each race/ethnicity group that live in a particular Census block<sup>17,27</sup>. This procedure is especially reasonable in New Jersey given the extremely low levels of school choice, meaning that most students attend the school where they are geographically assigned. For example, an amicus brief submitted to *Latino Action Network* by the Interdistrict Public School Choice Program, a statewide choice program allowing students to apply to attend schools in other municipalities, indicates the program has approximately 5,000 students enrolled—less than half of one percent of the state’s public school enrollment. While some studies use total Census block population counts to calculate demographics for particular age groups<sup>17</sup>, this assumption may be less tenable in New Jersey due to rapid and ongoing diversification<sup>67</sup>, such that younger age groups are increasingly becoming more diverse over time.

Instead, I adopt a data-driven approach to estimate student residences by combining (exactly known) student enrollment counts with (aggregated) geographic demographic patterns from the American Community Survey. Formally, my goal is to estimate the number of students who belong to a given racial/ethnic group  $g$ , live in a given Census block  $b$ , and attend a particular school  $s$ . Thankfully, the NCES provides exact enrollment counts by school and racial / ethnic group, so the only remaining unknown is where these students live. I distribute these known numbers of students among blocks using racial demographics from the Census for children aged 5-9 at the tract level. I start with demographic patterns at the tract level, rather than a smaller level like block group, because my specific population of interest (elementary school age children by racial group) is often very small.

These small group estimates often have high associated sampling error, and so they are very often “suppressed” (not reported) by the ACS. I still opt to use demographics of minors, rather than the total population (which is less likely to be suppressed), due to the increasing diversity of younger US generations over time<sup>68</sup>. Similar decisions about suppression and small group estimates will continue to be relevant as the Census Bureau evolves their use of new privacy techniques<sup>69–72</sup>.

Finally, I multiply the share of third-grade students belonging to a particular racial / ethnic group in that school by the fraction of children belonging to that group who lives in a particular Census block. Intuitively, this procedure formalizes the idea that: “if 100 Black third grade students attend a particular school in this school district and 10% of the Black population aged 5–9 in the school district live in this Census block, then 10 Black third grade students live in this Census block. Formally, this quantity equals:

$$n_{bgs} = \frac{n_{gb}}{\sum_{b \in B_S} n_{gb}} * s_g$$

While these counts are no doubt imperfect, this procedure is reasonable for several reasons. First, I start with known enrollment data for each school, and am only estimating where students live within small geographic areas. This is an unexpected benefit of New Jersey’s small school districts, as I only need to make this assumption over relatively small geographic areas. The median school district used in my analysis covers only three Census tracts. Second, my primary focus is not in precisely measuring racial demographics in every Census block, but rather how two different policies compare at reducing segregation across many blocks. All algorithmic scenarios I run rely on this same reasonable, if imperfect, baseline. See<sup>73</sup> for a longer discussion about the role of “ground truth” data in policy evaluation. The authors argue, in part, that exact ground truth data is not always necessary when the policy question of interest compares between a status quo and new policy, using the same data.

### MCMC algorithm

To redraw feasible school boundaries, I use a Markov Chain Monte Carlo algorithm presented in<sup>74</sup> (from here, called “merge-split”), which builds on the Recom algorithm presented in<sup>75</sup>. I use the specific implementation from the R package *redist*<sup>76</sup> which combines a sampling merge-split algorithm with an optimization procedure called “shortburst”. This algorithm has primarily been used in redistricting applications<sup>77,78</sup>, and has also been used in litigation. For example, see Kosuke Imai’s expert witness report in *Merill v. Milligan* (2022), a US Supreme Court case where shortburst was used to evaluate majority-minority congressional districts in Alabama. I describe the algorithm and this optimization procedure below.

The algorithm<sup>74</sup> samples graph partitions through “a global merge and split algorithm to propose moves to the standard Metropolis-Hastings algorithm” (pg. 7). The merge-split algorithm works by taking two adjacent units (in this case, school attendance zones), spatially combining them to create a single larger unit, and then finding a new boundary “split” between the two that seeks to satisfy provided constraints. Constraints are built into a score function (see<sup>74</sup>, Section 3) that can accommodate both “hard” (enforced) and “soft” (probabilistic) constraints, as described above.

However, merge-split on its own is a sampling algorithm that seeks to respect constraints, and will not automatically seek to maximize an objective score between draws. The merge-split implementation I use from<sup>76</sup> combines merge-split with the “shortburst” procedure introduced in<sup>40</sup>. The shortburst procedure instructs an MCMC algorithm to take a series of short, unbiased random walks (called “bursts”) that, in this case, iteratively re-assign certain parts of the map to new districts. After each walk, the algorithm selects the best plan according to the provided score and restarts a new series of bursts. Over time, this ensures the score function either stays the same or increases.

My goal is to use this MCMC implementation to compare the promise of a set of policy options. My goal is not to (1) build a representative set of all possible plans that meet these constraints, or (2) to prove optimality (e.g. find the single plan that minimizes some segregation measure under these constraints). First, existing residential segregation and the location of existing school buildings mean that the vast majority of possible plans are likely to be highly segregated as well. My interest is in evaluating how different policy options could improve integration under a set of constraints, and not to build a representative set of results as is common in many MCMC and redistricting applications. Second, I seek to compare performance between policies like redrawing attendance zones, district lines, and district consolidations. While shortburst does not have optimization guarantees as a procedure, it is a useful tool for exploring performance between policy options.

For each scenario described above, I run 50,000 bursts of 15 draws each. I run ten independent chains with these parameters, as it is possible for MCMC algorithms to get stuck in local “maxima,” where the algorithm fails to find better scores far away from its current plan<sup>40</sup>. Instead, if all independent chains “converge” to report approximately the same result, we can be more confident that the algorithm has thoroughly explored the possible space of alternative plans. To initialize the algorithm, I follow existing work on attendance rezoning by using Voronoi boundaries<sup>17,18,79</sup> with additional block reassignment to ensure attendance zones are contiguous (see more justification for this decision in Supplementary Information A.11). In this case, this initializes the algorithm by assigning each Census block to the nearest school. All alternative plans in both scenarios then seek to improve upon this baseline according to the score and constraints described below. All plans are forced to be created from contiguous sets of Census blocks.

#### Algorithmic score function and constraints

As discussed in the previous section, simply drawing alternative plans is not enough for a feasible policy—my realistic school boundaries also incorporate a number of constraints determined by constituent preferences and local context. This algorithm combines a goal “score function” that it seeks to optimize with two kinds of

constraints: “hard constraints” which must be met at a particular numeric value and a set of “soft constraints” that assign probabilistic weights to nudge the algorithm to draw compliant plans. Both types of constraints can then be evaluated in diagnostics like those shown in Figs. 7, 8, 9 and 10 in the Supplementary Information. I describe each of these pieces below:

The score function combines two substantive goals of the algorithm: (1) racial integration and (2) a “hard constraint” that uses only existing school facilities. I use the dissimilarity index<sup>52</sup>, a widely used measure of segregation in education policy and beyond<sup>27,67,80</sup>. Academics and policymakers have several options to measure segregation, and here I use on the dissimilarity index because of its ongoing relevance for discussing segregation in New Jersey. For example, the ongoing segregation case *Latino Action Network v. New Jersey*, brought jointly by the LAN and NAACP, has featured a great deal of discussion around dissimilarity as a measure of how Black and Hispanic students are concentrated in particular school districts and separated from White and Asian students. For example, Ryan W. Coughlan, an expert for the plaintiffs in Latino Action Network, testified that New Jersey schools are segregated across a variety of measures: “I can certainly point to what a dissimilarity score says about New Jersey or what an isolation score says about New Jersey. They all say that the schools are segregated.” Similarly, I exclude students of two or more races due in part to the emphasis on Black and Hispanic students in litigation and policy discussions. Further, only 3% of students report identifying as two or more races in New Jersey. The dissimilarity index captures this idea of “evenness”—that is, how evenly do students of different racial groups attend schools in a particular area.

Here, I employ the dissimilarity index as a measure of segregation across schools in a given district. Formally, let  $n_s$  ( $n_d$ ) be the number of Black and Hispanic students in school  $s$  (district  $d$ ), and let  $t_s$  be the total number of students. Then, the dissimilarity index  $S$  for district  $d$  is given by the following:

$$S_d = \frac{1}{2} \sum_{s \in d} \left| \frac{n_s}{n_d} - \frac{t_s - n_s}{T_d - n_d} \right|$$

This index ranges from 0 (indicating the proportion of Black and Hispanic students in each school matches their proportion overall in the county) to 1 (indicating that every Black and Hispanic student would have to move to achieve an equal proportion across schools). One advantage of using the dissimilarity index in this context is that it does not depend on the relative sizes of the two groups (by taking the proportion), unlike other measures like the isolation index. This means that results are more directly comparable across counties even though demographics will differ, and changes can be interpreted as percentage point reductions in segregation.

I combine this measure of segregation with an indicator function that ensures each attendance zone has only a single school building. This ensures that only existing school facilities are used to produce integration, and maintains a neighborhood school principle. I create a vector  $v$  with binary values (1 or 0) that identifies whether each individual Census block  $b$  has a school building ( $v_b = 1$ ) or not ( $v_b = 0$ ).

I formalize this constraint by creating an indicator function to ensure that each attendance zone  $a$  (in district  $d$ ) has exactly one school building inside. I do this by summing  $v$  across all blocks  $b$  in each attendance zone  $a$  ( $v_{b \in a}$ ), and ensuring the value equals exactly 1 in each attendance zone. I call this function  $G$ , which takes an attendance zone  $a$  as argument and calculates:  $G(a) = \mathbb{1}\{(\sum_{b \in a} v_b) = 1\}$ . Including the indicator function in a score that must be minimized implements a hard constraint that each attendance zone will only ever have one school building. In legislative redistricting, such a constraint is often called “incumbent pairing,” as map-drawers may seek to ensure that no incumbent officials are grouped into a new district and thus forced to compete in a future election<sup>76</sup>.

I then replicate this sum for each attendance zone  $a$  in district  $d$ , a set which I call  $A_d$  (formally, I evaluate  $G(a)$  once for each attendance zone  $a \in A_d$ ). This nested summation is important because it ensures that there is one school building within each attendance zone, and not simply that the total number of school buildings within the district is correct.

Together, the algorithmic routine minimizes the following score  $T$  in district  $d$  by adding (1) the measure of segregation  $S_d$  and (2) the constraint on single-school attendance zones described above:

$$T_d = S_d + \mathbb{1}\{ \sum_{a \in A_d} (G(a)) = |A_d| \}$$

where:

$$G(a) = \mathbb{1}\{ (\sum_{b \in a} v_b) = 1 \}$$

Finally, I incorporate two additional probabilistic constraints to the algorithm that reflect commonly desired factors of schools for parents and district policymakers: maintaining existing enrollment and compactness<sup>27,81,82</sup>. These do not place precise cutoff values as in the hard constraints above, but they weight the algorithmic draws so that maps compliant with these constraints are more likely to occur. In later analyses, I can then evaluate the drawn maps on each of these criteria to assess compliance. The two constraints I include are:

1. *School Capacity*: parents and policymakers alike are often interested in minimizing potential increases to class sizes<sup>83–85</sup>, which is relevant here because each school building already has a fixed enrollment capacity. While policymakers could presumably open new schools to attract diverse enrollment<sup>86</sup>, my models are conservative and exclusively use existing school infrastructure. For example, districts have opened “magnet” schools with specialized curricular programs in efforts to promote diversity. See<sup>86</sup> for an overview of such efforts in San Antonio Independent School District. To account for these patterns, I follow previous work<sup>27,55</sup> by adopting a school capacity constraint. I incorporate a soft constraint on school capacity which nudges the simulations to

draw districts which avoid changing the grade enrollment of any school by more than 25%. Since schools in New Jersey are quite small (the average grade level enrollment for schools in my sample is only 68 students), this corresponds to an average change of no more than approximately 17 students in any given school. As a result of these small numbers, enrollment in New Jersey schools can be unusually volatile, as small numbers of students moving can lead to large proportional changes. A growing state and declining birth rate combine to leave some schools over-enrolled and some under-enrolled, leading to occasional closings<sup>87</sup>. Enrollment fluctuations, and their effect on budgets, are another common reason for proposed mergers and consolidations. See Supplementary Information Sect. A.4 for further discussion of these issues, and District Consolidations in the main text where my proposed methodology is applied to district mergers.

2. *Distance to School:* One of the most common parental concerns about school assignment is distance to school<sup>88</sup>. Residential segregation can lead to trade-offs between racial integration and travel times<sup>21</sup>, so rezoning efforts frequently attempt to ensure all students remain close to their zoned school<sup>27</sup>. To enforce this, I use a graph-based measure of compactness—specifically, the log of the number of “spanning trees” drawn in each district as built from Census blocks - as implemented in<sup>89</sup>. Intuitively, this captures the idea that more “compact” districts will have a denser set of possible connections between blocks, while a long, thin district made of individual blocks will have a smaller number of ways to connect them. This spanning tree measure is built into the simulation model, and later I evaluate districts on a set of compactness measures common in the redistricting literature, such as Polsby-Popper<sup>90–92</sup>. The combination of contiguity and compactness helps to maintain a sense of “neighborhood schools,” where the algorithm seeks to keep students assigned to schools close to them. Of course, it may not be possible to perfectly maintaining neighborhoods in situations when one’s perception of “neighborhood” overlaps with racially concentrated areas, but these constraints help minimize those concessions while keeping nearby areas together.

Together, these algorithmic constraints help to ensure the algorithm creates diverse school boundaries that meet commonly desired criteria. Crucially, by translating each of these substantive goals into measurable quantities, I can evaluate performance of maps across each of these goals. This measurability can help policymakers and community members evaluate trade-offs between policy proposals.

Much more detail can be found in the online Supplementary Information, on national (A.2), local (A.3-A.4), and methodological (A.5) context, heterogeneity within (A.6) and between (A.7) districts, algorithmic diagnostics (A.8), robustness (A.9), consolidations (A.10), and initialization (A.11).

## Data availability

The datasets used and/or analyzed in the current study are available from the corresponding author upon reasonable request.

Received: 15 February 2024; Accepted: 29 August 2024

Published online: 27 September 2024

## References

1. Reardon, S. F., Weathers, E., Fahle, E., Jang, H. & Kalogrides, D. *Is Separate Still Unequal? New Evidence on School Segregation and Racial Academic Achievement Gaps* (Center for Education Policy Analysis, 2019).
2. Reardon, S. F., Kalogrides, D. & Shores, K. The Geography of Racial/Ethnic Test Score Gaps. Stanford Center for Education Policy Analysis, Working Paper No. 16-10 (2018).
3. Chetty, R., Hendren, N., Kline, P. & Saez, E. Where is the land of Opportunity? The geography of intergenerational mobility in the United States. *Q. J. Econ.* **129**, 1553–1623 (2014).
4. Baker, B. D., Di Carlo, M. & Green, P. C. *Segregation and School Funding: How Housing Discrimination Reproduces Unequal Opportunity* (Albert Shanker Institute, 2022).
5. Baker, B. & Weber, M. Separate and Unequal: Racial and Ethnic Segregation and the Case for School Funding Reparations in New Jersey (2021).
6. Chingos, M. M. & Blagg, K. *Do Poor Kids Get Their Fair Share of School Funding* (Urban Institute, Washington, 2017).
7. Billings, S. B., Deming, D. J. & Rockoff, J. School segregation, educational attainment, and crime: Evidence from the end of busing in Charlotte-Mecklenburg. *Q. J. Econ.* **129**, 435–476 (2013).
8. Johnson, R. C. *Children of the Dream: Why School Integration Works* (Basic Books, 2019).
9. Johnson, R. C. *Long-run Impacts of School Desegregation and School Quality on Adult Attainments*. NBER Working Paper No. 16664 (2011).
10. Chapman, T. K. & Bhopal, K. The perils of integration: Exploring the experiences of African American and Black Caribbean students in predominately white secondary schools. *Ethn. Racial Stud.* **42**, 1110–1129 (2019).
11. Chetty, R. *et al.* Social capital II: Determinants of economic connectedness. *Nature* **608**, 122–134 (2022).
12. Montclair, NJ AGAP. The Montclair, NJ Achievement Gap Advisory Panel Report. Montclair AGAP (2015).
13. Moody, J. Race, school integration, and friendship segregation in America. *Am. J. Sociol.* **107**, 679–716 (2001).
14. Wells, A. S., Fox, L. & Cordova-Cobo, D. How Racially Diverse Schools and Classrooms Can Benefit All Students. The Century Foundation (2016).
15. Davies, K., Tropp, L. R., Aron, A., Pettigrew, T. F. & Wright, S. C. Cross-group friendships and intergroup attitudes: A meta-analytic review. *Pers. Soc. Psychol. Rev.* **15**, 332–351 (2011).
16. Wells, A. S. & Crain, R. L. Perpetuation theory and the long-term effects of school desegregation. *Rev. Educ. Res.* [SPACE] <https://doi.org/10.3102/00346543064004531> (1994).
17. Monarrez, T. E. School attendance boundaries and the segregation of public schools in the US. *Am. Econ. J. Appl. Econ.* [SPACE] <https://doi.org/10.1257/app.20200498> (2020).
18. Richards, M. P. The gerrymandering of school attendance zones and the segregation of public schools: A geospatial analysis. *Am. Educ. Res. J.* [SPACE] <https://doi.org/10.3102/0002831214553652> (2014).
19. Asson, S., Frankenberg, E., Fowler, C. S. & Buck, R. K. Attendance zones in the suburbs. *Phi Delta Kappan* **104**, 11–17 (2023).
20. Saporito, S. & Riper, D. V. Do irregularly shaped school attendance zones contribute to racial segregation or integration? *Soc. Curr.* [SPACE] <https://doi.org/10.1177/2329496515604637> (2016).
21. Smilowitz, K. & Keppler, S. On the use of operations research and management in public education systems. Pushing the Boundaries: Frontiers in Impactful OR/OM Research 84–105 (2020).

22. Heckman, L. B. & Taylor, H. M. School rezoning to achieve racial balance: A linear programming approach. *Socioecon. Plann. Sci.* **3**, 127–133 (1969).
23. Liggett, R. S. The application of an implicit enumeration algorithm to the school desegregation problem. *Manage. Sci.* **20**, 159–168 (1973).
24. Clarke, S. & Surkis, J. An operations research approach to racial desegregation of school systems. *Socioecon. Plann. Sci.* **1**, 259–272 (1968).
25. Holloway, C. A., Wehrung, D. A., Zeitlin, M. P. & Nelson, R. T. An interactive procedure for the school boundary problem with declining enrollment. *Oper. Res.* **23**, 191–206 (1975).
26. Diamond, J. T. & Wright, J. R. Multiobjective analysis of public school consolidation. *J. Urban Plan. Dev.* **113**, 1–18 (1987).
27. Gillani, N. *et al.* Redrawing attendance boundaries to promote racial and ethnic diversity in elementary schools. *Educ. Res.* [SPACE] <https://doi.org/10.3102/0013189X231170858> (2023).
28. Chen, F. *et al.* Exploring tradeoffs in automated school redistricting: computational and ethical perspectives. **37**, 15912–15920 (2023).
29. Owens, A., Reardon, S. F. & Jencks, C. Income segregation between schools and school districts. *Am. Educ. Res. J.* **53**, 1159–1197 (2016).
30. Stroub, K. J. & Richards, M. P. From resegregation to reintegration: Trends in the racial/ethnic segregation of metropolitan public schools, 1993–2009. *Am. Educ. Res. J.* **50**, 497–531 (2013).
31. Owens, A., Reardon, S. F., Kalogrides, D., Jang, H. & Tom, T. Trends in racial/ethnic and economic school segregation, 1991–2020. The Segregation Index Research Brief (2022).
32. Fischel, W. A. *Making the grade: The economic evolution of American school districts* (University of Chicago Press, 2009).
33. Sciarra, D. *Equity and diversity: Defining the right to education for the 21st century* (Education Law Center, 2023).
34. Tractenberg, P., Boddie, E., Roda, A., Dougherty, D. & Mader, N. A school integration plan for New Jersey. Chancellor's Seed Grant Project for 2018–2019 (2019).
35. Siegel-Hawley, G. Mitigating milliken? School district boundary lines and desegregation policy in Four Southern Metropolitan Areas, 1990–2010. *Am. J. Educ.* **120**, 391–433 (2014).
36. Dodge, J. Redrawing school district lines: Reducing the link between educational inequality and economic inequality. *Geo. J. Poverty L. & Pol'y* **26**, 165 (2018).
37. LoPresti, A. J. Blurring the lines: How consolidating school districts can combat New Jersey's public-school segregation problem. *Seton Hall Legis. J.* **45**, 235 (2021).
38. Boser, U. *Size matters: A look at school-district consolidation* (Center for American Progress, 2013).
39. Frankenberg, E., Siegel-Hawley, G. & Diem, S. Segregation by district boundary line: The fragmentation of memphis area schools. *Educ. Res.* **46**, 449–463 (2017).
40. Cannon, S., Goldbloom-Helzner, A., Gupta, V., Matthews, J. & Suwal, B. Voting rights, Markov Chains, and optimization by short bursts. *Methodol. Comput. Appl. Probab.* **25**, 36 (2023).
41. Tractenberg, P., Orfield, G. & Flaxman, G. New Jersey's apartheid and intensely segregated urban schools: Powerful evidence of an inefficient and unconstitutional state education system institute on education law and policy (2013).
42. Campos, C. & Kearns, C. *The Impact of Neighborhood School Choice: Evidence from Los Angeles' Zones of Choice*. SSRN Working Paper (2022).
43. Bell, C. A. All choices created equal? The role of choice sets in the selection of schools. *Peabody J. Educ.* **84**, 191–208 (2009).
44. Frankenberg, E. The role of residential segregation in contemporary school segregation. *Educ. Urban Soc.* **45**, 548–570 (2013).
45. Rich, P. M. & Jennings, J. L. Choice, information, and constrained options: School transfers in a stratified educational system. *Am. Sociol. Rev.* **80**, 1069–1098 (2015).
46. Rich, P. & Sprague, C. *Separate and Unequal Options: Neighborhood Educational Access in the Era of School Choice*. <https://osf.io/preprints/socarxiv/5euhc>. Accessed 7 June 2024.
47. Heyboer, K. Should some NJ school districts merge? The state is offering money to find out.. NJ.com (2022). <https://www.nj.com/education/2022/01/should-some-nj-school-districts-merge-the-state-is-offering-money-to-find-out.html>.
48. Saunders, S. *Bringing Students Together: The Obstacles and Opportunities of School District Consolidation*. ETS Policy Notes (2017).
49. Parcel, T. L. & Taylor, A. J. *The End of Consensus: Diversity, Neighborhoods, and the Politics of Public School Assignments* (UNC Press Books, 2015).
50. Carlson, D. *et al.* *Structured Choice: School Segregation at the Intersection of Policy and Preferences*. Annenberg Institute at Brown University (2023).
51. Davis, T. NJ advances school consolidation plan. Here's what that means. NJ.com (2021). <https://patch.com/new-jersey/tomsriver/nj-advances-plan-may-eliminate-many-school-districts>.
52. Massey, D. S. & Denton, N. A. The dimensions of residential segregation. *Soc. Forces* **67**, 281–315 (1988).
53. Theil, H. *Statistical Decomposition Analysis: With Applications in the Social and Administrative Sciences* (1972).
54. Siegel-Hawley, G. When the fences come down: Twenty-first-century lessons from metropolitan school desegregation. (UNC Press Books, 2015) (2016).
55. Allman, M. *et al.* *Designing School Choice for Diversity in the San Francisco Unified School District*. In: Proceedings of the 23rd ACM Conference on Economics and Computation, 290–291 (2022).
56. Kenny, C. T. censable: Making Census Data More Usable (2022). <https://christophertkenny.com/censable/>.
57. Bischoff, K. School district fragmentation and racial residential segregation: How do boundaries matter?. *Urban Affairs Rev.* **44**, 182–217 (2008).
58. Diaz, A. WS/FCS looks to magnet programming to increase diversity at four schools. WFDD (2023).
59. Wells, A. S. *et al.* Boundary crossing for diversity, equity and achievement. Boston: Inter-district School Desegregation and Educational Opportunity. Charles Hamilton Houston Institute for Race & Justice Report. Harvard Law School (2009).
60. Orfield, G. & Frankenberg, E. *Educational Delusions?: Why Choice can Deepen Inequality and How to Make Schools Fair* (Univ of California Press, 2013).
61. Wells, A., Warner, M. & Grzesikowski, C. The story of meaningful school choice: Lessons from interdistrict transfer plans. *Educ. Delusions* [SPACE] <https://doi.org/10.1525/9780520955103-012> (2013).
62. Reber, S. J. Court-ordered desegregation successes and failures integrating American schools since Brown v. Board of Education. *J. Hum. Resour.* **40**, 559–590 (2005).
63. Kruse, K. M. *White flight: Atlanta and the making of modern conservatism* (Princeton University Press, 2005).
64. Pathak, P. A. & Shi, P. *How Well Do Structural Demand Models Work? Counterfactual Predictions in School Choice*. NBER Working Paper No. 24017 (2017).
65. Walker, K. E. tigris: An R Package to Access and Work with Geographic Data from the US Census Bureau. Available at The Comprehensive R Archive Network (CRAN) Version 2.0.3 <https://cran.r-project.org/web/packages/tigris/index.html> (2016).
66. Kenny, C. T. geomander: Geographic tools for studying gerrymandering (2023). R package. Version 2.2.1 <https://christophertkenny.com/geomander/>.
67. Orfield, G., Ee, J. & Coughlin, R. New Jersey's segregated schools: Trends and paths forward (2017).
68. Rabe, M. & Jensen, E. *Exploring the Racial and Ethnic Diversity of Various Age Groups*. US Census Bureau (2023).

69. Kenny, C. T., McCartan, C., Kuriwaki, S., Simko, T. & Imai, K. Evaluating bias and noise induced by the US Census Bureau's privacy protection methods. *Sci. Adv.* **10**, eadl2524 (2024).
70. Muralidhar, K. & Domingo-Ferrer, J. Database reconstruction is not so easy and is different from reidentification. *J. Off. Stat.* **39**, 381–398 (2023).
71. Kenny, C. T. *et al.* The use of differential privacy for census data and its impact on redistricting: The case of the 2020 US census. *Sci. Adv.* **7**, eabk3283 (2021).
72. Ruggles, S., Fitch, C., Magnuson, D. & Schroeder, J. Differential privacy and census data: Implications for social and economic research. In: AEA Papers and Proceedings, vol. 109, 403–408 (American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, 2019).
73. Kenny, C. T. *et al.* Comment: The essential role of policy evaluation for the 2020 census disclosure avoidance system. *Harvard Data Science Review* (2023). <https://hdsl.mitpress.mit.edu/pub/6fzqu19>.
74. Autry, E., Carter, D., Herschlag, G., Hunter, Z. & Mattingly, J. C. Metropolized forest recombination for Monte Carlo sampling of graph partitions. arXiv preprint [arXiv:1911.01503](https://arxiv.org/abs/1911.01503) (2019).
75. DeFord, D., Duchin, M. & Solomon, J. Recombination: A family of Markov Chains for redistricting. *Harvard Data Sci. Rev.* [SPACE] <https://doi.org/10.1162/99608f92.eb30390f> (2021).
76. Kenny, C. T., McCartan, C., Fifield, B. & Imai, K. redist: Simulation methods for legislative redistricting. Available at The Comprehensive R Archive Network (CRAN) (2022). Version 3.1.6 <https://cran.r-project.org/web/packages/redist/index.html>
77. McCartan, C. Finding pareto efficient redistricting plans with short bursts (2023).
78. Palmer, M., Schneer, B., & DeLuca, K. A Partisan solution to Partisan gerrymandering: The define-combine procedure (2022).
79. Erwig, M. The graph voronoi diagram with applications. *Netw. Int. J.* **36**, 156–163 (2000).
80. Flaxman, G., Kuscera, J., Orfield, G., Ayscue, J. & Siegel-Hawley, G. A status quo of segregation: Racial and economic imbalance in New Jersey Schools, 1989–2010. UCLA Civil Rights Project (2013).
81. McMillan, S. M. Common practices in changing school attendance zone boundaries. Educational Data Systems (2018).
82. Montgomery County Public Schools. Montgomery County Public Schools Districtwide Boundary Analysis (2021).
83. Krueger, A. B. & Whitmore, D. M. The effect of attending a small class in the early grades on college-test taking and middle school test results: Evidence from project STAR. *Econ. J.* **111**, 1–28 (2001).
84. Gilraine, M., Macartney, H. & McMillan, R. Education reform in general equilibrium: Evidence from California's class size reduction. NBER Working Paper No. 24191 (2018).
85. Chetty, R. *et al.* How does your kindergarten classroom affect your earnings? Evidence from project STAR. *Q. J. Econ.* **126**, 1593–1660 (2011).
86. Opalka, A. & Heyward, G. Integrating Schools in San Antonio: Start with One. An Interview with Mohammed Choudhury CRPE (2018).
87. Symons, M. Where are all the kids? NJ school enrollment falling in your district. New Jersey 101.5 (2022).
88. Frankenberg, E. & Jacobson, R. The polls-trends: School integration polls. *Public Opin. Q.* **75**, 788–811 (2011).
89. McCartan, C. & Imai, K. Sequential Monte Carlo for sampling balanced and compact redistricting plans. *Ann. Appl. Stat.* [SPACE] <https://doi.org/10.1214/23-AOAS1763> (2023).
90. Polsby, D. D. & Popper, R. D. The third criterion: Compactness as a procedural safeguard against partisan gerrymandering. *Yale L. & Pol'y Rev.* **9**, 301 (1991).
91. Dube, M. P. & Clark, J. T. Beyond the circle: Measuring district compactness using graph theory. In: Northeast Political Science Association Conference (2016).
92. Kenny, C. T., McCartan, C., Fifield, B. & Imai, K. redistmetrics: Redistricting metrics. Available at The Comprehensive R Archive Network (CRAN) (2021) Version 1.0 <https://alarm-redist.org/redistmetrics/>

## Acknowledgements

I am grateful for invaluable feedback from Chris Kenny, Cory McCartan, Sun Young Park, María Ballesteros, Emma Ebowe, Kosuke Imai, Marty West, Steve Ansolabehere, Rebecca Johnson, Justin de Benedictis-Kessner, Nabeel Gillani, Doug Beeberman, members of the Imai Research Group, members of the Algorithm-Assisted Redistricting Methodology (ALARM) Project, and members of the Plural Connections Group.

## Author contributions

T.S. conducted all results and wrote the manuscript.

## Competing interests

The authors declare no competing interests.

## Additional information

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1038/s41598-024-71578-x>.

**Correspondence** and requests for materials should be addressed to T.S.

**Reprints and permissions information** is available at [www.nature.com/reprints](https://www.nature.com/reprints).

**Publisher's note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

**Open Access** This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2024