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Achieving Diversity in the *Parents Involved* Era:

Evidence for Geographic Integration Plans in Metropolitan School Districts

Meredith P. Richards*, Kori J. Stroub,
Julian Vasquez Heilig***, and Michael R.
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INTRODUCTION

Landmark legal victories over *de jure* segregation in the wake of *Brown v. Board of Education of Topeka*¹ helped to secure dramatic decreases in the racial and ethnic segregation of schools in subsequent decades, especially in the formerly segregated American South.² The promise of the post-*Brown* era

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1. *Brown v. Bd. of Educ. of Topeka*, 347 U.S. 483 (1954).

2. See generally Reynolds Farley, *Racial Integration in the Public Schools, 1967-1972: Assessing the Effects of Governmental Policies*, 8 Soc. Focus (1975); JAMES S. COLEMAN ET AL., TRENDS IN SCHOOL SEGREGATION, 1968-73 (The Urban Institute, 1975); JOHN R. LOGAN & DIERDRE OAKLEY, THE CONTINUING LEGACY OF THE BROWN DECISION: COURT ACTION AND SCHOOL DESEGREGATION, 1960-2000 (Lewis Mumford Center for Comparative Urban and Regional Research, 2004); GARY ORFIELD, PUBLIC SCHOOL DESEGREGATION IN THE UNITED

proved ephemeral, however; nearly sixty years after the Supreme Court ruled that segregation was inherently unequal, American schools remain remarkably segregated by race and ethnicity.³ Since the 1980s, the *de facto* segregation of schools has rapidly intensified, especially in the South and for Hispanic/Latino populations.⁴ Indeed, during the 1990s the proportion of Black students in majority-White schools decreased 13 percentage points, to a level not seen since 1970.⁵ This re-segregation of schools has been facilitated by weak executive enforcement of civil rights provisions and continued judicial retrenchment on school integration, exemplified by *Board of Education of Oklahoma City v. Dowell*⁶ and *Freeman v. Pitts*,⁷ which diminished desegregation standards and resulted in the release of hundreds of districts from their court-imposed desegregation orders.

A. Parents Involved

In 2007, the U.S. Supreme Court in *Parents Involved in Community Schools v. Seattle School District No. 1*⁸ dealt another blow to integration efforts, rendering unconstitutional school assignment plans that use individual student race or ethnicity as the sole factor in school assignment, punctuating the steady decline in support for school desegregation policies.⁹ In the case, which was decided with *Meredith v. Jefferson County Board of Education*,¹⁰ the Court ruled that the racial balancing efforts of the Seattle and Louisville school

STATES, 1968-1980 (Joint Center for Political Studies, 1983).

3. See generally GARY ORFIELD, *SCHOOLS MORE SEPARATE: CONSEQUENCES OF A DECADE OF RESEGREGATION* (The Civil Rights Project, 2001); Gary Orfield et al., *The Resurgence of School Segregation*, 60 *Educ. Leadership* 16 (2002); ERICA FRANKENBERG & CHUNGMEI LEE, *RACE IN AMERICAN PUBLIC SCHOOLS: RAPIDLY RESEGREGATING SCHOOL DISTRICTS* (The Civil Rights Project, 2002).

4. See generally GARY ORFIELD, *SCHOOLS MORE SEPARATE: CONSEQUENCES OF A DECADE OF RESEGREGATION* (The Civil Rights Project, 2001); Sean F. Reardon et al., *The Changing Structure of School Segregation: Measurement and Evidence of Multiracial Metropolitan-Area School Segregation, 1989-1995*, 37 *Demography* 351 (2000); GARY ORFIELD & JOHN T. YUN, *RESEGREGATION IN AMERICAN SCHOOLS* (Harvard University Civil Rights Project, 1999); Gary Orfield et al., *Deepening Segregation in American Public Schools: A Special Report from the Harvard Project on School Desegregation*, 30 *Equity and Excellence in Education* 5 (1997); GARY ORFIELD ET AL., *THE GROWTH OF SEGREGATION IN AMERICAN SCHOOLS: CHANGING PATTERNS OF SEPARATION AND POVERTY SINCE 1968* (Harvard Project on School Desegregation, 1993); GARY ORFIELD & FRANKLIN MONFORT, *STATUS OF SCHOOL DESEGREGATION: THE NEXT GENERATION* (Harvard Opportunity Project, 1992); CHARLES CLOTFELTER, *AFTER BROWN: THE RISE AND RETREAT OF SCHOOL DESEGREGATION* (Princeton University Press, 2004).

5. ERICA FRANKENBERG ET AL., *A MULTIRACIAL SOCIETY WITH SEGREGATED SCHOOLS: ARE WE LOSING THE DREAM?* 37 (Civil Rights Project, 2003).

6. See *Bd. of Educ. of Okla. City v. Dowell*, 498 U.S. 237 (1991).

7. See *Freeman v. Pitts*, 503 U.S. 467 (1992).

8. *Parents Involved in Cmty. Schs. v. Seattle Sch. Dist. No. 1*, 551 U.S. 701 (2007).

9. CLOTFELTER, *supra* note 4.

10. *Meredith v. Jefferson Cnty. Bd. of Educ.*, 551 U.S. 701 (2007), decided with *Parents Involved*.

districts, which were undertaken voluntarily in the absence of evidence that either district had deliberately practiced *de jure* racial discrimination, were impermissible and unconstitutional violations of the Equal Protection Clause.¹¹ Consequently, districts that had been using such policies to achieve and maintain racial and socioeconomic balance across campuses were denied the primary weapon with which they had historically combated racial and socioeconomic segregation.¹²

In the Seattle student assignment plan, which was challenged under *Parents Involved*, students were permitted to apply to any high school in the district.¹³ However, if the demographics of any school deviated from the demographics of the district as a whole (within a specified percentage), a racial “tiebreaker” was used to determine which students were admitted to the school. Thus, if a school had too many whites, admission might be restricted to only non-whites (including Asians, Latinos, Native Americans, or African Americans); if a school had too few whites, admission might be restricted to only whites. As the foregoing illustrates, the Seattle plan was concerned only with racial balance among “whites” and “non-whites,” not with the racial distribution within non-white populations. In the Jefferson County, Kentucky plan, which was challenged under the *Meredith* case, students were classified as either “black” or “other,” with students assigned to schools in such a way as to ensure that schools were no less than 15 percent and no more than 50 percent black.

While acknowledging the pernicious effects of segregation, the Court held in *Parents Involved* that the use of racial classifications in Seattle and Louisville were not “narrowly tailored”¹⁴ to achieve a “compelling” government interest.¹⁵ First, the Court held that there was not a compelling interest that justified the use of race in their student assignment processes.¹⁶ In the plurality opinion, Roberts argued that while racial diversity is a compelling interest in higher education, the ruling in *Grutter v. Bollinger*¹⁷ and *Gratz v. Bollinger*¹⁸ did not apply to primary and secondary education, because the districts in question (i.e., Seattle and Louisville) did not use an individualized

11. *Parents Involved*, 551 U.S. at 702.

12. See generally ADAI TEFERA ET AL., SCHOOL INTEGRATION EFFORTS THREE YEARS AFTER PARENTS INVOLVED (The Civil Rights Project, 2010); ABBIE COFFEE & ERICA FRANKENBERG, TWO YEARS AFTER THE PICS DECISION: DISTRICTS' INTEGRATION EFFORTS IN A CHANGING CLIMATE (The Civil Rights Project, 2009); Amy Stuart Wells & Erica Frankenberg, *The Public Schools and the Challenge of the Supreme Court's Integration Decision*, 89 Phi Delta Kappan 178 (2007).

13. *Parents Involved*, 551 U.S. at 701-02 (contains additional information on Seattle and Louisville's student assignment plans discussed below).

14. *Id.* at 702.

15. *Id.*

16. *Id.* at 703-04.

17. *Grutter v. Bollinger*, 539 U.S. 306 (2003).

18. *Gratz v. Bollinger*, 539 U.S. 244 (2003).

consideration of students and utilized a very limited racial perspective on diversity (i.e., “white” vs. “non-white”).¹⁹ Moreover, the cases of Seattle and Louisville did not constitute a compelling interest because neither district had a legacy of past discrimination that the plans were designed to remedy.²⁰ In addition, the Court ruled that the plans of Seattle and Louisville were not sufficiently “narrowly tailored” to constitutionally justify the use of race.²¹ Indeed, Roberts notes that both plans were exclusively focused on achieving demographic goals, and not towards achieving any benefit of racial diversity.²² Moreover, the Court ruled that neither district had made a “serious, good faith consideration of workable race-neutral alternatives,” as required under *Grutter*.²³ Indeed, the Court held that the districts failed to show that the use of race was necessary to meet its diversity objectives, arguing that similar effects could have been achieved without race-conscious means.²⁴

In his concurrence, Justice Kennedy agreed that the Seattle and Louisville district plans were unconstitutional.²⁵ However, Kennedy argued that the plurality opinion was “too dismissive of the government’s legitimate interest in ensuring that all people have equal opportunity regardless of their race.”²⁶ Rather, he emphasized that in public schools it is “permissible to consider a schools’ racial makeup and adopt general policies to encourage a diverse student body, one aspect of which is its racial composition.”²⁷ As such, Kennedy concluded that schools are “free to devise race-conscious measures to address the problem in a general way,”²⁸ so long as they do not treat students differently “based solely on a systematic, individual typing by race.”²⁹ Indeed, Kennedy specifically endorses creating “attendance zones with general recognition of neighborhood demographics.”³⁰ Thus, while repudiating the use of individual student race, the Court left open the possibility of using non-individualized measures of race, such as those used in the Berkeley plan.

In the post-*Parents Involved* and post-*Meredith* legal environment, districts committed to integrating their schools have implemented several alternative race-neutral and race-conscious strategies to ameliorate segregation.³¹ This article examines one promising and innovative policy strategy, pioneered by Berkeley Unified School District (USD), which

19. *Parents Involved*, 551 U.S. at 703.

20. *Id.* at 703-04.

21. *Id.* at 704.

22. *Id.*

23. *Id.*

24. *Id.*

25. *Parents Involved*, 551 U.S. at 782 (Kennedy, J., concurring).

26. *Id.* at 787.

27. *Id.* at 788-89.

28. *Id.* at 789.

29. *Id.*

30. *Id.*

31. TEFERA ET AL., *supra* note 12.

leverages persistent patterns of residential racial and economic segregation by assigning students to schools on the basis of the characteristics of the neighborhoods in which they reside.³² Such plans exploit historic patterns of neighborhood racial and socioeconomic segregation, presuming that neighborhood characteristics will reliably predict student characteristics. Thus, a school that is diverse in terms of the neighborhoods it represents will also have a comparably diverse student body.

B. BERKELEY USD'S GEOGRAPHIC INTEGRATION PLAN

The use of geography-based integration approaches was pioneered by the Berkeley USD prior to *Parents Involved* as a means of complying with the stringent requirements of California's Prohibition Against Discrimination or Preferential Treatment (Proposition 209),³³ which prohibits public institutions from considering individual race/ethnicity and sex in education and hiring decisions. Previously, Berkeley USD had operated a controlled choice integration plan that considered individual student race/ethnicity and parental preferences in student assignment decisions.³⁴ Under this plan, parents were allowed to choose their child's school of attendance so long as their choice would not result in a school deviating significantly from the overall diversity of the attendance zone.³⁵ If, however, family school choices would result in significant declines in diversity at any of the schools, the district would assign students to schools on the basis of individual student race/ethnicity.³⁶

In response to concerns regarding a possible violation of Proposition 209, however, Berkeley USD redesigned its integration plan to pair controlled parental choice with innovative geographically-based diversity indices.³⁷ Under this plan, parents are still allowed to select their top school choices. So long as their choices would result in school racial/ethnic and socio-economic diversity remaining close to the attendance zone average, the parents' request is granted. However, when school demographics would deviate significantly from the attendance zone average, students may be assigned to campuses on the basis of their neighborhood's "diversity index" rather than their individual characteristics.³⁸

Specifically, Berkeley USD divides the district into 445 neighborhood

32. LISA CHAVEZ & ERICA FRANKENBERG, *INTEGRATION DEFENDED: BERKELEY UNIFIED'S STRATEGY TO MAINTAIN SCHOOL DIVERSITY* (The Chief Justice Earl Warren Institute on Race Ethnicity & Diversity ed., 2009).

33. CAL. CONST. art. I, § 31(a) (adopted November 5, 1996 through the ballot initiative measure Proposition 209).

34. See CHAVEZ & FRANKENBERG, *supra* note 32, at 3-5.

35. *Id.* at 5.

36. *Id.*

37. *Id.*

38. *Id.* at 6.

“planning areas”, each of which ranges in size from four to eight city blocks.³⁹ Each neighborhood is assigned a diversity index, which is calculated as a weighted function of the percent students of color, median household income, and mean level of adult education, using data from the U.S. Census 2000 and district K-12 data.⁴⁰ These diversity scores were divided into three categories, and each neighborhood assigned a code ranging from 1 to 3—where neighborhoods assigned a code of 1 are relatively less advantaged than neighborhoods assigned a code of 3. In the student assignment process, all students within each neighborhood are assigned identical diversity indices, regardless of their individual race/ethnicity or socio-economic status.⁴¹

The goal of Berkeley USD’s plan is for each school within an attendance zone to reflect the overall attendance zone average on the composite measure.⁴² For example, if it is estimated that, for a given attendance zone, 50 percent of the students reside in category “1” neighborhoods, 30 percent in category “2” neighborhoods, and 20 percent in category “3” neighborhoods, each school in the attendance zone should reflect that distribution. If, as a result of parental choice, any school deviates from the overall attendance zone average by more than 5-10 percent, any available seats are filled with students residing in neighborhood of the category that is needed to realign the schools diversity with that of its attendance zone.⁴³ Using the hypothetical attendance zone above, if a school’s percentage of category “2” students drops to 15 percent, then open seats at that school will be preferentially given to students residing in category “2” neighborhoods until that schools diversity realigns with the attendance zone average.

Legal Viability of Geographic Integration Plans

Berkeley USD’s plan has recently survived a major legal challenge to its constitutionality in *American Civil Rights Foundation v. Berkeley Unified School District*.⁴⁴ The American Civil Rights foundation challenged Berkeley USD’s student assignment policy on the grounds that it was racially discriminatory in violation of Section 31 of the California Constitution. As amended by Proposition 209, the California Constitution prohibits school districts, as government entities, from discriminating against or granting preferential treatment to “any individual or group on the basis of race, sex, color, ethnicity, or national origin.”⁴⁵ The American Civil Rights Foundation

39. *Id.* at 4.

40. CHAVEZ & FRANKENBERG, *supra* note 32, at 6.

41. *Id.*

42. *Id.* at 4-5.

43. *Id.* at 7.

44. *American Civil Rights Found. v. Berkeley Unified Sch. Dist.*, 90 Cal. Rptr. 3d 789 (2009).

45. CAL. CONST. art. I, § 31(a).

alleged that by using race in making student assignments, Berkeley was using race to discriminate against and grant preferences to certain students.⁴⁶

In deciding the case, the First District Court of Appeal ruled that Berkeley USD's plan was not racially discriminatory and did not violate Section 31.⁴⁷ Most importantly, the court rules that Berkeley USD's plan did not show any partiality according to an individual student's race, noting that all students in each neighborhood were treated equally and were not classified according to their personal attributes, as was prohibited by *Parents Involved*.⁴⁸ Indeed, in the court's opinion, Sepulveda noted that "white and African American students from the same neighborhood receive the same diversity rating and the same treatment."⁴⁹ Moreover, the court affirmed the constitutionality of the Berkeley USD plan's emphasis on diversity, arguing that Section 31 does not prohibit consideration of race for any and all purposes, but only prohibits "unequal treatment of particular persons,"⁵⁰ which is absent in the plan, which considers only community-wide demographic factors.

Empirical Support for Geographic Integration Plans

Since being implemented in 2004, Berkeley USD's plan has been credited with maintaining stable integration throughout the district, while still enabling a majority of parents to obtain their school of choice.⁵¹ Indeed, our analysis of data from the National Center for Education Statistics Common Core of Data reveals that Berkeley's segregation rates have remained extremely low since shifting from a race-based to a geography-based integration plan (multigroup entropy index of $H = .03$).⁵²

Although it contains a variety of programmatic and design features, at the crux of Berkeley's plan is the assumption that neighborhood characteristics are accurate predictors of the students living in those neighborhoods. This assumption is premised on the persistent and systematic segregation of individuals across geographic boundaries, which has resulted in a nation of neighborhoods that are relatively homogeneous in terms of the race, ethnicity and socioeconomic status of their residents.⁵³ Inasmuch as they use neighborhood racial/ethnic and socioeconomic characteristics as proxies for

46. *American Civil Rights Found.*, 90 Cal. Rptr. 3d at 789.

47. *Id.* at 801.

48. *Id.* at 797.

49. *Id.* at 798.

50. *Id.*

51. See CHAVEZ & FRANKENBERG, *supra* note 32, at 11-15.

52. See JOHN ICELAND ET AL., RACIAL AND ETHNIC SEGREGATION IN THE UNITED STATES: 1980-2000 (U.S. Census Bureau, 2002) (*noting* the multi group entropy index is a statistical measure of "evenness"). In this case, the entropy index indicates the segregation of racial/ethnic groups.

53. See generally WILLIAM A. V. CLARK, *Residential Segregation Trends, BEYOND THE COLOR LINE: NEW PERSPECTIVES ON RACE AND ETHNICITY IN AMERICA* 83-94 (2002).

individual student race/ethnicity, geographic integration plans are thus designed to achieve integration by exploiting the legacy of segregation.

Consistent with Berkeley's rationale, extant research supports the underlying assumption that racial/ethnic and socioeconomic residential segregation is still a salient feature of the American metropolitan landscape.⁵⁴ Although segregation is evident among all racial/ethnic groups, the segregation of Blacks remains particularly acute.⁵⁵ Indeed, despite declines in the absolute level of segregation of Blacks since the 1980s, the segregation of Blacks remains extremely high.⁵⁶ Moreover, the residential segregation of Hispanics and Asians, while still lower than that of Blacks, has steadily increased over the past decades.⁵⁷ Similar to racial/ethnic segregation, extant research suggest that socioeconomic segregation is a significant characteristic of American metropolitan areas.⁵⁸ Indeed, income segregation has steadily increased since the 1970s, particularly for Blacks and Hispanics.⁵⁹

Also consistent with Berkeley's use of neighborhoods as a proxy for individual characteristics is evidence suggesting that segregation continues to be a largely neighborhood-level phenomenon. In their analysis of the geographic scale of segregation, Iceland and Steinmetz established that residential racial segregation was higher in Census block groups than in larger Census tracts.⁶⁰ These findings are consistent with the notion that geographic units at smaller scales of analysis, on average, are more homogeneous than larger geographic units. Specifically, Reardon et al. found that racial/ethnic segregation was most acute at smaller geographic scales of analysis, although segregation at larger geographic scales increased relative to micro segregation over the study period of 1990 to 2000.⁶¹

Taken together, extant social science research lends empirical credence to the core assumptions of geographic integration plans. Coupled with evidence of Berkeley's success in maintaining high rates of racial/ethnic integration, this suggests that geographic integration plans are a promising pathway for school

54. See generally Iceland, *supra* note 52.

55. See generally Camille Z. Charles, *The Dynamics of Racial Residential Segregation*, ANN. REVIEW SOC., 2003, at 167-207.

56. ICELAND, *supra* note 52, at 7-9.

57. *Id.* at 10-13.

58. See generally Paul A. Jargowsky, *Take the Money and Run: Economic Segregation in U.S. Metropolitan Areas*, 61 AM. SOC. REV. 984, 984-998 (1996).

59. See generally Douglas S. Massey & Mitchell L. Eggers, *The Spatial Concentration of Affluence and Poverty During the 1970s*, 29 URBAN AFFAIRS REV. 299, 299-315 (1993); Douglas S. Massey & Mary J. Fischer, *The Geography of Inequality in the United States, 1950-2000*, BROOKINGS-WHARTON PAPERS ON URBAN AFFAIRS, 2003, at 1-40.

60. See generally John Iceland & Erika Steinmetz, *The Effects of Using Census Block Groups Instead of Housing Tracts When Examining Residential Housing Patterns*, U.S. Census Bureau (2003) http://www.census.gov/hhes/www/housing/housing_patterns/pdf/unit_of_analysis.pdf.

61. Sean F. Reardon, et al., *Race and Space in the 1990s: Changes in the Geographic Scale of Segregation, 1990-2000*, 38 SOC. SCI. RESEARCH, 2008, at 55-70.

integration. Despite their promise and burgeoning support from organizations such as the UCLA Civil Rights Project⁶², such geographic integration plans have been subjected to little empirical scrutiny regarding their potential effectiveness and generalizability. As such, it remains an open question whether Berkeley USD's success could be replicated in other districts, or whether it is merely an artifact of Berkeley's unique social climate and residential context.⁶³

Citing the legal viability of Berkeley's geographic integration plan and its success in maintaining integration, Berkeley's plan has been hailed as a model for other districts seeking integration in the *Parent Involved* era. Indeed, a recent joint report by the UCLA Civil Rights Project and the Chief Justice Earl Warren Institute on Race, Ethnicity, and Diversity has recommended the adoption of Berkeley-type plans as a viable alternative for other districts seeking to align their intervention efforts with the Supreme Court's ruling.⁶⁴ Despite the promise of such plans, however, no empirical evidence has assessed the potential generalizability of Berkeley's plan in other contexts or the degree to which geographic plans might reduce segregation in U.S. public schools.

I. THE CURRENT STUDY

This study constitutes an initial empirical effort to test the potential effectiveness of geographic integration models in ameliorating school segregation in a national context. Using an essentialized version of Berkeley's geographic integration model, we test whether neighborhood diversity indices such as those used by Berkeley USD are accurate enough proxies of student race/ethnicity to achieve integration objectives and whether they have the potential to meaningfully increase school diversity. Specifically, the study addresses the following research questions:

- (1) How accurately can student race/ethnicity be predicted as a function of the neighborhood characteristics?
- (2) Do geographic integration plans have the potential to meaningfully increase school racial/ethnic diversity?

To address these questions, we conducted two separate analyses. First, to determine the generalizability of Berkeley's diversity indices across contexts, we assess the accuracy of prediction of student race/ethnicity as a function of neighborhood characteristics in a diverse, national sample of large, metropolitan districts (see Tables 1, 2 and 3). Second, we examine whether these prediction rates would translate into higher rates of school diversity, using a simulated student assignment procedure for one metropolitan area (see Tables

62. Chavez & Frankenberg, *supra* note 32.

63. See *id.* at 9-11 for a discussion of Berkeley USD's characteristics.

64. See *id.*

4 and 5). Below, we address each of these analyses in turn, presenting the method and results related to each research question.

*A. HOW ACCURATELY DO NEIGHBORHOOD CHARACTERISTICS
PREDICT STUDENT RACE/ETHNICITY?*

In the first phase of analysis, we address Research Question 1, testing the assumption underlying Berkeley-style geographic integration plans that neighborhood demographic and socioeconomic characteristics accurately predict the race and ethnicity of students. We estimated a series of logistic regression models predicting student race/ethnicity as a function of different configurations of the block group demographic and socioeconomic characteristics used in Berkeley's plan. For each model, we found the predicted race/ethnicity of each student based on their neighborhood characteristics and compared the predicted race/ethnicity of each student to their actual race/ethnicity to assess the prediction accuracy of each model for each district.

Method

Analysis of the prediction accuracy of student race/ethnicity was conducted on the 10 most populous metropolitan districts in the country, including: Los Angeles Unified School District, CA; Broward County Public Schools, FL; Miami-Dade County Public Schools, FL; Chicago Public School, IL; Detroit Public Schools, MI; Clark County School District, NV; New York Public Schools, N.Y.; The School District of Philadelphia, PA; Dallas Independent School District, TX; and Houston Independent School District, TX.

The sample districts were spatially linked to Census demographic data for each of their component neighborhoods. While Berkeley defines "neighborhoods" as units consisting of four to eight consecutive city blocks, this study uses Census block groups⁶⁵ as proxies for neighborhoods. Block groups were chosen as proxies for neighborhoods for two reasons. First, because Berkeley's neighborhood definition is unique to the Berkeley context, in that it is not based on standard Census geographic regions, it is not generalizable to other districts. As such, we opted to use Census block groups, which is a standard geographic unit of analysis available for all U.S. districts. Second, because Census block groups are larger than Berkeley's neighborhood units, they offer a more conservative estimate of the predictive validity of the models presented below.⁶⁶ School districts were linked to neighborhood racial/ethnic and socioeconomic data by layering school district boundaries and

65. Census block groups, which are nested within tracts, typically contain between 600 and 3,000 people, with an average size of 1,500 people.

66. Whereas Berkeley's plan divides the district into 445 neighborhood zones, the Census divides Berkeley up into only 99 block groups.

block group boundaries merged with Census data in ArcGIS. All boundary shape files were obtained from the U.S. Census Tiger/LINE® system.

Because school district boundaries do not map perfectly to Census geographic boundaries, if any part of a block group was located in a school district, that block group was coded as being in the district. As a result of this procedure, any students residing outside a district, but inside a block group partially contained by the district were retained in the final sample. As such, our sampling procedure has the potential to slightly overestimate the population. As Table 1 reveals, however, our procedure did not systematically inflate estimates, likely because the district and block group boundaries were generally coterminous.

Table 1
Sample and Population Demographic Characteristics

| | Enrollment | | % Asian | | % Black | | % Hispanic | | % White | | % Other | |
|---|------------------|------------------|-----------|-----------|------------|------------|------------|------------|------------|------------|-------------|-------------|
| | Sample (Sam) | Pop | Sam | Pop | Sam | Pop | Sam | Pop | Sam | Pop | Sam | Pop |
| Los Angeles Unified School District | 796,129 | 710,007 | 6% | 6% | 12% | 13% | 69% | 71% | 12% | 10% | 1.0% | 0.3% |
| Broward County Public Schools | 226,208 | 241,094 | 2% | 3% | 34% | 36% | 21% | 19% | 42% | 41% | 0.3% | 0.3% |
| Miami-Dade County Public Schools | 357,742 | 360,136 | 1% | 1% | 31% | 31% | 52% | 56% | 16% | 11% | 0.3% | 0.1% |
| Chicago Public Schools | 437,530 | 431,750 | 3% | 3% | 49% | 52% | 35% | 35% | 12% | 10% | 0.5% | 0.2% |
| Detroit Public Schools | 202,258 | 154,648 | 1% | 1% | 86% | 91% | 5% | 4% | 8% | 4% | 0.3% | 0.2% |
| Clark County School District | 206,523 | 217,518 | 5% | 7% | 12% | 14% | 31% | 29% | 51% | 50% | 1.0% | 0.9% |
| New York Public Schools | 1,122,448 | 1,074,175 | 10% | 12% | 36% | 35% | 37% | 38% | 16% | 15% | 1.0% | 0.4% |
| The School District of Philadelphia | 213,180 | 205,199 | 4% | 5% | 62% | 65% | 13% | 13% | 20% | 17% | 0.5% | 0.2% |
| Dallas Independent School District | 164,133 | 160,477 | 2% | 1% | 34% | 36% | 51% | 55% | 13% | 8% | 1.0% | 0.4% |
| Houston Independent School District | 194,676 | 209,716 | 3% | 3% | 30% | 32% | 54% | 55% | 12% | 10% | 1.0% | 0.1% |
| Total / Average | 3,920,827 | 3,764,720 | 4% | 4% | 39% | 41% | 37% | 38% | 20% | 18% | 0.7% | 0.3% |
| <p><i>Source:</i> Sample: U.S. Census 2000; Population: NCES CCD 1999-2000 <i>Note.</i> The “Sample” columns reflect the estimated district population according to Census data on students enrolled in public schools by block group of residence, as calculated by summing the student populations residing in each Census block group located within a given district. The “Pop” column reflects the actual district student population, as reported in the NCES CCD.</p> | | | | | | | | | | | | |

To arrive at the final student-level dataset, the Census block group-level racial/ethnic frequency data on students enrolled in public schools were

disaggregated. For example, if a block group had one hundred students, forty White and sixty Black, this would be converted to a dataset with one hundred unique student records with the race/ethnicity of the student coded as a single variable. This procedure is possible because our analysis requires only one student-level variable, race/ethnicity, which will be predicted as a function of several block group-level characteristics (discussed in detail below). The final sample of ten districts accounts for just over 8 percent of the population of U.S. students, yielding a student-level dataset of 3.9 million student records.

Table 1 reports the overall demographic characteristics of the sample by district. Because the student-level sample is drawn from Census reports of student enrollment in public schools, not from school data as reported in the NCES CCD, it is possible that the sample deviates slightly from the actual population of students. To test whether this sampling procedure resulted in a systematic bias in the sample, the sample of students reported by the sample was compared to the population as reported by the NCES CCD. As Table 1 reveals, while Census- and NCES-reported data do not match perfectly, the sample does not seem to systematically over- or under-estimate population values. For example, across all race/ethnic groups, the average deviation between the sample and the population was only 2 percent.

Analytic Technique

To assess the accuracy of prediction of student race/ethnicity as a function of neighborhood characteristics, for each district in the sample, we obtained information on student race/ethnicity linked to the characteristics of the neighborhoods in which they live. We tested sixteen models predicting student race/ethnicity, regressing four different outcome variables on four different configurations of neighborhood-level demographic and socioeconomic predictors. Below we describe each of the outcomes and predictors used in our models.

As noted previously, student race/ethnicity data were obtained from Census 2000 Summary File 1 block group data on students over the age of three, enrolled in public school in grades one through twelve. Students were categorized according to six racial/ethnic groups as collected by the U.S. Census: White alone, Black alone, Hispanic/Latino, Asian alone, American Indian/Alaska Native, and Native Hawaiian/Other Pacific Islander. To ensure that racial/ethnic data were comparable to NCES CCD reported data, which tracks five mutually-exclusive racial/ethnic groups (i.e., White, Black, Hispanic, Asian, American Indian/Alaskan Native) we collapsed two of the six census racial/ethnic categories, Native Hawaiian and American Indian/Alaska Native, into a single category comparable to the NCES CCD's American Indian/Alaskan Native category.

We tested four different categorical student racial/ethnic comparisons for

configuration of neighborhood-level predictors. Three of the measures were dichotomous, predicting whether a student was White (vs. non-White), Black (vs. non-Black), or Hispanic (vs. non-Hispanic). In addition, we employed a single multinomial measure of student race/ethnicity capturing the five categories from the NCES CCD. Compared to the three dichotomous models, which predict whether a student is of a given racial/ethnic group or not, the multinomial model estimated the race/ethnicity of a student by selecting from all five possible racial categories. We also tested the prediction accuracy of a set of demographic and socioeconomic factors comparable to those used in Berkeley's geographic integration plan. Each of the neighborhood-level predictors was obtained from Census 2000 Summary File 3 block group-level data and is described in detail below.

Median Household Income. The median household income, in thousands, was obtained for each block group in the sample. Although Berkeley's model uses an ordinal measure of income categorizing neighborhood income into seven strata, we opted to employ a continuous measure of income which reports each household's actual income, rather than the range of incomes in which they fall. This change was necessary because Berkeley's seven income categories are computed from the distribution of household incomes within the Berkeley Unified School District. Berkeley is a relatively wealthy school district, with a median household income of approximately \$60,000. This is substantially higher than that of any of the districts in our sample (e.g., Chicago is the highest, with a median household income of \$51,000, while Miami has a median household income of only \$38,000). As such, categories premised on Berkeley's income distribution will not capture the variability in incomes in these districts. Moreover, because average household income varies considerably across the U.S., any categorical measure would be problematic in capturing income variability across national sample of districts. As such, we opted to use a generalizable, continuous measure of household income, capturing the actual median income of each block group.

Average Educational Attainment. Reflecting Berkeley's procedure for measuring average educational attainment, the adults in each block group were classified by their level of education reported on the Census, according to the following categories: (1) eighth grade or less, (2) some high school, (3) high school graduate, (4) some college, (5) college graduate, (6) masters/professional degree, or (7) doctorate degree. Individuals were assigned a value ranging from one to seven corresponding to their level of education, as enumerated above, and the average education values for each block group were computed.

Percentage of Students of Color. Consistent with Berkeley's model, we computed the percentage of "students of color" enrolled in public schools in each neighborhood. Following Berkeley's approach, students of color include those students with the following four racial/ethnic classifications: Black,

Hispanic, Asian, or American Indian/Alaska Native. Because Census data reports more than five racial/ethnic categories, we consolidated their categories to be consistent with categories used by Berkeley.

Berkeley's Diversity Factor. Approximating the diversity index used by Berkeley USD, we computed a diversity factor for each block, composed of the three neighborhood characteristics described above: median household income, average level of adult education, and the percentage of students of color. To weight each of the components equally, despite their different scales of measurement, a factor was created by converting each value to a z-score⁶⁷ (standardized at the district level), and averaging the z-scores for each block group.

Models

For each neighborhood-level demographic and socioeconomic predictor, we ran three binary logistic models using a dichotomous outcome predicting whether a student was White (vs. non-White), Black (vs. non-Black), or Hispanic (vs. non-Hispanic). We also ran a multinomial logistic model predicting five categories of student race/ethnicity (i.e., White, Black, Hispanic, Asian, other) as a function of each of the neighborhood predictors. For each outcome variable, we analyzed four models testing Berkeley USD's diversity factor as well as the three individual predictors that comprise the factor, to determine which neighborhood characteristics were the best predictors of student race/ethnicity. For each model, we found the predicted race/ethnicity of each student obtained by the logistic/multinomial regression. We then compared the predicted race/ethnicity of each student to their actual race/ethnicity to determine whether or not the prediction was accurate. The number of students in each block group that were accurately predicted was aggregated at the district level to determine the overall prediction accuracy of each district in the sample.

Results

Table 2 reports the estimated prediction accuracy of each of the four racial comparisons for each of the four geographic integration models by district. The first, second, and third panels of the table feature the accuracy with which each logistic model predicts whether a student is White (vs. non-White), Black (vs.

67. Converting raw scores to standardized z-scores allows for direct comparison of two variables that are on different scales. For example, median family income is measured in dollars, while "students of color" is measured as a percent. Because the scale of family income (\$4,000-\$200,000) is much larger than the scale of "students of color" (0%-100%), when averaged together, family income will have a much stronger effect on the final value than "students of color". Converting to z-scores prior to averaging, however, results in both variables being on the same scale. Z-scores can be interpreted as the number of standard deviations a given value is away from the average value.

non-Black), and Hispanic (vs. non-Hispanic). The fourth panel of the table features the accuracy with which each multinomial model predicts a student's race/ethnicity. The first, second and third column of each panel reports the prediction rates of the models using only median income, average education, and percent students of color, respectively. The fourth column of each panel features the prediction rates of the models containing the Berkeley USD's diversity factor, comprised of each of the three predictors. For each racial/ethnic comparison for each district, the model with the lowest prediction rate is non-shaded, while the model with the highest prediction rates is shaded.

Table 2

District Prediction Accuracy Rates by Racial Comparison by Geographic Integration Model

| District | White/Non-White | | | | Black/Non-Black | | | |
|-------------------------------------|-----------------|-----------|---------|-----------|-----------------|-----------|---------|-----------|
| | Income | Education | % Color | Diversity | Income | Education | % Color | Diversity |
| Los Angeles Unified School District | 0.90 | 0.90 | 0.91 | 0.91 | 0.88 | 0.88 | 0.88 | 0.88 |
| Broward County Public Schools | 0.66 | 0.67 | 0.75 | 0.70 | 0.74 | 0.76 | 0.83 | 0.81 |
| Miami-Dade County Public Schools | 0.84 | 0.84 | 0.86 | 0.85 | 0.70 | 0.68 | 0.80 | 0.69 |
| Chicago Public Schools | 0.88 | 0.88 | 0.91 | 0.90 | 0.67 | 0.57 | 0.76 | 0.60 |
| Detroit Public Schools | 0.92 | 0.92 | 0.96 | 0.92 | 0.86 | 0.86 | 0.91 | 0.86 |
| Clark County School District | 0.66 | 0.69 | 0.72 | 0.71 | 0.88 | 0.88 | 0.88 | 0.88 |
| New York Public Schools | 0.85 | 0.85 | 0.88 | 0.87 | 0.64 | 0.64 | 0.71 | 0.61 |
| The School District of Philadelphia | 0.80 | 0.80 | 0.90 | 0.86 | 0.64 | 0.62 | 0.81 | 0.73 |
| Dallas Independent School District | 0.89 | 0.89 | 0.92 | 0.90 | 0.69 | 0.62 | 0.66 | 0.66 |
| Houston Independent School District | 0.91 | 0.91 | 0.92 | 0.92 | 0.70 | 0.70 | 0.70 | 0.70 |
| Average | 0.83 | 0.83 | 0.87 | 0.85 | 0.74 | 0.72 | 0.79 | 0.74 |

| District | Hispanic/Non-Hispanic | | | | Student Race/Ethnicity (Multinomial) | | | |
|--|-----------------------|-------------|-------------|-------------|--------------------------------------|-------------|-------------|-------------|
| | Income | Education | % Color | Diversity | Income | Education | % Color | Diversity |
| Los Angeles Unified School District | 0.74 | 0.77 | 0.77 | 0.77 | 0.71 | 0.73 | 0.74 | 0.73 |
| Broward County Public Schools | 0.79 | 0.79 | 0.79 | 0.79 | 0.54 | 0.58 | 0.65 | 0.63 |
| Miami-Dade County Public Schools | 0.52 | 0.50 | 0.52 | 0.54 | 0.53 | 0.52 | 0.65 | 0.63 |
| Chicago Public Schools | 0.64 | 0.76 | 0.65 | 0.65 | 0.52 | 0.62 | 0.65 | 0.62 |
| Detroit Public Schools | 0.95 | 0.95 | 0.95 | 0.95 | 0.86 | 0.86 | 0.90 | 0.89 |
| Clark County School District | 0.70 | 0.73 | 0.74 | 0.74 | 0.57 | 0.61 | 0.62 | 0.62 |
| New York Public Schools | 0.61 | 0.68 | 0.63 | 0.66 | 0.41 | 0.47 | 0.54 | 0.51 |
| The School District of Philadelphia | 0.87 | 0.88 | 0.87 | 0.87 | 0.63 | 0.64 | 0.76 | 0.75 |
| Dallas Independent School District | 0.55 | 0.70 | 0.59 | 0.64 | 0.57 | 0.60 | 0.57 | 0.56 |
| Houston Independent School District | 0.63 | 0.70 | 0.62 | 0.66 | 0.58 | 0.63 | 0.60 | 0.60 |
| Average | 0.70 | 0.75 | 0.71 | 0.73 | 0.59 | 0.62 | 0.67 | 0.65 |
| <i>Note.</i> Each column reports the proportion of students whose race/ethnicity was correctly predicted by the model. | | | | | | | | |

Consistent with the logic underlying Berkeley's model, prediction rates suggest that, owing to the segregated nature of metropolitan residential patterns, block group-level demographic and socioeconomic characteristics are fairly accurate proxies for student race/ethnicity.

Comparison of the panels in Table 2 reveals that, not surprisingly, prediction accuracy was higher for the dichotomous models than the multinomial models. Thus, models were more accurate at predicting whether a student was White, Black, or Hispanic or not than they were at specifically predicting a student's race/ethnicity (average accuracy of 77 percent vs. 63 percent). The higher accuracy of the dichotomous models is attributable to their higher baseline probability of correctly predicting the race/ethnicity of a student in the binomial model than the multinomial model (1 in 2 vs. 1 in 5). Of the dichotomous models, on average, the neighborhood-level characteristics were better predictors of whether a student was White (average accuracy of 85 percent) than whether they were Black or Hispanic (average accuracy of 75 percent and 72 percent, respectively). Neighborhood-level characteristics were slightly better predictors of whether a student was Black than whether they were Hispanic.

Comparison of the columns in the fourth panel reveals that, in general, the percentage of students of color was the best predictor of student race/ethnicity. With the lone exception of Miami-Dade, median household income was the worst predictor of student race/ethnicity. The relatively poor prediction accuracy of household income is consistent with recent research demonstrating the imperfect association between socioeconomic status and race/ethnicity.⁶⁸

68. See generally Sean F. Reardon, et al., *Implications of Income-Based School Assignment Policies for Racial School Segregation*, 28 *Educ. Eval. and Pol'y Analysis* 67 (2006)

Average education performed substantially worse than the percentage of students of color, but better than income, in predicting student race/ethnicity. Berkeley's diversity factor comprised of all three indicators performed better than both income and education, but worse than the percentage of students of color alone.

Examination of the first two panels, featuring the accuracy of predicting whether a student is White or Black, reveals patterns similar to the multinomial models. For both racial dichotomies, the percentage of students of color was generally the best predictor of whether or not a student was White or Black. Although rates of prediction were fairly comparable for income and education models for both dichotomies, income was the worst predictor of whether a student was White, while education was the worst predictor of whether a student was Black. For both White/non-White and Black/non-Black comparisons, the diversity factor performed better than income and education, but worse than the percentage of students of color alone.

The third panel reveals a somewhat different pattern of results for the Hispanic/non-Hispanic comparison. As with the other racial/ethnic comparisons, median income was the worst predictor of whether a student was Hispanic. Unlike the other racial comparisons, the percentage of students of color was a relatively poor predictor of whether a student was Hispanic or not. Rather, neighborhood average education level was the strongest predictor of whether a student was Hispanic. Berkeley's diversity factor performed better than income and percentage of students of color, but worse than education.

Comparison of the rows in Table 2 reveals that prediction rates would vary substantially by district context. Although the sample is not large enough to permit inferences about how prediction rates vary by context or to generalize to other districts, it is clear that such models will perform better in some districts than others. Prediction rates were highest overall in Detroit (average accuracy of 91 percent across all models) and lowest in New York (average accuracy of 66 percent across all models). Again, although the size of the sample is too small to generate sufficient power to detect a significant effect, prediction accuracy seems to be positively associated with the degree of multiracial segregation between block groups in a district ($r = 0.398$; see Table 3 for district segregation values, computed per Iceland⁶⁹) and negatively associated with the amount of diversity within each block group ($r = -0.437$). Put simply, as block groups become more racially/ethnically homogenous, prediction accuracy improves.

(noting that plans that achieve socioeconomic integration cannot guarantee even modest decreases in racial/ethnic segregation).

69. John Iceland, *The Multigroup Entropy Index (Also Known as Theil's H or the Information Theory Index)*, U.S. Census Bureau (2004), http://www.census.gov/hhes/www/housing/housing_patterns/pdf/unit_of_analysis.pdf.

Table 3
Block Group/Neighborhood Characteristics by Districts

| District | Block Group Segregation ¹ | Block Group Diversity ² | |
|-------------------------------------|--------------------------------------|------------------------------------|-----------------|
| | | Mean | SD ³ |
| Los Angeles Unified School District | .44 | .29 | .26 |
| Broward County Public Schools | .30 | .44 | .25 |
| Miami-Dade County Public Schools | .23 | .35 | .25 |
| Chicago Public Schools | .54 | .22 | .27 |
| Detroit Public Schools | .59 | .13 | .21 |
| Clark County School District | .26 | .48 | .22 |
| New York Public Schools | .55 | .28 | .27 |
| The School District of Philadelphia | .61 | .21 | .27 |
| Dallas Independent School District | .47 | .23 | .25 |
| Houston Independent School District | .48 | .23 | .24 |
| Total/Average | .45 | .27 | .27 |

¹ Block group segregation represents the degree of racial/ethnic segregation between block groups in a district. Values of multiracial segregation range from 0 to 1, where a 0 indicates that all block groups have the same racial composition as the district in which they are located. A value of 1 indicates that each block group within a district contains a single racial/ethnic group.

² Block group diversity represents the average level of racial/ethnic heterogeneity within a district. The diversity score, which ranges from 0 to 1, can be interpreted as the probability that two students, living within the same block group are of different racial/ethnic groups.

³ The column labeled "SD" reports the standard deviation for the average block group diversity of a given district.

Taken together, these findings suggest that neighborhood characteristics are fairly strong predictors of student race/ethnicity, although these effects vary by the racial comparison being conducted, by the type of neighborhood predictor, and by district context. Overall, prediction rates were highest for dichotomous racial categories, and highest for predicting whether or not a student was White. The percentage of neighborhood students of color was the best predictor of student race/ethnicity, while median income was the worst predictor. Berkeley's composite diversity index, while never the best predictor of race/ethnicity, generally performed marginally better than socioeconomic indicators alone. Data are also consistent with the assumption that neighborhood characteristics predict student race/ethnicity better in more segregated districts with less diverse neighborhoods.

B. DO GEOGRAPHIC INTEGRATION PLANS HAVE THE POTENTIAL TO INCREASE SCHOOL DIVERSITY?

To provide a more direct test of whether geographic integration plans would be effective in achieving integration in practice (Research Question 2), we conducted a simulation of the effects of a student assignment procedure based on neighborhood characteristics on measures of school diversity. These simulated diversity scores were compared to measures of current school diversity as reported in the NCES CCD to determine the expected change in diversity that would be expected under a geographic integration plan premised on each of the four types of demographic and socioeconomic predictors tested above.

Method

We conducted a student assignment simulation on a random sample of 20 schools from Dallas Independent School District (ISD). Dallas was selected because it was fairly typical among the sample districts in terms of its level of segregation and block group diversity. Table 3 indicates that, with a segregation value of 0.47, Dallas is fairly close to the average segregation level of all districts in the sample 0.45. Likewise, the average diversity of block groups in Dallas is 0.23, while the average diversity of block groups in all districts in the sample is 0.27. The random sample consists of 10 elementary schools, 5 middle schools, and 5 high schools, which roughly approximates the proportions of schools of those levels in the district as a whole. Table 4 reports the demographic characteristics of the sample. Overall, the sample of schools displays a wide range of racial/ethnic compositions. For example, the percentage of Black students in the schools sampled varies from 1 percent in one elementary school to 96 percent in another; the percentage Hispanic students varies from 1 percent to 99 percent; and the percentage White students varies from 0 percent to 20 percent. This allows for a test of the proposed geographic integration plan across a variety of school contexts.

Table 4
Dallas ISD School Demographic Characteristics

| | Enrollment | % Asian | % Black | % Hispanic | % White | % Other |
|---------------------------|--------------|-----------|------------|------------|------------|--------------|
| Elementary Schools | | | | | | |
| ES-1 | 247 | 0% | 75% | 20% | 5% | 0% |
| ES-2 | 374 | 0% | 96% | 1% | 2% | 0% |
| ES-3 | 519 | 0% | 22% | 78% | 0% | 0% |
| ES-4 | 588 | 0% | 71% | 17% | 11% | 1% |
| ES-5 | 323 | 1% | 93% | 4% | 3% | 0% |
| ES-6 | 727 | 1% | 94% | 5% | 0% | 0% |
| ES-7 | 164 | 0% | 1% | 99% | 0% | 0% |
| ES-8 | 543 | 1% | 47% | 50% | 2% | 0% |
| ES-9 | 1,098 | 1% | 42% | 36% | 20% | 1% |
| ES-10 | 829 | 2% | 42% | 38% | 17% | 1% |
| <i>Average</i> | <i>541</i> | <i>1%</i> | <i>58%</i> | <i>35%</i> | <i>6%</i> | <i>0%</i> |
| Middle Schools | | | | | | |
| MS-1 | 497 | 0% | 18% | 11% | 71% | 1% |
| MS-2 | 976 | 4% | 43% | 41% | 12% | 1% |
| MS-3 | 822 | 5% | 41% | 32% | 22% | 1% |
| MS-4 | 990 | 0% | 12% | 87% | 1% | 0% |
| MS-5 | 181 | 3% | 41% | 34% | 20% | 1% |
| <i>Average</i> | <i>693</i> | <i>2%</i> | <i>31%</i> | <i>41%</i> | <i>25%</i> | <i>1%</i> |
| High Schools | | | | | | |
| HS-1 | 1,254 | 1% | 92% | 4% | 2% | 1% |
| HS-2 | 542 | 3% | 38% | 52% | 7% | 1% |
| HS-3 | 1,484 | 2% | 41% | 32% | 24% | 1% |
| HS-4 | 1,509 | 2% | 86% | 10% | 3% | 0% |
| HS-5 | 1,574 | 0% | 42% | 52% | 6% | 0% |
| <i>Average</i> | <i>1,273</i> | <i>2%</i> | <i>60%</i> | <i>30%</i> | <i>8%</i> | <i>1%</i> |
| Sample Average | 731 | 1% | 53% | 34% | 11% | 0.01% |

Analytic Technique

First, the target profile of each school was determined for each neighborhood-level predictor used in this analysis. Specifically, each block group was assigned a numeric code, ranging from 1 to 5, corresponding to its quintile on each of the 4 predictor variables described above. For example, if a

block group had a median household income of \$35,000 and was at the 37th percentile of household income among the block groups in Dallas, the block group would be assigned a diversity code of “2”. Block groups were assigned to quintile categories because this method is faithful to Berkeley’s procedure and because it simplifies the computational requirements of the simulated assignment plan. Once all the block group codes had been assigned, we computed the overall percentage of students that were in each percentile. For example, in Dallas, 25 percent of students reside in block groups within the first income quintile, while 28 percent, 26 percent, 15 percent, and 6 percent reside in block groups in the second, third, fourth, and fifth income quintiles, respectively.

To ensure that each school has the potential to reflect the overall level of diversity of the district, Berkeley’s model splits the district into three attendance zones. Each zone contains four to five elementary schools from which parents may choose (with some overlap across attendance zones). Each attendance zone is drawn such that it roughly mirrors the overall diversity of the district. While this approach is appealing, inasmuch as it retains a more traditional attendance zone model coupled with parental choice, it would be difficult to model in a national context, as zones would be drawn differently based on the unique demographic patterns of each district. In addition, because Berkeley’s model allows parents to choose their schools, it has the potential to permit stratification across schools within attendance zones, depending upon parental preferences. It would be difficult to estimate the expected level of diversity under such a plan, especially given a lack of data on parental preferences. Because of these shortcomings, we elected to design a more generalizable geographic integration model using a proximity-based algorithm instead of choice-based algorithm.

Under our model, to ensure that each school reflects the maximum possible diversity of the district at the block group level (since student-level information is not relevant to student assignment), a student assignment algorithm was designed to approximate the level of district diversity at each school while still maximizing student proximity to school of attendance. While approximating district diversity for any given school might not result in the maximum diversity achievable at that school, it will on average maximize diversity across the district’s schools.

We conducted four simulations on each school, using the four geographic integration models above (i.e., median income, average education, percentage of students of color and the diversity factor). Thus, each block group was assigned four different quintile codes based on their standing on each of the predictors, and a separate district profile was created for each predictor.

C. Part I Models: Student Assignment Simulation

For each school, we computed the target number of students in each quintile. For example, if a school in Dallas has 1,509 students, based on the median income quintiles above, to ensure that its diversity approaches that of the district as a whole it should have 383 slots for students in the first quintile, 420 slots for students in the second quintile, 385 slots for students in the third quintile, 229 slots for students in the fourth quintile and 94 slots for students in the fifth quintile.

To fill these slots, we first assigned all students in the nearest block group (of that school's level) that was categorized as a "1" (1st quintile) to the school. Proximity was determined as the Euclidean, or linear, distance between the geographic center of each block group and each school (calculated in ArcGIS). If there were still slots remaining for students in the first quintile after assigning the first block group, we assigned the students from the next nearest block group, and so forth, until all slots were filled. If adding the students from an additional block group would result in the number being closer to the target number (whether above or below), all students from that block group would be assigned to that school. Thus, if a high school has 50 slots remaining, and a block group has 75 high school students, all 75 students would still be assigned to that school because this would result in a smaller absolute deviation from the target number (+25) than already exists (-50). However, if a school has 50 slots remaining and a block group has 125 students, the students in that block group would not be assigned to that school because this would result in a greater absolute deviation from the target number (+75) than already exists (-50).

This procedure was repeated to fill the slots for each quintile. Then, using the actual student racial characteristics of each block group (from Census data), we calculated what the racial diversity of the school would be. We conducted this procedure for all schools in the sample, proceeding from lowest diversity to highest diversity, ensuring that no block group was assigned to more than one school.

School Diversity

Current and predicted school diversity was calculated using student racial/ethnic data from the 1999-2000 NCES CCD and simulation data from the Census described above. For each school, we computed diversity of using Simpson's diversity index, as follows:⁷⁰

$$D = 1 - \sum_{i=1}^F R_i^2$$

Where r is the number of racial ethnic groups in a population and p refers to a particular racial/ethnic group's proportion of the school population. Because the NCES CCD classifies students according to five racial/ethnic groups (i.e., White, Black, Hispanic, Asian, and American Indian/Pacific Islander), r was five for our analyses. Simpson's diversity index may be interpreted as the probability that two students at a given school or district belong to different racial/ethnic categories. Accordingly, 0 means that all students belong to the same racial/ethnic group (i.e., perfect homogeneity) and 1 means that all students belong to different racial/ethnic groups (i.e., perfect heterogeneity).

Results

Findings of the analysis, disaggregated by school level and geographic integration model type, are presented in Table 5. Column 1 lists the actual diversity values of the sample schools. The first sub-column of columns 2 through 5 reports the predicted school diversity under geographic integration models using income only, education only, the percentage of students of color only, and Berkeley's diversity factor. The second sub-column features the predicted change in diversity expected under each geographic integration model. Diversity values highlighted in gray represent decreases in the average level of school diversity in that district.

Table 5
Predicted and Actual Diversity of Schools for Each Geographic Model

| | Income | | | Education | | Race/Ethnicity | | BUSD Diversity | |
|---------------------------|--------------|--------------|-------------------|--------------|--------------|----------------|--------------|----------------|--------------|
| | Actual | Predicted | Difference (Diff) | Predicted | Diff. | Predicted | Diff. | Predicted | Diff. |
| Elementary Schools | | | | | | | | | |
| ES-1 | 0.070 | 0.552 | 0.482 | 0.269 | 0.199 | 0.525 | 0.455 | 0.285 | 0.215 |
| ES-2 | 0.450 | 0.592 | 0.142 | 0.634 | 0.184 | 0.574 | 0.124 | 0.506 | 0.056 |
| ES-3 | 0.130 | 0.181 | 0.051 | 0.213 | 0.083 | 0.302 | 0.172 | 0.190 | 0.060 |
| ES-4 | 0.020 | 0.352 | 0.332 | 0.219 | 0.199 | 0.338 | 0.318 | 0.443 | 0.423 |
| ES-5 | 0.350 | 0.386 | 0.036 | 0.499 | 0.149 | 0.539 | 0.189 | 0.282 | -0.068 |
| ES-6 | 0.660 | 0.616 | -0.044 | 0.622 | -0.038 | 0.618 | -0.042 | 0.642 | -0.018 |
| ES-7 | 0.400 | 0.617 | 0.217 | 0.484 | 0.084 | 0.586 | 0.186 | 0.530 | 0.130 |
| ES-8 | 0.110 | 0.223 | 0.113 | 0.223 | 0.113 | 0.391 | 0.281 | 0.440 | 0.330 |
| ES-9 | 0.530 | 0.574 | 0.044 | 0.483 | -0.047 | 0.580 | 0.050 | 0.545 | 0.015 |
| ES-10 | 0.650 | 0.675 | 0.025 | 0.577 | -0.073 | 0.609 | -0.041 | 0.579 | -0.071 |
| <i>Average</i> | <i>0.337</i> | <i>0.477</i> | <i>0.140</i> | <i>0.422</i> | <i>0.085</i> | <i>0.506</i> | <i>0.169</i> | <i>0.444</i> | <i>0.107</i> |
| Middle Schools | | | | | | | | | |
| MS-1 | 0.630 | 0.651 | 0.021 | 0.618 | -0.012 | 0.624 | -0.006 | 0.612 | -0.018 |
| MS-2 | 0.670 | 0.541 | -0.129 | 0.587 | -0.083 | 0.602 | -0.068 | 0.562 | -0.108 |
| MS-3 | 0.460 | 0.650 | 0.190 | 0.645 | 0.185 | 0.632 | 0.172 | 0.644 | 0.184 |
| MS-4 | 0.680 | 0.676 | -0.004 | 0.596 | -0.084 | 0.581 | -0.099 | 0.600 | -0.080 |
| MS-5 | 0.230 | 0.416 | 0.186 | 0.451 | 0.221 | 0.570 | 0.340 | 0.426 | 0.196 |
| <i>Average</i> | <i>0.534</i> | <i>0.587</i> | <i>0.053</i> | <i>0.579</i> | <i>0.045</i> | <i>0.602</i> | <i>0.068</i> | <i>0.569</i> | <i>0.035</i> |
| High Schools | | | | | | | | | |
| HS-1 | 0.140 | 0.332 | 0.192 | 0.539 | 0.399 | 0.328 | 0.188 | 0.493 | 0.353 |
| HS-2 | 0.560 | 0.582 | 0.022 | 0.625 | 0.065 | 0.605 | 0.045 | 0.631 | 0.071 |
| HS-3 | 0.580 | 0.570 | -0.010 | 0.553 | -0.027 | 0.630 | 0.050 | 0.621 | 0.041 |
| HS-4 | 0.670 | 0.284 | -0.386 | 0.492 | -0.178 | 0.405 | -0.265 | 0.469 | -0.201 |
| HS-5 | 0.250 | 0.389 | 0.139 | 0.462 | 0.212 | 0.396 | 0.146 | 0.462 | 0.212 |
| <i>Average</i> | <i>0.440</i> | <i>0.431</i> | <i>-0.009</i> | <i>0.534</i> | <i>0.094</i> | <i>0.473</i> | <i>0.033</i> | <i>0.535</i> | <i>0.095</i> |
| District Average | 0.412 | 0.493 | 0.081 | 0.490 | 0.078 | 0.522 | 0.110 | 0.498 | 0.086 |

Examination of the second sub-columns reveals that the majority of schools in the study sample would experience gains in diversity under all four of the geographic integration models tested, if the models were implemented

according to the proximity-weighted student assignment procedure outlined above. Fifteen of the 20 schools in the sample (75 percent) would experience gains in diversity under an income-only geographic integration plan. Twelve schools (60 percent) would experience gains in diversity under an education-only geographic integration model. Fourteen schools (70 percent) would experience gains in diversity under a geographic integration plan using only the neighborhood's percentage of students of color. Fourteen schools (70 percent) would experience gains in diversity using a geographic integration approach premised on Berkeley's composite diversity factor.

Although *more* schools in the sample would experience gains in diversity under the income-only geographic integration model than under any other model, it is important to note that, consistent with the findings from the first analysis, the schools would experience the *largest* gains in diversity under the race-only model. Specifically, an integration approach using only the percentage of students of color in a neighborhood would result in an 11 percentage-point increase in the probability that two students at a given school belong to different racial/ethnic groups. Integration approaches using median income and average educational attainment alone would be slightly less effective in achieving integration objectives, resulting in 8.1 and 7.8 percentage-point increases in diversity, respectively. Finally, Berkeley's diversity factor would fare better than the income- and education-only models, but worse than aggregate race alone, resulting in an 8.6 percentage-point increase in diversity.

Table 5 also reveals systematic differences in the expected changes in diversity by school level. Across all geographic integration models tested, elementary schools would experience the largest gains in diversity (13 percent), while middle and high schools would generally experience smaller gains (both 5 percent). Because elementary schools tend to be smaller than middle and high schools, this finding may be related to systematic differences in school size, which is negatively related to the predicted change in diversity across all models. Indeed, correlations between school size and the expected change in diversity under each integration model reveal that larger schools would experience smaller increases in diversity than small schools (i.e., $r = -0.502$ for income, $r = -0.279$ for education, $r = -0.554$ for percent students of color, $r = -0.192$ for Berkeley's diversity factor).

Not surprisingly, results suggest that schools that already have high rates of school diversity would likely fare worse under geographic integration plans than schools with low diversity. Indeed, rates of actual diversity were highly negatively correlated with the predicted change in diversity across all models. Reflecting the pattern of results for prediction accuracy and predicted change in diversity, correlations between change in diversity and actual diversity were highest for the geographic integration model using the percentage of neighborhood students of color ($r = -0.881$, $p < .01$) and lowest for income ($r =$

-0.734, $p < .01$) and education ($r = -0.795$, $p < .01$). The correlation between actual diversity and change in diversity using Berkeley's diversity factor was higher than the socioeconomic predictor models, but lower than the aggregate race alone model ($r = -0.840$, $p < .01$).

Overall, results of the simulation of each of the proximity-weighted geographic student assignment plans suggest that schools in the sample would, on average, experience a moderate 8 to 11 percent increase in diversity under such plans. Gains would be largest for elementary schools and small schools across all models. Consistent with the pattern of results for the prediction accuracy of each geographic integration model, schools would experience the largest increases in diversity under a model using only the percentage of neighborhood students of color and the smallest increases in diversity using neighborhood median income and average education. Berkeley's composite diversity factor would be more effective at increasing school diversity than each of the socioeconomic predictor models, but worse than using aggregate race alone.

II. SUMMARY OF FINDINGS

In this study we provide an initial empirical test of Berkeley-style geographic integration plans in the nation's 10 largest metropolitan school districts, investigating whether such models have the potential to help districts wishing to integrate their schools in the wake of the *Parents Involved* decision.⁷¹ We find encouraging evidence that districts could make meaningful progress towards their equity objectives via geographic integration plans. Specifically, our analyses reveal that neighborhood-level demographic and socioeconomic characteristics are relatively accurate predictors of student race/ethnicity. Even more compelling, using a simulation assigning students to school on the basis of neighborhood characteristics in a single school district, we find that geographic integration plans hold the potential to modestly increase diversity in schools. Our findings indicate that geographic integration plans would be especially effective at integrating elementary schools, small schools, and schools in relatively more segregated districts with less diverse neighborhoods.

Regarding the specific design elements of such a plan, we find that, not surprisingly, a model assigning students to schools solely on the basis of the percentage of students in their block group who are non-White (i.e., using aggregate race alone) would be most effective at achieving gains in racial/ethnic diversity across schools. Contrastively, models using only neighborhood-level socioeconomic predictors, including median household income and average educational attainment, would perform worse than the race-based models. A composite model, similar to that used by Berkeley, employing a diversity factor weighting demographic and socioeconomic characteristics, would perform worse than a race-alone model, but better than the socioeconomic models.

71. See *Parents Involved*, 551 U.S. at 701.

III. STUDY LIMITATIONS

A number of limitations to the study should be acknowledged. First, it should be emphasized that the findings above represent mean effects, or effects from a simulation on a single district, and the actual effectiveness of geographic integration plans would likely vary significantly across district contexts. While some districts may experience large increases in diversity, other districts may experience small benefits. Further, districts that are already very integrated may even experience reductions in diversity. Because the study sample was limited to large metropolitan districts, it is possible that such plans would be less effective in less populous districts. Additionally, the finding that geographic integration plans would be most effective in more diverse districts, and relatively ineffective in homogeneous districts, underscores the limitations of intra-district approaches to achieving integration. Without access to potential sources of diversity in neighboring districts, integration may be unfeasible for many of the nation's school districts based on their current boundaries.

Second, the simulation algorithm used in this analysis is an essentialized geographic integration model designed to assess the maximum possible increment in diversity while minimizing the distance between students and schools. We certainly would not expect districts to assign students to schools using this exact algorithm, as it does not account for numerous other factors that districts may wish to consider in designing attendance plans, such as socioeconomic balance, transportation costs, attendance zone contiguity, and parental choice. Rather, this parsimonious model is intended to provide a best-case scenario for the impact of geographic integration plans on integration by student race/ethnicity. Assigning students to schools by block group using this algorithm may not always be feasible. However, districts may choose to use block group diversity indices to assist in drawing attendance zones that will likely facilitate equity, as Berkeley has done (e.g., zones maximize heterogeneity of neighborhood diversity).

Third, although our results provide encouraging preliminary evidence that geographic integration plans such as Berkeley's hold the potential to increase school diversity, they should be interpreted with caution, as they are based on a relatively small sample of school districts and may not generalize to all contexts. As such, additional research is necessary to enhance the timeliness and generalizability of the study's findings and to refine the particular design elements of such a plan. Future research should validate the findings of the study on a larger, more representative sample of districts, and examine variation by district population and the level of segregation. In addition, because our analyses were conducted on Census 2000 data (at the time of writing, Summary File 1 has not yet been released for Census 2010), future

research could examine how demographic shifts over the past decade would change the landscape in which geographic integration plans would operate. Moreover, this study operationalized neighborhoods as Census block groups. Further research could utilize alternative definitions of neighborhood (e.g., Census tract and block) to investigate how the effectiveness of geographic integration plans vary by the scale at which neighborhood is measured. Finally, the current analyses were limited to the predictors used in Berkeley's model. Future research could incorporate additional neighborhood-level predictors (e.g., housing value, children living below the poverty threshold, and language spoken at home) to assist districts in refining their models and tailoring geographic integration plan to their specific needs.

Finally, the model tested in this study assesses the effects of Berkeley's integration model exclusively on racial/ethnic diversity, and does not assess the effect that models would have on socioeconomic diversity or other measures of diversity that may be of value to school districts. For example, the espoused goal of Berkeley's model is to couple racial integration with attention to other factors, such as the economic and educational background of the districts residents. However, owing to limitations in the Census data, which do not permit a two-way disaggregation of student counts by race/ethnicity and socioeconomic status, it is not possible to simultaneously assess the effects of geographic integration plans on racial/ethnic and socioeconomic diversity. As such, while the race-alone model would clearly be more effective in achieving racial/ethnic integration, the model may underestimate the effects of models containing income and education predictors on socioeconomic integration.

CONCLUSION

The vacuum left by the *Parents Involved* and *Meredith* decisions have invalidated many school districts' integration policies, leaving many school districts looking for new, legal ways to integrate students voluntarily. By using neighborhood diversity in determining student assignment, Berkeley's integration plan presents a legally viable alternative to plans considering individual student race/ethnicity that avoids the problem of using individual student race/ethnicity that was invalidated in *Parents Involved* and which has withstood legal challenge in *American Civil Rights Foundation*. Moreover, this study finds that in addition to being legally valid, such plans would likely be effective in achieving meaningful increases in racial/ethnic diversity.

This study, which tested both a multifactorial model such as that used by Berkeley as well as single predictor models using race alone, socioeconomic status alone, and parent education alone, finds that single predictor models may be more effective and parsimonious than multifactorial "diversity models. In particular, a model using only aggregate race would perform better than a multifactorial diversity factor. Indeed, the addition of predictors beyond race

will necessarily reduce prediction rate. Because such models still do not use individual student race (i.e., a black student and a white student in a given area would still be treated equally), such a single-predictor model would likely still be upheld under *Parents Involved*.⁷² It is important to note, however, such plans may be less politically feasible than plans using multiple indicators, considering the current climate favors more holistic approaches to diversity and integration than race alone. In particular, socioeconomic integration has received considerable attention in recent years, with many districts incorporating socioeconomic factors into their existing models or replacing their traditional race-based plans with plans that consider only economic factors.⁷³

72. See *Parents Involved*, 551 U.S. at 701.

73. RICHARD D. KAHLBERG, *RESCUING BROWN V. BOARD OF EDUCATION: PROFILES OF TWELVE SCHOOL DISTRICTS PURSUING SOCIOECONOMIC SCHOOL INTEGRATION* (The Century Foundation 2007).