Abstract Title Page

Not included in page count.

Title: The Impact of School Improvement Grants on Achievement: Plans for a National Evaluation Using a Regression Discontinuity Design

Authors and Affiliations:
John Deke and Lisa Dragoset from Mathematica Policy Research

Funding from the U.S. Department of Education (ED) Institute of Education Sciences (IES) is gratefully acknowledged. Many thanks to Tom Wei, the project officer for the large scale evaluation of School Improvement Grants under which this research is being conducted. All errors are our own.

Abstract Body

Limit 4 pages single-spaced.

Background / Context:

Description of prior research and its intellectual context.

The School Improvement Grants (SIG) program received over $3 billion through the American Recovery and Reinvestment Act of 2009. Through grants to states, SIG focuses on turning around the nation's persistently lowest-achieving schools using one of four school intervention models, with the aim of substantially improving student achievement. Consistent with the conference theme, SIG is designed to create sustained achievements over time. Rigorous evidence of the impact of this program on student outcomes has been limited to a study by Dee (2012) that focused on a single state (California). Dee used school-level data, an approach that conflates impacts on student achievement with impacts on student mobility. That is, the positive impacts found by Dee could be because SIG schools are more effective at educating children or because SIG schools simply attracted higher-achieving students.

Purpose / Objective / Research Question / Focus of Study:

Description of the focus of the research.

Does receipt of SIG funding to implement a school intervention model have an impact on outcomes for low-performing schools? We will answer this question using a regression discontinuity design (RDD) that exploits cutoff values on the continuous variables used to define SIG eligibility tiers, comparing outcomes in schools that just met the eligibility criteria to outcomes in schools that just missed the eligibility cutoff (while controlling for the variable used to determine tier assignment). Using student-level data, we will assess whether SIG affected student mobility and will calculate "mobility-robust" impacts using students slated to attend study schools in the implementation year based on the school they attended the prior year. In essence, we will use the school attended the prior year as an "instrument" for school attendance during the implementation year. This approach yields impacts on student achievement that are not conflated with impacts on student mobility. For comparison, we will also calculate "place-based" impacts using students who attended study schools in the implementation year.

Setting:

Description of the research location.
(May not be applicable for Methods submissions)

Low-performing schools in 21 states and the District of Columbia (DC).

Population / Participants / Subjects:

Description of the participants in the study: who, how many, key features, or characteristics.
(May not be applicable for Methods submissions)

We will focus on the effect of SIG awards made in 2010, when over $3 billion in awards were made to all 50 states and DC. Our sample was purposively selected to (1) include only those schools that can contribute to a valid RDD and (2) maximize the precision of impacts. The sample includes 1,100 low-performing schools in about 60 districts in 21 states and DC. Using estimates of fuzziness and sample size based on information gathered through a review of states'

SIG application materials and conversations with state administrative staff, we calculated the minimum detectable effect size (MDES) corresponding to every opportunity to estimate an RDD impact in every state. We then ranked those opportunities and prioritized states and districts corresponding to the opportunities with lower MDES values.

The characteristics of states in our sample do not differ significantly from states nationwide (insert Table 1 here). The districts in our sample differ from all districts in which SIG schools are located on students' race and school location. Our sample districts have a higher percentage of non-Hispanic black students and are more likely to be in an urban area.

Intervention / Program / Practice:
Description of the intervention, program, or practice, including details of administration and duration.
(May not be applicable for Methods submissions)

The treatment is defined as receiving SIG funds for implementing one of four school intervention models. States categorized low-performing schools into three eligibility tiers defined by ED. ED required each SIG-awarded school in Tier I or II to implement one of four school intervention models over the course of three school years (starting in 2010–2011). Each model prescribed specific practices (insert Exhibit 1 here). Schools in Tier III were permitted but not required to implement a model. Table 2 shows award amounts and the distribution of SIG grantees across tiers and models (insert Table 2 here).

Significance / Novelty of study:
Description of what is missing in previous work and the contribution the study makes.

To our knowledge, this is the first large-scale RDD that tackles a host of methodological issues simultaneously (including multiple sites, multiple assignment variables, fuzziness, clustering of individuals within schools, and standard errors that take into account the bandwidth selection method). Although many of these issues are not new to the field, this study is the first to face them all at once. Because our analysis methods are based on simulation work and consultation with RDD experts, we think other education researchers will benefit from learning about them.

Statistical, Measurement, or Econometric Model:
Description of the proposed new methods or novel applications of existing methods.

We will use an RDD to estimate the impact of SIG-funded intervention models on student outcomes, taking advantage of RDD opportunities created by ED rules about the prioritization of SIG funds, which use cutoffs on continuous school-level variables such as achievement and graduation rates. The definitions of SIG eligibility tiers are in Table 3 and the opportunities they create to estimate RDD impacts are in Table 4 (insert Tables 3 and 4 here). Schools in Tiers I and II form the treatment group; schools in Tier III and ineligible schools form the comparison group. Our analytic approach has the following features:

Local linear impact estimation. We will estimate impacts within a bandwidth around the cutoff value, adjusting for the assignment variable (i.e., the variable used to assign schools to the intervention) using a linear functional form. The coefficient on the assignment variable will be estimated separately above and below the cutoff.

Bandwidth selection based on the Imbens & Kalyanaraman (2012) (IK) method. We will use the IK bandwidth selection method to estimate a single study-wide bandwidth. We will first standardize the outcome and assignment variables from each grade and RDD opportunity. Outcome variables will be centered at their means and assignment variables will be centered at their cutoff values. Both will be divided by their standard deviations. The standardized variables will be pooled. The IK method will be applied to the pooled data. Impacts will be estimated separately in each grade within the IK bandwidth that was selected using pooled data. We chose this method based on its performance relative to alternatives in simulations. First, we selected the IK method relative to cross-validation (Ludwig & Miller, 2007) because, in simulations, it produced estimated impacts with less bias (insert Table 5 here). Second, our simulations suggested that calculating an IK bandwidth using pooled data (which we call "study-wide IK") yielded smaller standard errors than either (1) applying the IK method to each grade and RDD opportunity separately (which we call "local IK") or (2) modifying the IK method so that sample sizes and densities are estimated locally while derivatives and conditional variances are estimated using pooled data (a method suggested by Imbens which we call "hybrid IK") (insert Table 7 here).

Both single and multiple assignment variable RDD. Some grades have a single assignment variable (either average achievement or graduation rate) and others have two assignment variables (both average achievement and graduation rate). For grades with two assignment variables we will calculate impacts using both the "Frontier" and "Fuzzy Frontier" methods (Reardon and Robinson, 2010). When calculating the weighted average of the impacts from the two assignment variables, we will adjust the standard errors to account for overlap of schools across the two impact estimates.

Aggregation of impacts across grades. For each outcome measure, we will estimate impacts separately for each grade so that the relationship between the assignment variable and outcome is modeled separately across grades. We will then calculate an aggregate impact that is a sample size weighted average of the grade-specific impacts, where the sample size is the number of students in study schools within the bandwidth. In calculating the weighted average of these impacts and the corresponding standard errors, we will account for impact covariance due to the overlapping samples between impacts.

Covariates. We will include pre-intervention test scores and an indicator of eligibility for free or reduced-price lunch as covariates to increase precision. We will include site (i.e., state) dummies to control for variation across sites in the relationship between the assignment variable and the outcome.

Bootstrapped standard errors. We will estimate standard errors through residual bootstrapping to account for clustering of students within unique values of the assignment variable (Lee and Card 2008), fuzziness (described below), correlations among grade impacts due to overlapping samples (for example, schools that meet the requirement for inclusion in more than one eligibility tier), and variance introduced by the bandwidth selection method.

Fuzzy RDD impacts. This study is a "fuzzy" RDD, meaning that not all schools below the cutoff implemented a SIG-funded intervention model, and some schools above the cutoff did. We will calculate the impact of SIG-funded intervention models on outcomes by estimating the local average treatment effect (LATE). The LATE equals the RDD impact on the outcome divided by the RDD impact on the proportion of schools implementing a SIG-funded intervention model.

Usefulness / Applicability of Method:
Demonstration of the usefulness of the proposed methods using hypothetical or real data.

We conducted Monte Carlo simulations to show that the analytic approach described above yields unbiased and efficient impact estimates, and to compare the performance of the various bandwidth selection methods described above. The process used to generate simulated data mimics study data observed from the year before SIG had an opportunity to affect outcomes. Thus, the simulations were conducted under the null hypothesis of no true impact, using a data generating process (DGP) that mimics the relationships between outcomes and assignment variables observed in our actual data.

Research Design:
Description of the research design.
(May not be applicable for Methods submissions)

See the "Statistical, Measurement, or Econometric Model" section.

Data Collection and Analysis:
Description of the methods for collecting and analyzing data.
(May not be applicable for Methods submissions)

Assignment variable values for each school were collected from states. Outcomes—student standardized test scores on state assessments, high school graduation, and college enrollment (a longer-term outcome consistent with the conference theme)—were collected from student-level administrative data maintained by states and districts. We will examine each outcome for the 2010–2011, 2011–2012, and 2012–2013 school years. Our "mobility-robust" method described above calculates impacts based on following students over time, including any transitions they make from one school level to the next (e.g., elementary to secondary).

Findings / Results:
Description of the main findings with specific details.
(May not be applicable for Methods submissions)

Not applicable. Findings will be presented in a future IES report.

Conclusions:
Description of conclusions, recommendations, and limitations based on findings.

Not applicable. Conclusions will be presented in a future IES report.

Appendices

Not included in page count.

Appendix A. References

References are to be in APA version 6 format.

Dee, T. (2012, April). *School turnarounds: Evidence from the 2009 stimulus.* Working paper 17990. Cambridge, MA: National Bureau of Economic Research. Retrieved from: http://www.nber.org/papers/w17990 on February 13, 2013.

Hurlburt, S., Carlson Le Floch, K., Bowles Therriault, S., & Cole, S. (2011, May). Baseline analyses of SIG applications and SIG-eligible and SIG-awarded schools. Report no. NCEE 2011-4019. Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance. Retrieved from: http://ies.ed.gov/ncee/pubs/20114019/pdf/20114019.pdf on February 13, 2013.

Imbens, G., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *The Review of Economic Studies, 79*(3), 933–959.

Lee, D., & Card, D. (2008). Regression discontinuity inference with specification error. *Journal of Econometrics,142*(2), 655–674.

Ludwig, J,, & Miller, D. L. (2007). Does Head Start improve children's life chances? Evidence from a regression discontinuity design. *The Quarterly Journal of Economics, 122* (1), 159–208.

Reardon, S.F., & J.P. Robinson. (2010). *Regression discontinuity designs with multiple rating-score variables.* Working paper. Palo Alto, CA: Stanford University.

U.S. Department of Education. (2012). *Guidance on fiscal year 2010 School Improvement Grants under Section 1003(g) of the Elementary and Secondary Education Act of 1965.* Washington, DC: Office of Elementary and Secondary Education, U.S. Department of Education. Retrieved from: http://www2.ed.gov/programs/sif/sigguidance05242010.pdf on May 30, 2014.

Appendix B. Tables and Figures

Not included in page count.

Table 1. Baseline Characteristics of the State and District Samples

	Study States	All States	Study Districts	Districts in the U.S. With at Least One School Implementing a SIG-Funded Intervention Model
Average Percentage of Students by Racial/Ethnic Category				
White, non-Hispanic	55.3	61.8	19.5*	33.4
Black, non-Hispanic	19.5	15.8	38.7*	30.3
Hispanic	18.3	13.7	32.0	25.8
Asian	3.8	4.6	3.3	2.5
Other	3.1	4.1	6.5	8.0
Average Percentage of Students Eligible for Free or Reduced-Price Lunch	48.0	45.5	72.4	68.1
Percentage of Schools That Are Title I Eligible	68.1	67.8	81.4	83.0
Percentage of Schools by Location				
Urban	30.0	23.3	68.2*	37.7
Suburban	25.7	22.5	17.3	20.0
Town or rural	44.3	54.2	14.5*	42.3
Number of States or Districts	**22**	**51**	**60**	**610**

Sources: Common Core of Data, 2009–2010; Institute of Education Sciences database of SIG-awarded schools.

Note: Data from 2008–2009 were used for states and districts with data missing in 2009–2010. Data from 2007–2008 were used for states and districts with data missing in both 2009–2010 and 2008–2009. Data from 2009–2010 were used whenever possible because that was the school year just before the first year of implementation of the ARRA-funded SIG intervention models. Percentages of students are unweighted state-level and district-level averages. The column for all states includes data for 50 states and the District of Columbia. The column for districts in the U.S. with at least one school implementing a SIG-funded intervention model include data for districts in 49 states and the District of Columbia because the database of SIG-awarded schools does not include information for Hawaii. The percentages of U.S. districts with at least one school implementing a SIG-funded intervention model are based on schools' planned implementation as of 2009–2010 for cohort 1 grantees (which received awards in 2010) and as of 2010–2011 for cohort 2 grantees (which received awards in 2011) and include only Tier I and II schools (because Tier III schools that received SIG awards did not have to use those funds to implement a school intervention model). Two study districts were each composed of two districts located within a larger school system. For each of these districts, data for the two districts have been combined in the above analyses.

* Significantly different from districts in the U.S. with at least one school implementing a SIG-funded intervention model at the 0.05 level, two-tailed test.

Exhibit 1. SIG Intervention Models as Described by the U.S. Department of Education SIG Guidance (2012)

I. Turnaround Model

A turnaround model is one in which a local education agency (LEA) must do the following:

1) Replace the principal and grant the principal sufficient operational flexibility (including in staffing, calendars/time, and budgeting) to implement fully a comprehensive approach in order to substantially improve student achievement outcomes and increase high school graduation rates

2) Use locally adopted competencies to measure the effectiveness of staff who can work within the turnaround environment to meet the needs of students:

   A. Screen all existing staff and rehire no more than 50 percent

   B. Select new staff:

      (1) Implement such strategies as financial incentives, increased opportunities for promotion and career growth, and more flexible work conditions that are designed to recruit, place, and retain staff with the skills necessary to meet the needs of the students in the turnaround school.

      (2) Provide staff with ongoing, high-quality, job-embedded professional development that is aligned with the school's comprehensive instructional program and designed with school staff to ensure that they are equipped to facilitate effective teaching and learning and have the capacity to successfully implement school reform strategies.

      (3) Adopt a new governance structure, which may include, but is not limited to, requiring the school to report to a new "turnaround office" in the LEA or state education agency (SEA), hire a "turnaround leader" who reports directly to the superintendent or chief academic officer, or enter into a multiyear contract with the LEA or SEA to obtain added flexibility in exchange for greater accountability.

      (4) Use data to identify and implement an instructional program that is research-based and vertically aligned from one grade to the next as well as aligned with state academic standards.

      (5) Promote the continuous use of student data (such as from formative, interim, and summative assessments) to inform and differentiate instruction in order to meet the academic needs of individual students.

      (6) Establish schedules and implement strategies that provide increased learning time.

      (7) Provide appropriate social-emotional and community-oriented services and supports for students.

(U.S. Department of Education, 2012, pp. 27–28)

II. Restart Model

A restart model is one in which an LEA converts a school or closes and reopens a school under a charter school operator, a charter management organization (CMO), or an education management organization (EMO) that has been selected through a rigorous review process. A restart model must enroll, within the grades it serves, any former student who wishes to attend the school (see C-6).

(U.S. Department of Education, 2012, p. 31)

III. Closure Model

School closure occurs when an LEA closes a school and enrolls the students who attended that school in other schools in the LEA that are higher achieving. These other schools should be within reasonable proximity to the closed school and may include, but are not limited to, charter schools or new schools for which achievement data are not yet available.

(U.S. Department of Education, 2012, p. 34)

IV. Transformation Model

An LEA implementing a transformation model must:

1) Replace the principal who led the school prior to commencement of the transformation model.

2) Use rigorous, transparent, and equitable evaluation systems for teachers and principals that —

A. Take into account data on student growth as a significant factor as well as other factors, such as multiple observation-based assessments of performance and ongoing collections of professional practice reflective of student achievement and increased high school graduation rates.

B. Are designed and developed with teacher and principal involvement.

3) Identify and reward school leaders, teachers, and other staff who, in implementing this model, have increased student achievement and high school graduation rates and identify and remove those who, after ample opportunities have been provided for them to improve their professional practice, have not done so.

4) Provide staff with ongoing, high-quality, job-embedded professional development that is aligned with the school's comprehensive instructional program and designed with school staff to ensure they are equipped to facilitate effective teaching and learning and have the capacity to successfully implement school reform strategies.

5) Implement such strategies as financial incentives, increased opportunities for promotion and career growth, and more flexible work conditions that are designed to recruit, place, and retain staff with the skills necessary to meet the needs of the students in a transformation model.

(U.S. Department of Education, 2012, pp. 27–28)

Source: U.S. Department of Education. "Guidance on Fiscal Year 2010 School Improvement Grants Under Section 1003(g) of the Elementary and Secondary Education Act of 1965." Washington, DC: Office of Elementary and Secondary Education, U.S. Department of Education, 2012. Available at http://www2.ed.gov/programs/sif/ sigguidance05242010.pdf. Accessed May 30, 2014.

Table 2. SIG Funding Awarded in 2010 and Number of Schools Implementing Each Intervention Model

	School Intervention Model				
	Transformation	Turnaround	Restart	Closure	Tier III Strategies[a]
Number of Schools Implementing Each Intervention Model					
Tier I	354	138	24	8	0
Tier II	255	40	9	8	0
Tier III	14	0	0	0	403
Total	623	178	33	16	403
Distribution of Award Amounts (Over Three Years)					
10th Percentile	$942,892	$1,236,632	$1,187,500	$31,935	$60,190
50th Percentile	$2,100,000	$2,684,490	$2,167,965	$50,000	$300,000
90th Percentile	$5,114,190	$5,190,000	$5,490,491	$254,323	$900,405

Source: Institute of Education Sciences database of SIG-awarded schools; Hurlburt et al. (2011).

Note: The SIG awards summarized in this table are from the round of state applications due to the U.S. Department of Education on February 8, 2010. The award amount percentiles are based on the total award amount per school. The maximum award amount was $2 million per year for three years (or $6 million in total over three years).

[a] Tier III strategies refer to all school improvement strategies adopted by SIG-awarded Tier III schools. Federal rules did not require Tier III schools to implement one of the four school intervention models.

Table 3. Eligibility Requirements for Implementing SIG-Funded Intervention Models[a]

	Original Tier Definitions	Expanded Tier Definitions
Tier I	Any school receiving Title I funds in improvement, corrective action, or restructuring that— (i) is among the lowest-achieving 5 percent of Title I schools in improvement, corrective action, or restructuring or the lowest-achieving five Title I schools in improvement, corrective action, or restructuring in the state, whichever number of schools is greater; or (ii) is a high school that has had a graduation rate that is less than 60 percent over a number of years	Title I–eligible elementary schools[b] that are no higher achieving than the highest-achieving school that meets the original Tier I definition *and* that are: • in the bottom 20 percent of all schools in the state based on proficiency rates; *or* • have not made AYP for two consecutive years.
Tier II	Any secondary school that is eligible for, but does not receive, Title I funds that— (i) is among the lowest-achieving 5 percent of secondary schools or the lowest-achieving five secondary schools in the state that are eligible for, but do not receive, Title I funds, whichever number of schools is greater; or (ii) is a high school that has had a graduation rate that is less than 60 percent over a number of years.	Title I–eligible secondary schools[b] that are (1) no higher achieving than the highest-achieving school that meets the original Tier II definition or (2) high schools that have had a graduation rate of less than 60 percent over a number of years *and* that are: • in the bottom 20 percent of all schools in the state based on proficiency rates; *or* • have not made AYP for two consecutive years.
Tier III	Schools receiving Title I funds in improvement, corrective action, or restructuring that are not in Tier I.	Title I–eligible schools[b] that do not meet the requirements to be in Tier I or Tier II *and* that are: • in the bottom 20 percent of all schools in the state based on proficiency rates; *or* • have not made AYP for two years.

Source: U.S. Department of Education.

[a]The original tier definitions were published in the Federal Register on December 10, 2009. The expanded tier definitions were published in the Appropriations Act on December 16, 2009.

[b]Title I-eligible schools include all schools eligible to receive Title I-funds, including both those that do and do not actually receive the funds.

Table 4. Opportunities to Implement an RDD Based on SIG Eligibility Tier Definitions[a]

Opportunity	Treatment Group	Comparison Group	Assignment Variable[b]
1	Original Tier I Elementary	Original Tier III Elementary	Achievement
2	Original Tier I Secondary	Original Tier III Secondary	Achievement
3	Original Tier I Secondary	Original Tier III Secondary	Graduation Rate
4	Original Tier II Secondary	Original Tier II Secondary, but above the cutoff[c]	Achievement
5	Original Tier II Secondary	Original Tier II Secondary, but above the cutoff[d]	Graduation Rate
6	Expanded Tier I Elementary	Expanded Tier III Elementary	Achievement
7	Expanded Tier II Secondary	Expanded Tier III Secondary	Achievement
8	Expanded Tier II Secondary	Expanded Tier III Secondary	Graduation Rate

Source: State administrative records.

[a]In an RDD, the assignment variable is the variable used to assign units to the intervention.

[b]The original tiers are those based on the definitions published in the Federal Register on December 10, 2009. The expanded tiers are those based on the definitions published in the Appropriations Act on December 16, 2009.

[c]Schools that are eligible for, but do not receive, Title I funding and are above the 5 percent achievement cutoff.

[d]Schools that are eligible for, but do not receive, Title I funding and are above the 60 percent graduation rate cutoff.

Table 5. Comparing IK and Cross-Validation (CV)

School Sample Size	Failure %		Mean of Absolute Value of Bias		Impact Standard Deviation		Mean Square Error	
	IK	CV	IK	CV	IK	CV	IK	CV
Mean Across 31 Data Generating Processes								
10	20	44	0.19	7.92	2.35	185.7	5.79	208161
20	0	2	0.07	0.17	2.38	3.64	5.98	19.9
50	0	0	0.02	0.09	0.86	0.55	0.76	0.31
500	0	0	0.01	0.05	0.22	0.17	0.05	0.03
Percentage of Data Generating Processes for Which Each Statistic Is Smaller Than for Competing Bandwidth Method								
10	--	--	87	13	100	0	100	0
20	--	--	87	13	65	35	65	35
50	--	--	94	6	0	100	0	100
500	--	--	100	0	0	100	0	100

Source: Monte Carlo simulations, 1,000 replications.

Note: We assessed the performance of the analytic methods described above, and compared the performance of different bandwidth selection methods, using Monte Carlo simulations that mimic study data observed from the year before SIG had an opportunity to affect outcomes. Thus, the simulations were conducted under the null hypothesis of no true impact, using a data generating process (DGP) that mimics the relationships between outcomes and assignment variables observed in our actual data. To estimate these relationships, we ran quartic regressions of test scores on assignment variables for every grade and RDD opportunity for which we have data. These regressions were run as mixed effects models to account for clustering of students within unique values of the assignment variable. Test scores were converted to z-scores; assignment variables were centered at the cutoff and divided by the standard deviation. We recorded the coefficient estimates from each regression, the intraclass correlation, and the cluster-level regression R2; these parameter estimates from each regression constituted a potential DGP for our simulations. We limited the simulations to 31 DGPs (shown in Table 6 below) that were stable (i.e., had ICC and R2 estimates between 0 and 1) and had a strong relationship between the outcome and assignment variable (meaning that they were more prone to creating bias in RDD impact estimates). Error terms and assignment variables were generated as standard normal. For each of the 31 DGPs, and for 4 different sample sizes, we ran simulations in which impacts were calculated using bandwidths selected by both IK and cross-validation. For larger sample sizes (50 or 500 schools) we see that the IK method results in impact estimates with smaller bias but greater variance and greater mean square error. For smaller sample sizes (10 or 20 schools), we see that the IK method has smaller bias, smaller variance, a smaller mean square error, and a lower failure rate (the failure rate is the proportion of Monte Carlo replications where it was not possible to estimate a valid impact). The sites in our study are more likely to have sample sizes in the range of 10 to 20 schools; IK outperformed cross-validation by all metrics in those cases.

Table 6. Regression Estimates Using Data from 31 Grade/RDD Opportunity Combinations

Combination	b0	b1	b2	b3	b4	ICC	R^2
1	-0.531	0.085	0.024	0.031	-0.011	0.101	0.243
2	-0.454	0.08	0.004	0.034	-0.008	0.095	0.386
3	-0.439	0.105	-0.065	0.024	0.004	0.097	0.511
4*	-0.474	0.057	0.006	0.025	-0.017	0.081	0.455
5	-0.436	0.045	-0.033	0.026	-0.008	0.103	0.28
6*	-0.552	-0.177	-0.327	0.549	-0.142	0.088	0.55
7	-1.021	-0.074	-0.026	0.243	-0.073	0.129	0.447
8*	-0.787	0.332	0.361	-0.233	0.032	0.1	0.553
9	-0.672	-1.645	3.214	-1.547	0.224	0.101	0.549
10	-1.062	0.252	-0.089	-0.091	0.049	0.109	0.403
11	-0.729	0.324	-0.557	0.369	-0.064	0.063	0.569
12	-0.285	-0.55	1.025	0.772	-0.9	0.075	0.286
13	-0.525	2.073	-12.808	15.198	-4.996	0.122	0.241
14	-0.812	-0.212	-0.07	0.244	0.102	0.067	0.23
15*	-0.768	0.066	0.021	0.177	-0.061	0.143	0.391
16	-0.852	-0.257	-0.225	0.335	-0.088	0.058	0.27
17	-1.196	3.127	-6.21	4.77	-1.15	0.126	0.516
18	-1.055	0.938	0.026	-1.23	0.582	0.118	0.305
19	-1.035	-0.149	0.266	-0.054	0.002	0.148	0.484
20	-0.918	0.073	0.011	0.024	-0.004	0.129	0.529
21	-0.985	0.146	-0.068	0.054	-0.008	0.128	0.518
22	-0.707	0.326	-0.385	0.243	-0.044	0.137	0.278
23*	-0.795	0.459	-0.057	-0.169	0.03	0.102	0.358
24	-0.418	-0.298	0.046	0.275	-0.096	0.061	0.452
25	-0.441	-0.122	0.158	0.302	-0.143	0.117	0.45
26	-0.557	0.044	0.109	-0.046	0.013	0.094	0.512
27	-0.976	-0.717	-0.339	1.745	-0.687	0.123	0.406
28	-0.914	-0.121	0.086	0.04	-0.01	0.126	0.27
29	-0.983	-0.048	0.051	0.017	-0.003	0.123	0.231
30	-1.059	0.209	-0.173	0.021	0.012	0.107	0.237
31	-1.479	0.004	-0.168	0.062	0.03	0.062	0.275

Source: Regression estimates using data from the year prior to SIG impact analysis.

Note: The regression equation is $Y = b0 + b1*X + b2*X^2 + b3*X^3 + b4*X^4$, where Y is a test score on a state standardized assessment and X is the RDD assignment variable.

*These five sets of coefficient estimates yielded the largest bias using the IK bandwidth selection method.

Table 7. Comparing Local, Hybrid, and Study-Wide IK Methods

Sample Size		Failure %			Bias			Impact Standard Deviation		
Schools	Sites	Local	Hybrid	Study-wide	Local	Hybrid	Study-wide	Local	Hybrid	Study-wide
100	5	28	44	5	-0.02	0.00	0.00	1.19	1.07	0.76
200	5	4	9	5	0.00	0.00	0.00	0.70	0.62	0.59

Source: Monte Carlo simulations, 10,000 replications, results shown for Fuzzy Frontier impact estimate (Reardon and Robinson, 2010).

Note: From among the 31 data generating processes (DGPs) shown in Table 6 above, we identified the 5 that resulted in the largest bias using IK (these are indicated in Table 6). We then constructed a simulated study consisting of 5 sites, each of which involves two assignment variables that influence the outcome through different combinations of those 5 DGPs. Using the three different bandwidth selection methods described above (local IK, study-wide IK, and hybrid IK), we calculated a study-wide impact using the Fuzzy Frontier method (Reardon and Robinson, 2010). We focused on the 5 DGPs with the largest site-level bias both to be conservative with respect to bias and to limit the computational cost of these simulations. We concluded that the study-wide IK method is the most effective because it yields no bias, has the smallest variance, and has the lowest failure rate with small sample sizes.