# Is the Red-Blue Achievement Gap Due to State Policy?

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**Abstract**

In the US, the general consensus is that Democrats exhibit greater support for education, including funding education more generously. Consistent with this fact, students in Democratic states score higher on standardized tests than Republican states. I implement two research designs and ask whether Democrats cause these differences in test scores through state-level policy. I find that Democrats do not causally increase test scores. Further, despite the view that Democrats promote equity in education, I do not find that Democrats close achievement gaps between white and black students, male and female students, or rich and poor students.

**JEL Classification Codes: H75, I21, I24**

## 1 Introduction

Democrats are generally viewed as providing greater support for education. The 2022 Public Elementary-Secondary Education Finance Data (from the US Census Bureau) indicate that in the 2022-2023 school year states that Joe Biden won in the 2020 presidential election, ("blue" states) spent approximately $5,200 more per student in K-12 than states than voted Republican, ("red" states) compared to a national average of $15,600 per student.[1] Further, Open Secrets (an organization that tracks campaign donations) documents that in the 2021-2022 elections for the US House and US Senate, The American Federation of Teachers (one of the largest teachers unions in the US) donated $24,000 to Republican candidates compared to $4 million to Democratic candidates.[2] This suggest that unions believe Democrats are more supportive of education and/or working conditions for teachers.

[1] See US Census Bureau, 2024.

[2] See Open Secrets, 2024

Beyond teachers' unions, ordinary voters have historically believed that Democrats exhibit stronger support for education, though this clear preference for Democrats has declined in recent years in the wake of COVID-19 and is documented in polling data and in the media. Hess, 2022 compiles repeated polling of the same 1,000 voters from 2003–2022 on which party a respondent has more confidence in regarding education. Democrats lead Republicans in this poll by more than 10 percentage points until 2020. The US News & World Report reported on July 20,2022 that "Democrats Cede 'Party of Education' Label to GOP" (Camera, 2022) and the Atlantic titled a July 2022 article "The Real Reason Democrats are Losing Ground on Education" (Friedersdorf, 2022).

The literature documents a positive correlation (e.g. Clark, 2003; Hill and Kiewiet, 2014; Lafortune, Rothstein, and Schanzenbach, 2018) as well as a positive causal impact (e.g. Beland and Oloomi, 2015; Jackson, Johnson, and Perisco, 2015; Lee and Polachek, 2018; Jackson, Wigger, and Xiong, 2018; Burner, Hyman, and Ju, 2018; Baron, 2019) between higher funding per student and student performance on standardized tests. If Democratic policy favors education, in particular funding for education, it is therefore reasonable to suspect that greater support for education by Democrats would (i) translate into higher student achievement in areas controlled by Democrats, and (ii) that this impact would operate in part through the causal channel of state-level educational policy.

The official Democratic party platform concerning education also highlights their specific commitment to equity in education (Democratic National Committee, 2024). Hill and Jones (2017) uses a regression discontinuity design with gubernatorial elections and finds that states with Democratic governors provide higher levels of funding to areas with a greater share of minority students. If Democratic attitudes towards promoting equity in education also translate into observable educational outcomes, I would expect that differences in student performance on standardized state tests between different demographic groups may be lower in Democratic states, and that the overall variation in student performance may be lower in Democratic versus Republican states.

On the other hand, these differences in student performance, and student performance gaps, may not be due to state policy but due to partisan differences regarding education. In the same paper, Hill and Jones (2017) find no effect of partisanship on the white-black achievement gap nor overall achievement using NAEP scores. These partisan differences in education may stem from demographic differences between the two parties. A Pew Research poll (Pew Research Center, 2023) notes that 58% of voters with a bachelor's degree identify as Democrats, and 37% identify as Republican. The literature generally documents a positive correlation between parental education and student achievement (e.g. Björklund and Salvanes, 2011; Fruehwirth and Gagete-Miranda, 2019), as well as a positive correlation between parental education and parental time spent on educational activities with children (e.g. Aguiar and Hurst, 2007; Guryan, Hurst, and Kearney, 2008; Ramey and Ramey, 2009; Dotti Sani and Treas, 2016). Therefore I expect differences in attitudes relating to education, such as time spent helping kids with homework, to be correlated with partisanship. I refer to these attitudes as "culture". If these differences in culture are more important for test scores than state-level policy, the observed differences in student performance may be caused by these cultural differences rather by than differences in policy.

To determine the degree to which differences in student performance result from state-level policy, I implement two research designs described in Bhattarai, Slichter, and Tatro (2024), where my coauthors and I study the causal effect of partisanship on mortality rates. Both research designs note that state policy is not a function of a given county's characteristics, but of the characteristics of the rest of the state. Therefore the designs utilize quasi-random variation in rest of state partisanship through exploiting two "coincidences" about which state a given county is a part of based on the drawing of state borders. The first coincidence is that for counties on the border between two states, which side of the border a given county is on determines which other counties belong to the same state as the county in question. The second coincidence is that for a given county, state borders determine which other counties are included in the same state as the county of interest, even if these other same-state counties are far away from the county of interest.

The first design is an instrumental-variable approach in which partisanship of the far half of a given state serves as an instrument for overall state partisanship. The identifying assumption is that, conditional on the partisanship of counties in the near part of the state, the partisanship of counties in the far part of the state is uncorrelated with a given county's student achievement values. The second design combines the far part design with a typical border county design. This design instruments the difference in state partisanship with difference in far part partisanship, controlling for the difference in near part partisanship, within a border county pair.

I provide empirical evidence the identifying assumptions of both designs are satisfied before presenting results. I find that Democrats do not have any causal effect on student achievement or student achievement gaps between white and black, male and female, or rich and poor students.

The rest of the paper proceeds as follows. I describe the data sources in Section 2 and present baseline results in Section 3. I discuss the far part design in Section 4, and the border county design in Section 5. I discuss the results and conclude in Section 6

## 2 Data

My main source of data comes from the Stanford Education Data Archive (SEDA) which measures overall achievement and achievement gaps. SEDA provides data at the county-year-grade-subject level using test score information on state standardized tests for students in grades 3-8 on math and reading from 2009–2019. In order to compare student performance across states and across years, SEDA compiles a baseline achievement score for each grade and subject using the average test scores from National Assessment of Educational Progress (NAEP) for students in fourth grade in 2009, 2011, 2013, and 2015. Using this benchmark, SEDA produces measures of student achievement in terms of standard deviations above or below the benchmark. These estimates are available for all students and for each racial, gender, and socioeconomic group. SEDA then estimates achievement gaps as the difference in student achievement between groups. For example, a value of 0.62 for the white-black achievement gap indicates that white students, on average, score 0.62 standard deviations higher than black students for a given grade and subject. I aggregate the SEDA data for overall achievement and the three (white-black, male-female, rich-poor) achievement gaps to the county-year level by first averaging across subjects in order to aggregate to the county-year-grade level. I then average over grades 3-8 to aggregate my date to the county-year level.

I also use the SEDA data to determine a proxy for student achievement variation within a given county and year. The SEDA data does not directly record variation (i.e. standard deviation of student achievement) at the county-level. My proxy, which I refer to as "within-county achievement variation" measures the standard deviation of district-level achievement within a given county and year. I calculate the standard deviation of achievement for all geographic districts (the smallest unit available in the SEDA data) based on the 2019 Elementary and Unified District Boundaries.[3]

I combine these data with presidential election data from the MIT Election Lab. I define partisanship as the percentage (0-100) of Republican votes in the most recent presidential election. For example, the partisanship of a county that voted 60% for Trump in 2016 would be 60 from 2017-2020. The county's partisanship is 2016 is based on the 2012 election, as the presidential election occurred in November of 2016.

I select county-level overall achievement, the White-Black achievement gap, the male-

[3]See `https://nces.ed.gov/programs/edge/Geographic/DistrictBoundaries`, as noted in Fahle et al., 2024. Note that SEDA calculates their standardized measure of achievement separately for each level of geographic aggregation. Therefore using SEDA's district level data for all variables would result in slightly different measurements at the county-level data compared to using SEDA's county level data.

female achievement gap, and the rich-poor achievement gap (as defied by SEDA) as my main outcome variables. I also include my proxy for within-county variation in achievement. Overall achievement allows for an analysis of the impact of state policy on achievement levels, while the other outcome variables allow for an analysis on potential distributional impacts of state policy on test scores.

## 2.1 Covariates

I also include covariates to use as controls in my analyses. These covariates fall into two broad categories: i)own-county characteristics and ii) connected-county characteristics. From the SEDA data I include own county-level racial shares of students for Whites, Asians, Blacks, and Hispanics. I also include the share of students receiving free or reduced lunch, and the share of students designed as English language learners or special education. I also include the share of students residing in an urban and suburban setting, and SEDA's measure of socioeconomic status for all students within a particular county.

The connected-county characteristics are a weighted average of each outcome variable described above in counties defines as being connected to a particular county $c$.[4] Denote each connected county $c'$. First, I calculate a "sending counties" variable as the average outcome variable in all counties $c'$ where at least one person migrated from $c$ to $c'$ from 2016-2019., weighted by the number of people who moved. Second, I calculate a "receiving counties" the average outcome variable in all counties $c'$ where at least one person migrated to $c$ from $c'$ from 2016-2019, weighted by the number of people who moved. Third, I calculate an "facebook counties" variable as the average outcome variable in all counties $c'$ where at least one facebook friend connection between $c$ and $c'$, weighted by the number of facebook friend connections.[5]

Note that for each of the three measures I exclude any counties $c'$ within the same state as county $c$ to avoid contamination in these variables by treatment. I obtain the migration data using the US Census's County-to-County Migration Flows from 2016-2019 (US Census Bureau, 2016–2020). I obtain the facebook friend connection data using the Social Connectedness Index (SDI) from Bailey et al., 2018.

I provide summary statistics for all variables in Table 1. I report summary statistics for own-county characteristics in Panel A, followed by sending county characteristics in Panel

[4] i.e. for the overall achievement variable I construct three measures of overall achievement in connected counties, where the difference in each of these three measures is the difference in how I define which counties are connected to county $c$.

[5] Note that these are analogous measures to those constructed in Bhattarai, Slichter, and Tatro, 2024.

B, receiving county characteristics in Panel C, and facebook county characteristics in Panel D.

# 3 OLS results and the endogeneity problem

I begin by estimating the correlation between state-level partisanship and average student achievement, in addition to the correlation between state-level partisanship and achievement groups. For each of these outcomes $Y$ I estimate models of the form

$$Y_{ct} = \beta_0 + \beta_1 StatePart_{s(c)t} + X'_{ct}\Gamma + \epsilon_{ct},$$

at the county $c$ state $s(c)$ year $t$ level. $StatePart$ measures state partisanship, the percentage of votes for the Republican candidate in the last presidential election, and $X$ represents a vector of the control variables discussed above in Section 2.1. $\epsilon_{ct}$ represents cluster-robust standard errors at the state level.

I report the estimates from this model without $X$ in Column 1 of Table 2. Each outcome is measured in standard deviations from the national average. The coefficient on Overall Achievement, for example, means that each one-percentage point increase in state partisanship is correlated with a 1/1000th standard deviation decrease in achievement. The same increase in state partisanship is also correlated with a i) $\sim$ 0.5% of a standard deviation decrease in the white-black achievement gap, rich-poor achievement gap, and within-county variation and ii) 0.04% of a standard deviation increase in the male-female gap.

It is unlikely that these correlations represent the true causal impact of state policy on educational outcomes. The treatment effect I seek to measure is the impact of state partisanship on local educational outcomes exclusively through state-level policy. State partisanship, however, proxies for broad attitudes towards education, such as parental involvement and support of public education and state testing. I therefore expect confounding between local educational outcomes and state partisanship via local characteristics.

I therefore report estimates of Equation 3 with controls in Column 2 of Table 2 as described above in Section 2.1. Note that with compared to Column 1 the statistical significance of the white-black and rich-poor achievement gaps disappears and the effect sizes are closer to 0. I observe a more negative coefficient on my measure for within-county achievement, though the standard error remains large and the overall estimate remains insignificant.

To better understand the magnitude of these estimates in Column 2, suppose these estimates represent a causal impact of state policy on educational outcomes. Now consider a state that shifts from being a blue state with a republican vote share of approximately 40% to a red state with a republican vote share of approximately 60%. The estimates in column

2 would tell you that this shift would raise overall achievement by 0.026 standard deviations (SD) and have an almost zero impact on achievement gaps. Even the largest reasonable estimates based on these coefficients (i.e. the coefficient plus twice the standard error) would translate into small changes in educational outcomes. For example, the upper end of the coefficient on the White-Black achievement gap would yield a coefficient of approximately 0.0027. Again using the 40% to 60% republican vote share hypothetical, the effect size translates to just 0.054 SD compared to the average White-Black achievement gap of 0.61 SD, or less than 10% of the average White-Black achievement gap.

Note that the coefficient on within-county variation in student achievement is statistically insignificant. The coefficient, however, is large in magnitude. Using the smallest (most negative) reasonable estimate under the same hypothetical would yield an effect size of approximately -0.42 SD, or about two-thirds of the average in the within-county variation variable. This provides weak evidence that state policy may reduce variation in student achievement.

In order to assess the degree to which endogeneity remains in my estimates, I evaluate the correlation between local educational outcomes and the average partisanship of other counties within the same state. If the correlation is equally strong between i) local educational outcomes and partisanship of far-away counties within the same state and ii) local educational outcomes and partisanship of nearby counties within the same state, then that would provide empirical evidence the controls in Column 2 are sufficient for addressing endogeneity. If the correlation is stronger for nearby counties than for far away counties, that would suggest that there still exists confounding and the result in Column 2 is biased upward.

I implement this empirical test in Columns 3 and 4 of Table 2. For a given county with $N$ other counties in the same state I place $\frac{N}{2}$ counties into the furthest half of the same state and $\frac{N}{2}$ counties into the nearest half of the same state based on the distance between county centroids.[6] I then instrument state partisanship using the near half of the state, controlling for partisanship in the far part of the state, in Column 3. In Column 4 I instrument state partisanship using the far half of the state, controlling for partisanship in the near part of the state. Columns 3 and 4 also include the controls used in Column 2.

The results in Columns 3 and 4 indicate that I likely do not have remaining endogeneity in my OLS results when I include controls, and that the estimates in Column 2 represent a causal estimate of the impact of state partisanship on overall achievement, achievement gaps, and within-county deviations in student achievement. Given that this context closely aligns with that of my other paper Bhattarai, Slichter, and Tatro, 2024, I believe it may be interesting to use two designs, the far part design and the border county design, from

[6]When $N$ is odd I assign the median county to the nearest half of the state.

that paper and compare the estimates from the two designs to the coefficients I obtain in Column 2 of Table 2, subject to passing model selection tests for the far part and border county designs. As all three designs should eliminate any endogeneity, the estimates from all three designs should give not only the same qualitative answer but also quantitative answers statistically indistinguishable from each other. I describe the results using the far part design in the next section, and the results from the border county design in Section 5.

# 4 Far part design

I begin with the far part design in which I estimate instrumental variable models of the form

$$\begin{aligned} Y_{ct} &= \alpha_0 + \alpha StatePart_{s(ct)t} + \alpha_1 Near_{ct} + X_{ct}'\Psi + \mu_{ct} \\ StatePart_{s(c)t} &= \delta_0 + \delta_1 Far_{ct} + X'\Sigma + \epsilon_{ct}, \end{aligned}$$

where I divide the rest of counties in the same state $s(c)$ as county $c$ into the near part of the state or the far part of the state, based on distance between county centroids. I then calculate the average partisanship of counties in the near part of the state as $Near_{ct}$ and the average partisanship of counties in the far part of the state as $Far_{ct}$. The coefficient $\alpha_1$ represents the causal impact of state partisanship on local educational outcome $Y$ (i.e. Overall achievement, achievement gaps, and the variation in within-county student achievement) and is the coefficient of interest. This coefficient results from instrumenting $StatePart$ using $Far$.

I estimate a wide range of specifications varying i)the cutoff, ii)the inclusion of covariates $X$, and iii) whether $X$ includes a regional control (US Census region dummies or the average partisanship of states bordering $s(c)$) or not. I vary the cutoff by changing the proportion of counties classified into the near part of the state. For example, in Table 2 I assigned half of the other counties in the same state to the near part of the state, but I could also assign one-fifth of the other counties to the near part, and thereby assign the remaining four-fifths of the other counties to the far part.

In addition to varying whether or not I include a vector of controls $X$ I also vary whether this vector controls for the average characteristics of counties in the near part of the state or whether $X$ is limited to those covariates used in my OLS specification.

## 4.1 Cutoff Selection and Model Tests

I next conduct the two validity tests for the far part design. I begin with the neighboring state placebo test and then report results for the balance tests.

### 4.1.1 Neighboring State Placebo Test

For the neighboring state placebo test I restrict my sample to counties that lie on the border between two states. For each border county I select a county on the other side of the border (therefore in a different state) and calculate the partisanship in the near and far part of the neighboring state using the same set of possible cutoffs I use in my baseline specifications.[7] I then estimate models of the form

$$
\begin{aligned}
LocalY_{ct} &= \gamma_0 + \gamma_1 BorderStatePart_{s(c)t} + \gamma_2 BorderNear_c t + \epsilon_{ct} \\
BorderStatePart_{s(ct)t} &= \eta_0 + \eta_1 BorderFar + \eta_2 BorderNear + \theta_{ct},
\end{aligned}
$$

where *LocalY* emphasizes that the dependent variable is each educational outcome $Y$ within a given county, and $BorderStatePart$ represents state partisanship of the neighboring state. I instrument $BorderStatePart$ using $BorderFar$, or partisanship in the far part of neighboring state, controlling for $BorderNear$, or partisanship in the near part of the state. An estimate in which $\gamma_1 = 0$ would suggest that a particular cutoff does not contain confounding due to regional factors.

I present the results of the neighboring state placebo test in Table 3. All columns include year fixed effects, but do not include the full vector of controls $X$ in order to assess the validity of cutoffs not conditional on controls. I do include US Census Region dummies in order to control for regional culture. Column titles indicate the proportion of other counties in the same state included in the near part of the state. The "OLS" column reports the results obtained for the OLS regression of $LocalY_{ct}$ on $BorderStatePart_{s(c)t}$ with year fixed effects.

I begin by discussing the results in Panel A, in which I do not include any regional controls. I include results from running an OLS regression of each outcome on state partisanship in Column 1 for comparison with the results from the IV regression. Note that all cutoffs return a coefficient not statistically different from zero but with relatively large standard errors for cutoffs smaller than or equal to one-half. For cutoffs at or greater than one-half,

[7] For border counties that lie adjacent to multiple counties, I select a county on the other side of the border randomly. Results are not sensitive to choice of the county in the neighboring state.

the point estimates are closer to zero with smaller standard errors. This suggests that any cutoff equal to or greater than one half likely addresses endogeneity and provides sufficiently small standard errors to have reasonable confidence. When I add regional controls using US Census Region dummies (Panel B) or using the average partisanship of neighboring states (Panel C) I observe qualitatively similar results, though with smaller standard errors for a cutoff of one-half. This model tests therefore suggest that a preferred specification should use any cutoff greater than or equal to one-half and regional controls.

#### 4.1.2 Balance Tests

The second validity test for the far half design tests the correlation between the partisanship of the far part of the state (for each given cutoff) and local characteristics. I estimate these correlations by estimating the far half model, described in Equation 4, in which I replace local educational outcomes, $Y_{ct}$ with local characteristics. Specifically I estimate the correlations for local partisanship, percentage of urban and suburban students, racial shares, socioeconomic variables, and the educational outcomes of connected counties (as defined using Facebook counties, sending counties, and receiving counties). Similar to the Neighboring County Placebo test, I estimate these regressions with year fixed effects but without the set of controls $X$ in order to assess unconditional correlations.

The key variable in this balance test is local partisanship. The source of endogeneity is regional confounding in which regional culture influences both regional partisanship, and therefore state partisanship, in addition to local culture and therefore local partisanship. A cutoff which provides balance on local partisanship should therefore also address confounding due to regional factors.

I report the results of the balance tests in Table 4. Column titles again indicate the proportion of other counties classified into the near part of the state. Column 1 ("OLS") reports the OLS regression of the local characteristic indicated by the row title on state partisanship, with year fixed effects. For local partisanship, note that estimates for cutoffs smaller than one-half suggest a failure of balance. I observe balance for the other covariates for most if not all cutoffs. I do observe a failure of balance for the percentage of white students across all cutoffs and I observe a weak failure of balance on the percentage of students receiving free and reduced lunch. Given the number of hypotheses I am testing this result is unsurprising.

## 4.2 Baseline Results

I report baseline estimates from the far half design in Table 5 using a cutoff of one-half for each educational outcome. These results do not include the vector of covariates $X$. Note that I include extra columns illustrating the effects on White, Black, male, and female as additional information. Panel A reports the far half results without any regional controls. Panel B reports the far half results including US Census region dummies. Panel C reports the far half results controlling separately for the average partisanship of adjacent states. For comparison, I include the OLS estimates without controls (from Column 1 of Table 2) in Panel D.

I focus my attention on Panel B and Panel C, as I believe controlling for regional effects may be important for the estimation and something not included in the Panel D OLS results. I observe that the estimates in Panel B and Panel C are statistically indistinguishable from each other, with similar standard errors. Controlling for regional effects does not substantial reduce the errors in the estimates for any outcome variable. Within a column, the coefficients in all four panels are indistinguishable from each other and only statistically significant in Panel D. These results are also statistically indistinguishable from the results in Column 2 of Table 2. This provides further evidence that i) OLS with controls may be sufficient for obtain a causal estimate of the effect of state policy on educational outcomes and ii) that causal effect is very small or zero for all of these outcome variables.

## 4.3 Specification Curve

The baseline estimates I include represent one set of estimates for each outcome variable using a particular cutoff and vector of controls. I now estimate a range of specifications for each educational outcome in which I vary i) the cutoff used for the far half design, ii) whether the vector of controls contains local characteristics, near-part characteristics, both, or is omitted from the regression and iii) if/how I control for regional characteristics using US Census region dummies or the average partisanship of neighboring states. All specifications include year fixed effects. In order to present these results cohesively for each educational outcome I present a specification curve for each estimate. I include the specification curve for overall achievement in Figure 1. For brevity, I include the other specification curves in Appendix A. The analogous specification curves for the White-Black achievement gap is presented in Figure A1, the specification curve for the male-female achievement gap is included as Figure A2, and the specification curve for the rich-poor achievement gap is included as Figure A3.

In each figure, the coefficient for each combination of cutoff, sets of variables included in the vector of controls, and regional controls is presented as a dot. The bars around each dot represent the 95% confidence interval for each estimate. The dots below the figure illustrate the combination of regional controls, the set of variables included in the vector of controls, and the cutoff used to generate a particular estimate and confidence interval. I highlight my preferred estimate in black, in which I use a cutoff of one-half, the control vector includes both local and near-part controls, and I control for census region by including US Census Region dummies.

I begin by discussing the results regarding overall achievement, as reported in Figure 1. Note that the scale of axis spans from negative two one-hundredths of a standard deviation to one-hundredth of a standard deviation. All estimates are statistically indistinguishable from 0, and all point estimates are qualitatively 0 as well. In addition, the confidence intervals for all estimates are overlapping, indicating that the choice of cutoff or controls does not impact the magnitude nor significance of the estimate.

I observe a qualitatively similar picture using the male-female achievement gap and the rich-poor achievement gap. The specification curve for the white-black achievement gap does include 4 specifications in which the estimate is statistically significant at the 95% level (3 positive, 1 negative). These estimates, however, are still qualitatively small and do not represent preferred specifications. The negative and significant specification, for example, only includes regional controls and uses a small cutoff of one-fifth.

These specification curves provide an additional piece of evidence that the estimates I obtained in Column 2 of Table 2 most likely represent the causal impact of state partisanship on educational outcomes. I now turn to the border county design as an additional point of comparison to both my OLS results and now the estimates I obtained from the far part design.

## 5 Border county design

I next turn to the border county design, in which I estimate models of the form

$$\Delta Y_{bt} = \eta_0 + \eta_1 \Delta StatePart_b + \Delta X'_{bt}\Gamma + \epsilon_b t,$$

where I index observations by border county pair $b$ in year $t$, in which each county within a border county pair lies in a different state. The operator $\Delta$ represents a first difference operator within a border county pair. For consistency, the difference is defined as a given variable in the more Republican county minus the variable in the less Republican county. For example, $\Delta StatePart$ represents the state partisanship of the more Republican county minus the state partisanship of the less Republican county. $\Delta X$ represents the vector of differences in each control included in Column 2 of Table 2. These are the same controls included in the baseline far half design.

For completeness, I also estimate the combined far part design with border county design from Bhattarai, Slichter, and Tatro, 2024. I therefore estimate models of the form

$$\begin{aligned} \Delta Y_{bt} &= \eta_0 + \eta_1 \Delta StatePart_{bt} + \eta_2 \Delta NearPart_{bt} + X'_{bt}\Gamma + \epsilon_{bt} \\ \Delta StatePart_{bt} &= \psi_0 + \psi_1 FarPart_{bt} + \psi_2 NearPart_{bt} + v_{bt}, \end{aligned}$$

where I instrument the difference in state partisanship $\Delta StatePart$ with the difference in far part partisanship $\Delta FarPart$ controlling for the difference in near part partisanship $\Delta NearPart$ for the two states pertaining to the border county pair $b$.

## 5.1 Results

I present the results of my estimation for each educational outcome in Table 6. In columns 1 and 2 I report results for the baseline border county design. Column 1 does not include controls. In Column 2 I include the same set of controls from the baseline far part design report in Table 5. For each covariate, I take the difference in as the variable in the redder county minus the variable in the bluer county). Columns 3 and 4 are analogous to columns 1 and 2 except that I instrument the difference in state partisanship with the difference in far part partisanship, controlling for the difference in near part partisanship, using a cutoff of one-half.

For each outcome variable I continue to observe small and statistically insignificant results. Note that the standard errors in Columns 2 and 4 are much smaller than the standard errors from the far half design as reported in Table 5. This suggests that the border county design may provide more precise estimates than the far part design, and that combined far part border county design provides a degree of precision in between the far part design and the border county design. This also gives further evidence that there is very little to no causal impact of state policy on my outcome variables.

## 5.2 Specification Curve

Using the combined far part border county design allows me to estimate a range of specifications in which I modify the cutoff using the same set of cutoffs I use in the far part design. I can also estimate a variety of the border county design, without the far part instrument, in which I vary the controls I include. I therefore perform a variety of estimations for the border county design, similar to the far part design, and report the specification curves for each outcome variable. I present the specification curves for overall achievement as Figure 2, and include the specification curves for the other educational outcomes in Appendix A. I continue to highlight the preferred specification in black. For the border county design I designate the preferred specification as the combined far part border county design with a cutoff of one half that includes both local and near controls.

In Figure 2, the estimates for all specifications are statistically indistinguishable from each other and remain close to 0. This is true for all outcome variables. Note that for the White-Black achievement gap I do observe positive and statistically significant estimates for some specifications, and these estimates are similar to and not statistically different from the effect sizes found using OLS with controls or from using the far part design. The preferred estimate for the male-female achievement gap is almost exactly 0, and all specifications are within 0.0025 of each other. This is true for the rich-poor achievement gap as well.

# 6 Discussion

I find that state policy has very little to no causal impact on county-level educational outcomes, in particular on overall test scores or achievement gaps defined using average test scores across racial, gender, and socioeconomic gaps. This is unsurprising for a number of reasons. First, educational outcomes are most closely related to decisions made at the school or school-district level, rather than at the state level. State policy does set broad educational policy and allocate education funding, but this is often through state bureaucracy than through elected officials.

While I find an insignificant result I am able to make an econometric contribution. I assess to what extent the far part design and border county designs described in Bhattarai, Slichter, and Tatro, 2024 yield similar effect size estimates and to what extent the assumptions behind those methods hold in my setting.

I do find that all three designs yield statistically similar estimates close to 0, but with varying standard errors. The border county design provides the most precision, or smallest standard errors. The combined far part border county designs provides larger standard errors, and the far part design and OLS with controls provide even larger standard errors.

## References


Aguiar, Mark and Erik Hurst (2007). "Measuring trends in leisure: The allocation of time over five decades". In: *The quarterly journal of economics* 122.3, pp. 969–1006.

Bailey, Michael et al. (Aug. 2018). "Social Connectedness: Measurement, Determinants, and Effects". In: *Journal of Economic Perspectives* 32.3, pp. 259–80.

Baron, Jason E. (2019). "School Spending and Student Outcomes: Evidence from Revenue Limit Elections in Wisconsin". In: *SSRN*.

Beland, Louis-Philippe and Sara Oloomi (2015). "Party Affiliation and Public Spending". In: *LSU Working Paper Series*.

Bhattarai, Jijee, David Slichter, and Case Tatro (2024). *Is the mortality gap between red and blue states caused by policy?* Working Paper.

Björklund, Anders and Kjell G. Salvanes (2011). "Chapter 3 - Education and Family Background: Mechanisms and Policies". In: ed. by Eric A. Hanushek, Stephen Machin, and Ludger Woessmann. Vol. 3. Handbook of the Economics of Education. Elsevier, pp. 201–247. DOI: `https://doi.org/10.1016/B978-0-444-53429-3.00003-X`. URL: `https://www.sciencedirect.com/science/article/pii/B978044453429300003X`.

Burner, Eric, Joshua Hyman, and Andrew Ju (2018). "School Finance Refors, Teachers' Unions, and the Allocation of School Resources". In: *ED Working Papers*.

Camera, Lauren (July 20, 2022). "Democrats Cede 'Party of Education' Label to GOP: Poll". In: *The US News World Report*. URL: `https://www.usnews.com/news/education-news/articles/2022-07-20/democrats-cede-party-of-education-label-to-gop-poll` (visited on 05/07/2024).

Clark, Melissa A. (2003). "Education Reform, Redistribution, and Student Achievement: Evidence From the Kentucky Education Refore Act". In: *Matghematica Policy Research*.

Democratic National Committee (2024). *Where We Stand: Education*. URL: `https://democrats.org/where-we-stand/the-issues/education/`.

Dotti Sani, Giulia M and Judith Treas (2016). "Educational gradients in parents' child-care time across countries, 1965–2012". In: *Journal of marriage and Family* 78.4, pp. 1083–1096.

Fahle, E. M. et al. (2024). *Stanford Education Data Archive: Technical Documentation (Version 5.0)*. URL: `https://purl.standford.edu/cs829jn7849`.

Friedersdorf, Conor (July 1, 2022). "The Real Reason Democrats Are Losing Ground on Education". In: *The Atlantic*. URL: `https://www.theatlantic.com/newsletters/archive/2022/07/democrat-republican-voters-critical-race-theory/670584/` (visited on 05/07/2024).

Fruehwirth, Jane Cooley and Jessica Gagete-Miranda (2019). "Your peers' parents: Spillovers from parental education". In: *Economics of Education Review* 73, p. 101910. ISSN: 0272-7757. DOI: https://doi.org/10.1016/j.econedurev.2019.101910. URL: https://www.sciencedirect.com/science/article/pii/S0272775719301219.

Guryan, Jonathan, Erik Hurst, and Melissa Kearney (Sept. 2008). "Parental Education and Parental Time with Children". In: *Journal of Economic Perspectives* 22.3, pp. 23–46. DOI: 10.1257/jep.22.3.23. URL: https://www.aeaweb.org/articles?id=10.1257/jep.22.3.23.

Hess, Frederick M. (2022). "Democrats Have Lost Public Confidence on Education, but the GOP Hasn't Gained It". In: *American Enterprise Institute*. URL: https://www.aei.org/research-products/report/democrats-have-lost-public-confidence-on-education-but-the-gop-hasnt-gained-it/.

Hill, Andrew J. and Danel B. Jones (2017). "Does partisan affiliation impact the distribution of spending? Evidence from state governments' expenditures on education". In: *Journal of Economic Behavior & Organization*.

Hill, Sarah A. and D. Roderick Kiewiet (2014). "The Impact of State Supreme Court Decisions on Public School Finance". In: *The Journal of Law, Economics, and Organization* 31.1, pp. 61–92.

Jackson, C. Kirabo, Cora Wigger, and Heyu Xiong (2018). "Do School Spending Cuts Matter? Evidence from the Great Recession". In: *NBER Working Paper Series*.

Jackson, C.K., R.C. Johnson, and C Perisco (2015). "The effects of school spending on educational and economic outcomes: evidence from school finance reforms". In: *National Bureau of Economic Research Working Paper*.

Lafortune, Julien, Jesse Rothstein, and Diane Whitmore Schanzenbach (Apr. 2018). "School Finance Reform and the Distribution of Student Achievement". In: *American Economic Journal: Applied Economics* 10.2, pp. 1–26. DOI: 10.1257/app.20160567. URL: https://www.aeaweb.org/articles?id=10.1257/app.20160567.

Lee, Kyung-Gon and Solomon W Polachek (2018). "Do school budgets matter? The effect of budget referenda on student dropout rates". In: *Education Economics* 26.2, pp. 129–144.

Open Secrets (2024). *Teachers unions PACs contributions to candidates, 2021-2022*. URL: https://www.opensecrets.org/political-action-committees-pacs/industry-detail/L1300/2022.

Pew Research Center (2023). "Wide Gender Gap, Growing Educational Divide in Voters' Party Identification". In: URL: %5Curl%7Bhttps://www.pewresearch.org/politics/2018/03/20/wide-gender-gap-growing-educational-divide-in-voters-party-identification/%7D.

Ramey, Garey and Valerie A Ramey (2009). *The rug rat race*. Tech. rep. National Bureau of Economic Research.

US Census Bureau (2024). *2022 Public Elementary-Secondary Education Finance Data*. https://www.census.gov/data/tables/2022/econ/school-finances/secondary-education-finance.html.

US Census Bureau (2016–2020). *County-to-County Migration Flows: 2016-2020 ACS*.

# 7 Tables and Figures

Table 1: Summary Statistics

| | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|
| **Panel A: Local Characteristics** | | | | |
| Overall Achievement | -0.04 | 0.26 | -1.52 | 0.98 |
| White-Black Achievement Gap | 0.61 | 0.22 | -0.39 | 1.68 |
| Male-Female Achievement Gap | -0.14 | 0.09 | -1.05 | 0.57 |
| Rich-Poor Achievement Gap | 0.54 | 0.17 | -0.71 | 1.53 |
| Within-County Achievement Std. Dev | 0.61 | 0.65 | 0.00 | 20.45 |
| Local Partisanship | 59.63 | 14.87 | 7.19 | 95.86 |
| State Partisanship | 51.52 | 8.18 | 30.27 | 72.79 |
| Share Asian | 1.26 | 2.40 | 0.00 | 46.69 |
| Share Black | 11.37 | 19.25 | 0.00 | 100.00 |
| Share Free/Reduced Lunch | 54.94 | 16.32 | 0.00 | 100.00 |
| Share Hispanic | 12.46 | 17.54 | 0.00 | 99.79 |
| Share White | 70.30 | 24.99 | 0.00 | 100.00 |
| Share English Language Learner | 3.88 | 5.97 | 0.00 | 63.93 |
| Share Special Education | 13.63 | 4.11 | 0.00 | 85.12 |
| Share Urban | 7.20 | 19.21 | 0.00 | 100.00 |
| Share Suburb | 9.88 | 22.10 | 0.00 | 100.00 |
| SES All Students | -0.10 | 0.74 | -4.20 | 2.08 |
| **Panel B: Sending County Characteristics** | | | | |
| Overall Achievement: Sending Counties | -0.00 | 0.11 | -0.69 | 0.65 |
| White-Black Achievement Gap: Sending Counties | 0.56 | 0.21 | 0.00 | 1.61 |
| Male-Female Achievement Gap: Sending Counties | -0.14 | 0.04 | -0.49 | 0.19 |
| Rich-Poor Achievement Gap: Sending Counties | 0.64 | 0.14 | 0.00 | 1.18 |
| Within-County Achievement Std. Dev: Sending Counties | 0.89 | 0.51 | 0.00 | 8.15 |
| Share White: Sending Counties | 58.31 | 14.93 | 0.00 | 96.52 |
| Share Asian: Sending Counties | 3.10 | 1.96 | 0.00 | 24.20 |
| Share Hispanic: Sending Counties | 17.33 | 9.52 | 0.00 | 71.36 |
| Share Black: Sending Counties | 14.28 | 9.57 | 0.00 | 88.40 |
| Share Free/Reduced Lunch: Sending Counties | 51.20 | 10.26 | 0.00 | 93.99 |
| Share English Language Learner: Sending Counties | 6.28 | 3.27 | 0.00 | 28.13 |
| Share Special Education: Sending Counties | 12.72 | 2.56 | 0.00 | 20.05 |
| Share Urban: Sending Counties | 25.75 | 13.85 | 0.00 | 99.89 |
| Share Suburb: Sending Counties | 26.44 | 14.31 | 0.00 | 94.19 |
| SES All Students: Sending Counties | 0.07 | 0.31 | -1.57 | 1.42 |
| **Panel C: Receiving County Characteristics** | | | | |
| Overall Achievement: Receiving Counties | -0.01 | 0.09 | -0.59 | 0.59 |
| White-Black Achievement Gap: Receiving Counties | 0.57 | 0.16 | 0.00 | 1.51 |
| Male-Female Achievement Gap: Receiving Counties | -0.14 | 0.03 | -0.77 | 0.06 |
| Rich-Poor Achievement Gap: Receiving Counties | 0.65 | 0.10 | 0.00 | 1.02 |
| Within-County Achievement Std. Dev: Receiving Counties | 0.95 | 0.42 | 0.00 | 5.13 |
| Share White: Receiving Counties | 58.03 | 10.96 | 0.00 | 94.34 |
| Share Asian: Receiving Counties | 3.40 | 1.80 | 0.00 | 38.10 |
| Share Hispanic: Receiving Counties | 18.62 | 7.81 | 0.00 | 65.32 |
| Share Black: Receiving Counties | 14.69 | 8.02 | 0.00 | 69.25 |
| Share Free/Reduced Lunch: Receiving Counties | 52.15 | 6.68 | 0.00 | 93.02 |
| Share English Language Learner: Receiving Counties | 6.74 | 2.69 | 0.00 | 26.76 |
| Share Special Education: Receiving Counties | 12.87 | 1.75 | 0.00 | 20.04 |
| Share Urban: Receiving Counties | 26.93 | 10.76 | 0.00 | 96.56 |
| Share Suburb: Receiving Counties | 28.00 | 11.69 | 0.00 | 81.62 |
| SES All Students: Receiving Counties | 0.07 | 0.26 | -1.54 | 1.30 |
| **Panel D: Facebook County Characteristics** | | | | |
| Overall Achievement: Facebook Counties | -0.05 | 0.08 | -0.60 | 0.29 |
| White-Black Achievement Gap: Facebook Counties | 0.24 | 0.11 | 0.00 | 0.61 |
| Male-Female Achievement Gap: Facebook Counties | -0.14 | 0.03 | -0.27 | 0.00 |
| Rich-Poor Achievement Gap: Facebook Counties | 0.46 | 0.07 | 0.00 | 0.65 |
| Within-County Achievement Std. Dev: Facebook Counties | 0.54 | 0.10 | 0.00 | 1.40 |
| Share Asian: Facebook Counties | 1.07 | 0.40 | 0.00 | 3.20 |
| Share Black: Facebook Counties | 11.21 | 9.25 | 0.00 | 70.22 |
| Share Free/Reduced Lunch: Facebook Counties | 54.74 | 6.16 | 0.00 | 89.39 |
| Share Hispanic: Facebook Counties | 10.63 | 4.69 | 0.00 | 45.27 |
| Share White: Facebook Counties | 71.58 | 9.50 | 0.00 | 93.83 |
| Share English Language Learner: Facebook Counties | 3.45 | 1.31 | 0.00 | 15.81 |
| Share Special Education: Facebook Counties | 13.59 | 1.08 | 0.00 | 18.75 |
| Share Urban: Facebook Counties | 5.88 | 2.84 | 0.00 | 30.94 |
| Share Suburb: Facebook Counties | 7.57 | 4.48 | 0.00 | 42.87 |
| SES All Students: Facebook Counties | -0.09 | 0.30 | -1.48 | 0.69 |

Table 2: Initial OLS Results: Achievement

| | (1) OLS | (2) OLS Controls | (3) IV: Near Half | (4) IV: Far Half |
|---|---|---|---|---|
| Overall Achievement | -0.0001 | 0.0013 | 0.0003 | 0.0021 |
| | (0.0026) | (0.0018) | (0.0022) | (0.0021) |
| White-Black Achievement Gap | -0.0051*** | -0.0001 | 0.0002 | 0.0013 |
| | (0.0013) | (0.0014) | (0.0025) | (0.0018) |
| Male-Female Achievement Gap | 0.0004 | 0.0002 | 0.0007 | 0.0002 |
| | (0.0009) | (0.0008) | (0.0010) | (0.0009) |
| Rich-Poor Achievement Gap | -0.0045*** | 0.0004 | 0.0007 | 0.0004 |
| | (0.0008) | (0.0007) | (0.0012) | (0.0009) |
| Within-County Achievement Std. Dev. | -0.0049 | -0.0097 | -0.0106 | -0.0126* |
| | (0.0073) | (0.0056) | (0.0088) | (0.0062) |

Table 3: Far Half Placebo Border County Results Summary

| | (1) OLS | (2) 1/5 | (3) 1/4 | (4) 1/3 | (5) 2/5 | (6) 1/2 | (7) 3/5 | (8) 2/3 |
|---|---|---|---|---|---|---|---|---|
| **Panel A: No Controls** | | | | | | | | |
| Overall Achievement | -0.0038* | -0.0142 | -0.0134 | -0.0200 | -0.0147 | -0.0161 | -0.0188 | -0.0158 |
| | (0.0018) | (0.1021) | (0.0919) | (0.0892) | (0.0725) | (0.1398) | (0.0350) | (0.0276) |
| White-Black Gap | -0.0056*** | -0.2212 | -0.2634 | -0.6599 | 0.0923 | -0.1326 | -0.0577 | -0.0215 |
| | (0.0011) | (2.5309) | (3.0147) | (23.2796) | (0.4283) | (0.7323) | (0.1255) | (0.0206) |
| Male-Female Gap | -0.0002 | -0.0170 | -0.0183 | -0.0094 | -0.0036 | 0.0005 | -0.0009 | -0.0011 |
| | (0.0005) | (0.0773) | (0.0666) | (0.0371) | (0.0267) | (0.0070) | (0.0046) | (0.0044) |
| Rich-Poor Gap | -0.0025** | -0.0177 | -0.0137 | -0.0201 | -0.0204 | -0.0085 | -0.0049 | -0.0015 |
| | (0.0007) | (0.0440) | (0.0324) | (0.0553) | (0.0692) | (0.0152) | (0.0067) | (0.0048) |
| **Panel B: Census Region** | | | | | | | | |
| Overall Achievement | -0.0003 | -0.0715 | 0.2820 | 0.2679 | 0.4094 | -0.0031 | -0.0134 | -0.0143 |
| | (0.0013) | (1.2632) | (17.7691) | (9.7578) | (25.8456) | (0.0343) | (0.0193) | (0.0192) |
| White-Black Gap | -0.0046** | -0.0597 | -0.0849 | -0.1032 | 0.3183 | -0.0879 | -0.0447 | -0.0250 |
| | (0.0015) | (0.2005) | (0.3186) | (0.5587) | (5.0997) | (0.3154) | (0.0723) | (0.0236) |
| Male-Female Gap | -0.0001 | -0.0136 | -0.0138 | -0.0092 | -0.0078 | -0.0034 | -0.0037 | -0.0038 |
| | (0.0004) | (0.0332) | (0.0273) | (0.0198) | (0.0181) | (0.0059) | (0.0044) | (0.0045) |
| Rich-Poor Gap | -0.0017* | -0.0092 | -0.0058 | -0.0085 | -0.0068 | -0.0047 | -0.0031 | -0.0003 |
| | (0.0007) | (0.0192) | (0.0129) | (0.0163) | (0.0155) | (0.0083) | (0.0046) | (0.0037) |
| **Panel C: Nbr State Partisanship** | | | | | | | | |
| Overall Achievement | 0.0008 | 0.0104 | 0.0111 | 0.0201 | 0.0183 | -0.0033 | -0.0134 | -0.0143 |
| | (0.0013) | (0.0399) | (0.0448) | (0.0675) | (0.0730) | (0.0350) | (0.0214) | (0.0192) |
| White-Black Gap | -0.0045*** | -0.0366 | -0.0461 | -0.0510 | -0.2108 | -0.0704 | -0.0401 | -0.0250 |
| | (0.0012) | (0.0681) | (0.0881) | (0.1280) | (1.9838) | (0.1862) | (0.0558) | (0.0236) |
| Male-Female Gap | -0.0000 | -0.0034 | -0.0048 | -0.0028 | -0.0005 | 0.0006 | -0.0008 | -0.0038 |
| | (0.0004) | (0.0114) | (0.0110) | (0.0102) | (0.0103) | (0.0062) | (0.0045) | (0.0045) |
| Rich-Poon Gap | -0.0018** | -0.0066 | -0.0055 | -0.0085 | -0.0071 | -0.0065 | -0.0042 | -0.0003 |
| | (0.0007) | (0.0105) | (0.0095) | (0.0135) | (0.0129) | (0.0098) | (0.0054) | (0.0037) |

## Table 4: Far Half Balance Test Table

| | (1) OLS | (2) 1/5 | (3) 1/4 | (4) 1/3 | (5) 2/5 | (6) 1/2 | (7) 3/5 | (8) 2/3 |
|---|---|---|---|---|---|---|---|---|
| **Local Characteristics** | | | | | | | | |
| Local Partisanship | 0.8983*** | 0.2198** | 0.2213** | 0.1848* | 0.1759* | 0.0756 | -0.0428 | -0.1232 |
| | (0.0804) | (0.0681) | (0.0783) | (0.0846) | (0.0886) | (0.1074) | (0.1512) | (0.1906) |
| Percentage Urban | -0.2689** | -0.0838 | -0.0686 | -0.0685 | -0.0495 | 0.0345 | 0.1061 | 0.1583 |
| | (0.0827) | (0.0887) | (0.0880) | (0.0892) | (0.0919) | (0.0902) | (0.0890) | (0.1041) |
| Percentage Subruban | -0.5804*** | 0.0732 | 0.0525 | 0.0176 | -0.0153 | 0.0256 | 0.0454 | -0.0014 |
| | (0.1138) | (0.1430) | (0.1384) | (0.1390) | (0.1464) | (0.1709) | (0.1828) | (0.2362) |
| Percentage White | -0.0249 | -0.5565 | -0.5415 | -0.5929 | -0.6656* | -0.8746** | -1.2781*** | -1.4712*** |
| | (0.2884) | (0.3000) | (0.2986) | (0.3054) | (0.3087) | (0.3299) | (0.3787) | (0.4329) |
| Percentage Black | 0.2091 | 0.6245* | 0.6066* | 0.6192* | 0.6539* | 0.7257* | 0.9009* | 1.0298* |
| | (0.1900) | (0.2554) | (0.2477) | (0.2543) | (0.2565) | (0.2872) | (0.3566) | (0.4370) |
| Percentage Hispanic | -0.1865 | -0.1325 | -0.1190 | -0.1035 | -0.0522 | 0.0129 | 0.2021 | 0.2770 |
| | (0.2277) | (0.2152) | (0.2195) | (0.2156) | (0.2128) | (0.2192) | (0.2436) | (0.2618) |
| Percentage Asian | -0.0837*** | -0.0233 | -0.0266 | -0.0255 | -0.0243 | -0.0174 | -0.0127 | -0.0195 |
| | (0.0225) | (0.0177) | (0.0178) | (0.0183) | (0.0176) | (0.0185) | (0.0195) | (0.0245) |
| Percentage Free Reduced Lunch | 0.4814** | 0.3442* | 0.3398* | 0.3687* | 0.4079** | 0.3941* | 0.4952* | 0.5754* |
| | (0.1377) | (0.1611) | (0.1569) | (0.1565) | (0.1565) | (0.1759) | (0.2085) | (0.2460) |
| Percentage English Language Learner | -0.0711 | -0.0372 | -0.0344 | -0.0271 | -0.0111 | 0.0077 | 0.0216 | 0.0432 |
| | (0.0657) | (0.0678) | (0.0683) | (0.0701) | (0.0715) | (0.0762) | (0.0820) | (0.0913) |
| Socioeconomic Status | -0.0170* | -0.0127 | -0.0125 | -0.0134 | -0.0140 | -0.0098 | -0.0126 | -0.0149 |
| | (0.0065) | (0.0075) | (0.0075) | (0.0075) | (0.0077) | (0.0081) | (0.0100) | (0.0125) |
| **Sending Counties Characteristics** | | | | | | | | |
| Overall Achievement: Sending Counties | -0.0021*** | -0.0015 | -0.0013 | -0.0013 | -0.0017* | -0.0020* | -0.0026** | -0.0033** |
| | (0.0006) | (0.0008) | (0.0007) | (0.0007) | (0.0008) | (0.0009) | (0.0010) | (0.0011) |
| White-Black Achievement Gap: Sending Counties | -0.0043*** | 0.0003 | 0.0005 | 0.0006 | 0.0006 | 0.0008 | 0.0009 | 0.0013 |
| | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0013) | (0.0015) | (0.0018) |
| Male-Female Achievement Gap: Sending Counties | 0.0003 | -0.0001 | -0.0001 | -0.0001 | -0.0002 | -0.0001 | -0.0002 | -0.0003 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0004) |
| Rich-Poor Achievement Gap: Sending Counties | -0.0023*** | 0.0002 | 0.0004 | 0.0005 | 0.0004 | 0.0007 | 0.0007 | 0.0009 |
| | (0.0005) | (0.0006) | (0.0007) | (0.0007) | (0.0007) | (0.0009) | (0.0010) | (0.0011) |
| Within-County Achievement Std. Dev.: Sending Counties | -0.0053* | 0.0021 | 0.0022 | 0.0034 | 0.0045 | 0.0062 | 0.0063 | 0.0078 |
| | (0.0024) | (0.0027) | (0.0028) | (0.0027) | (0.0028) | (0.0032) | (0.0039) | (0.0043) |
| **Receiving Counties Characteristics** | | | | | | | | |
| Overall Achievement: Receiving Counties | -0.0023*** | -0.0018* | -0.0017* | -0.0019* | -0.0022** | -0.0023** | -0.0030** | -0.0035** |
| | (0.0006) | (0.0008) | (0.0007) | (0.0007) | (0.0008) | (0.0008) | (0.0009) | (0.0011) |
| White-Black Achievement Gap: Receiving Counties | -0.0034*** | 0.0005 | 0.0007 | 0.0007 | 0.0006 | 0.0011 | 0.0016 | 0.0024 |
| | (0.0009) | (0.0009) | (0.0010) | (0.0010) | (0.0010) | (0.0011) | (0.0013) | (0.0016) |
| Male-Female Achievement Gap: Receiving Counties | 0.0001 | -0.0002 | -0.0002 | -0.0002 | -0.0002 | -0.0001 | -0.0003 | -0.0004 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0003) | (0.0003) | (0.0003) | (0.0004) |
| Rich-Poor Achievement Gap: Receiving Counties | -0.0017*** | 0.0000 | 0.0001 | 0.0002 | 0.0001 | 0.0004 | 0.0004 | 0.0010 |
| | (0.0004) | (0.0004) | (0.0005) | (0.0005) | (0.0005) | (0.0006) | (0.0007) | (0.0008) |
| Within-County Achievement Std. Dev.: Receiving Counties | -0.0062* | 0.0002 | 0.0005 | 0.0015 | 0.0019 | 0.0034 | 0.0038 | 0.0062 |
| | (0.0027) | (0.0026) | (0.0028) | (0.0028) | (0.0029) | (0.0033) | (0.0040) | (0.0044) |
| **Facebook Counties Characteristics** | | | | | | | | |
| Overall Achievement: Facebook Counties | -0.0020* | -0.0024* | -0.0023* | -0.0022* | -0.0024* | -0.0024 | -0.0030* | -0.0033 |
| | (0.0009) | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0013) | (0.0015) | (0.0018) |
| White-Black Achievement Gap: Facebook Counties | -0.0019 | 0.0014 | 0.0013 | 0.0011 | 0.0014 | 0.0017 | 0.0021 | 0.0025 |
| | (0.0014) | (0.0013) | (0.0013) | (0.0013) | (0.0014) | (0.0015) | (0.0017) | (0.0020) |
| Male-Female Achievement Gap: Facebook Counties | 0.0000 | -0.0005 | -0.0005 | -0.0004 | -0.0005 | -0.0005 | -0.0007 | -0.0008 |
| | (0.0004) | (0.0003) | (0.0003) | (0.0004) | (0.0004) | (0.0004) | (0.0005) | (0.0006) |
| Rich-Poor Achievement Gap: Facebook Counties | -0.0022** | -0.0005 | -0.0004 | -0.0002 | 0.0000 | 0.0005 | 0.0007 | 0.0009 |
| | (0.0006) | (0.0007) | (0.0007) | (0.0007) | (0.0008) | (0.0009) | (0.0011) | (0.0012) |
| Within-County Achievement Std. Dev.: Facebook Counties | -0.0026** | -0.0001 | -0.0001 | 0.0002 | 0.0005 | 0.0015 | 0.0013 | 0.0012 |
| | (0.0009) | (0.0009) | (0.0009) | (0.0010) | (0.0011) | (0.0013) | (0.0015) | (0.0016) |

Figure 1: Far Part Specification Curve: Overall Achievement

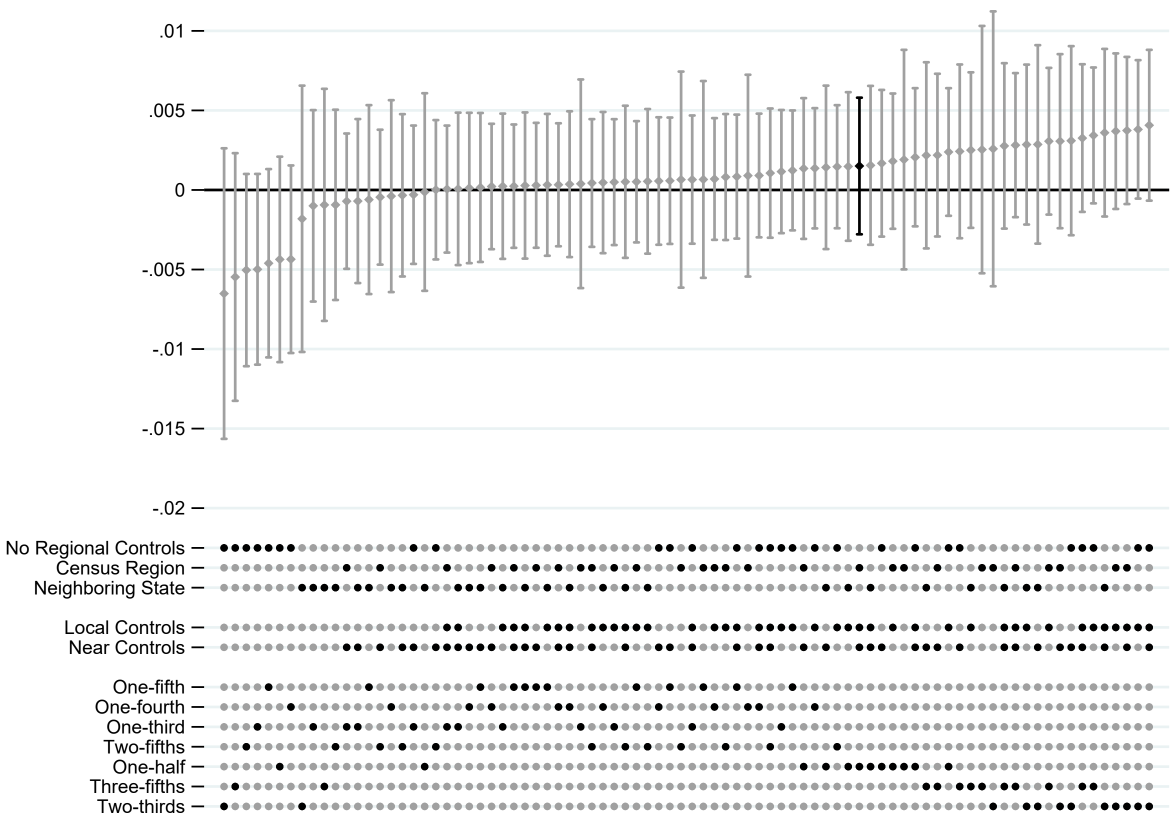


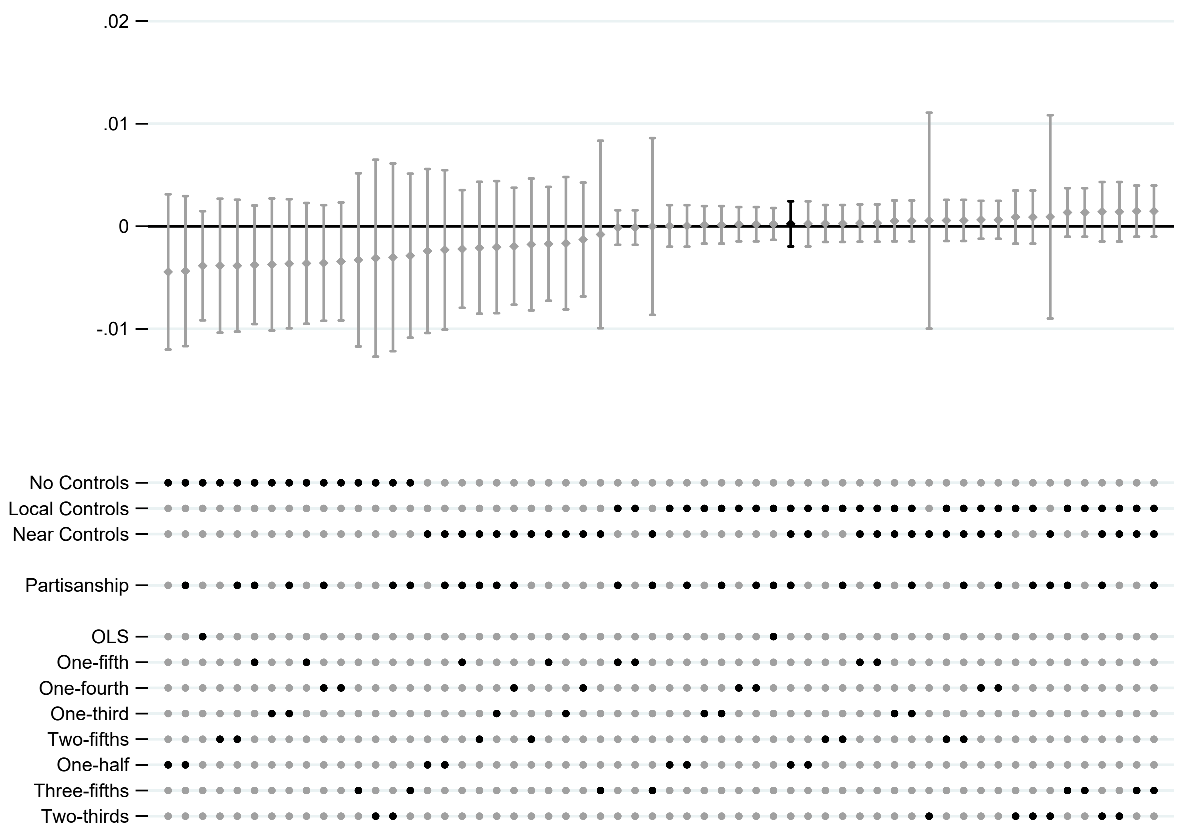
Table 5: Achievement Gap Far Half Baseline Results

| | (1) Overall | (2) White-Black Gap | (3) Male-Female Gap | (4) Rich-Poor Gap | (5) Std. Dev | (6) White | (7) Black | (8) Male | (9) Female |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: No Controls** | | | | | | | | | |
| State Partisanship | -0.0039 | 0.0006 | -0.0002 | 0.0011 | -0.0128 | 0.0006 | -0.0059 | -0.0035 | -0.0034 |
| | (0.0033) | (0.0017) | (0.0012) | (0.0012) | (0.0088) | (0.0027) | (0.0034) | (0.0036) | (0.0030) |
| *N* | 32295 | 14211 | 30827 | 29271 | 31883 | 31046 | 14729 | 31299 | 31205 |
| $R^2$ | 0.0283 | 0.0595 | 0.0267 | 0.0541 | 0.0553 | 0.0514 | 0.0445 | 0.0264 | 0.0311 |
| Stage 1 F Stat. | | | | | | | | | |
| Controls | | | | | | | | | |
| **Panel B: Regional Controls** | | | | | | | | | |
| State Partisanship | 0.0024 | 0.0016 | 0.0004 | 0.0006 | 0.0030 | 0.0033 | -0.0043 | 0.0029 | -0.0034 |
| | (0.0036) | (0.0016) | (0.0014) | (0.0012) | (0.0096) | (0.0030) | (0.0039) | (0.0039) | (0.0030) |
| Obs | 32295 | 14211 | 30827 | 29271 | 31883 | 31046 | 14729 | 31299 | 31205 |
| $R^2$ | 0.1429 | 0.0920 | 0.0761 | 0.0766 | 0.1399 | 0.0754 | 0.0608 | 0.1460 | 0.0311 |
| Stage 1 F Stat. | 218 | 342 | 239 | 245 | 214 | 276 | 357 | 237 | |
| Controls | Y | Y | Y | Y | Y | Y | Y | Y | |
| **Panel C: Nbr State Partisanship** | | | | | | | | | |
| State Partisanship | -0.0001 | 0.0016 | 0.0001 | 0.0005 | -0.0074 | 0.0012 | -0.0043 | 0.0006 | -0.0034 |
| | (0.0031) | (0.0018) | (0.0014) | (0.0012) | (0.0098) | (0.0030) | (0.0041) | (0.0035) | (0.0030) |
| Obs | 32071 | 14171 | 30651 | 29113 | 31703 | 30905 | 14689 | 31116 | 31205 |
| $R^2$ | 0.0775 | 0.0649 | 0.0299 | 0.0578 | 0.0721 | 0.0521 | 0.0500 | 0.0788 | 0.0311 |
| Stage 1 F Stat. | 218 | 214 | 193 | 187 | 212 | 209 | 221 | 198 | |
| Controls | Y | Y | Y | Y | Y | Y | Y | Y | |
| **Panel D: OLS Results** | | | | | | | | | |
| State Partisanship | -0.0048 | $-0.0061^{***}$ | -0.0002 | $-0.0035^{***}$ | $-0.0179^{*}$ | $-0.0051^{*}$ | -0.0047 | -0.0050 | -0.0034 |
| | (0.0024) | (0.0013) | (0.0010) | (0.0009) | (0.0072) | (0.0021) | (0.0024) | (0.0026) | (0.0030) |
| Controls | N | N | N | N | N | N | N | N | |

Table 6: Border County Results: Achievement

| | (1)<br>OLS No Controls | (2)<br>OLS Controls | (3)<br>IV No Controls | (4)<br>IV Controls |
|---|---|---|---|---|
| Overall Achievement | -0.0038 | 0.0002 | -0.0044 | 0.0007 |
| | (0.0027) | (0.0008) | (0.0039) | (0.0010) |
| White-Black Achievement Gap | 0.0024 | 0.0004 | 0.0046 | 0.0022 |
| | (0.0015) | (0.0012) | (0.0028) | (0.0021) |
| Male-Female Achievement Gap | 0.0005 | 0.0002 | -0.0002 | 0.0001 |
| | (0.0009) | (0.0004) | (0.0012) | (0.0005) |
| Rich-Poor Achievement Gap | -0.0000 | -0.0007 | 0.0016 | -0.0004 |
| | (0.0007) | (0.0005) | (0.0011) | (0.0007) |
| Within-County Achievement Std. Dev. | -0.0078 | -0.0035 | -0.0103 | -0.0053 |
| | (0.0046) | (0.0027) | (0.0059) | (0.0036) |

Figure 2: Border County Specification Curve: Overall Achievement



# A Appendix A: Additional Tables & Figures

Below I include the specification curves for the far part design and the border county design. Figure titles indicate both whether the specification curve shows estimates from the far part design or the border county design and the particular educational outcome. I describe the specification curves for the far part design in Section 4.3 and the specification curves for the border county design in Section 5.2.

Within each specification curve, the estimate for each specification is represented as a grey diamond, with 95% confidence intervals as the bars. The estimate and confidence interval for the preferred specification in each design is shaded in black. Below the graph are the indicators for the choices made in each specification, collected into three groups, with the colored in dots representing the chosen options for that specific specification. For example, below in Figure A1, the preferred specification controls for regional effects using Census Region dummies, with Local Controls and Near Controls, and uses a cutoff of One-half.

For the border county specification curves, the option Partisanship indicates whether the controls included the difference in local partisanship within a border county pair. OLS indicates a specification using the border county design without the far part instrumental variable, and the cutoffs indicate which particular cutoff was used in the combined far part border county design.

Figure A1: Far Part Specification Curve: White-Black Achievement Gap

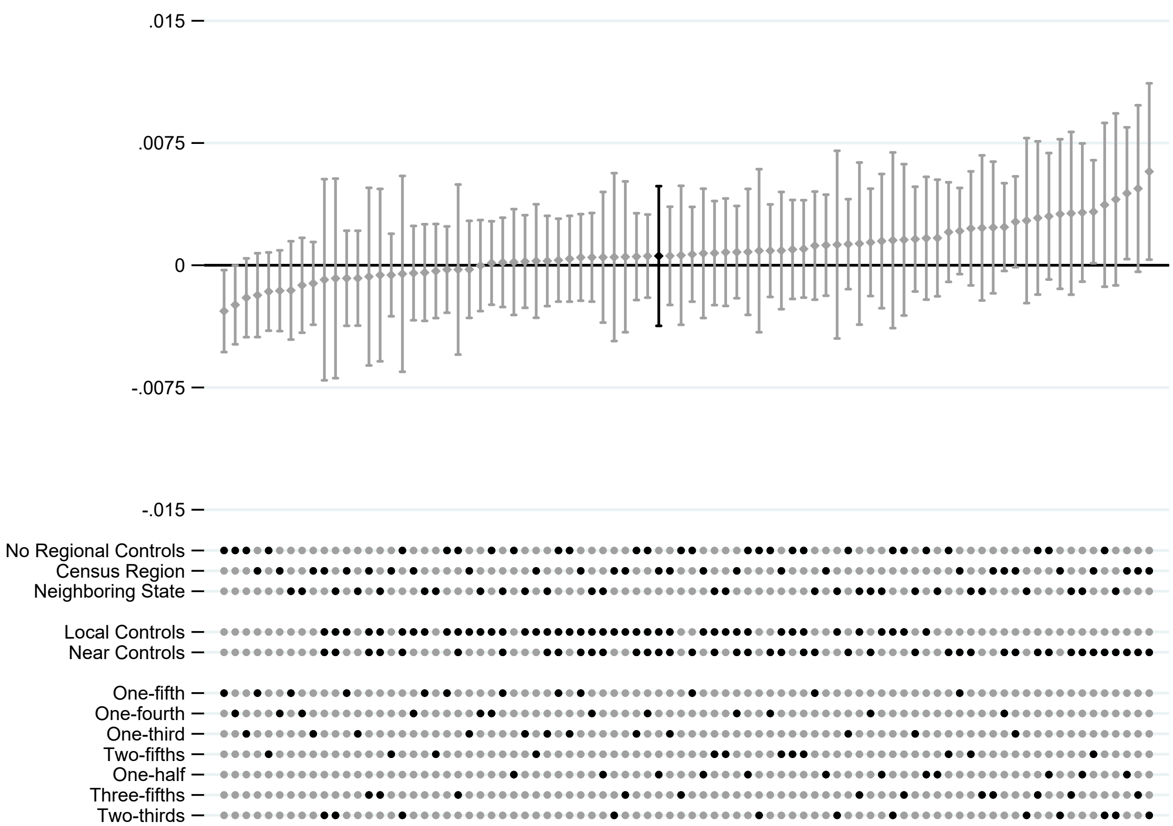


Figure A2: Far Part Specification Curve: Male-Female Achievement Gap

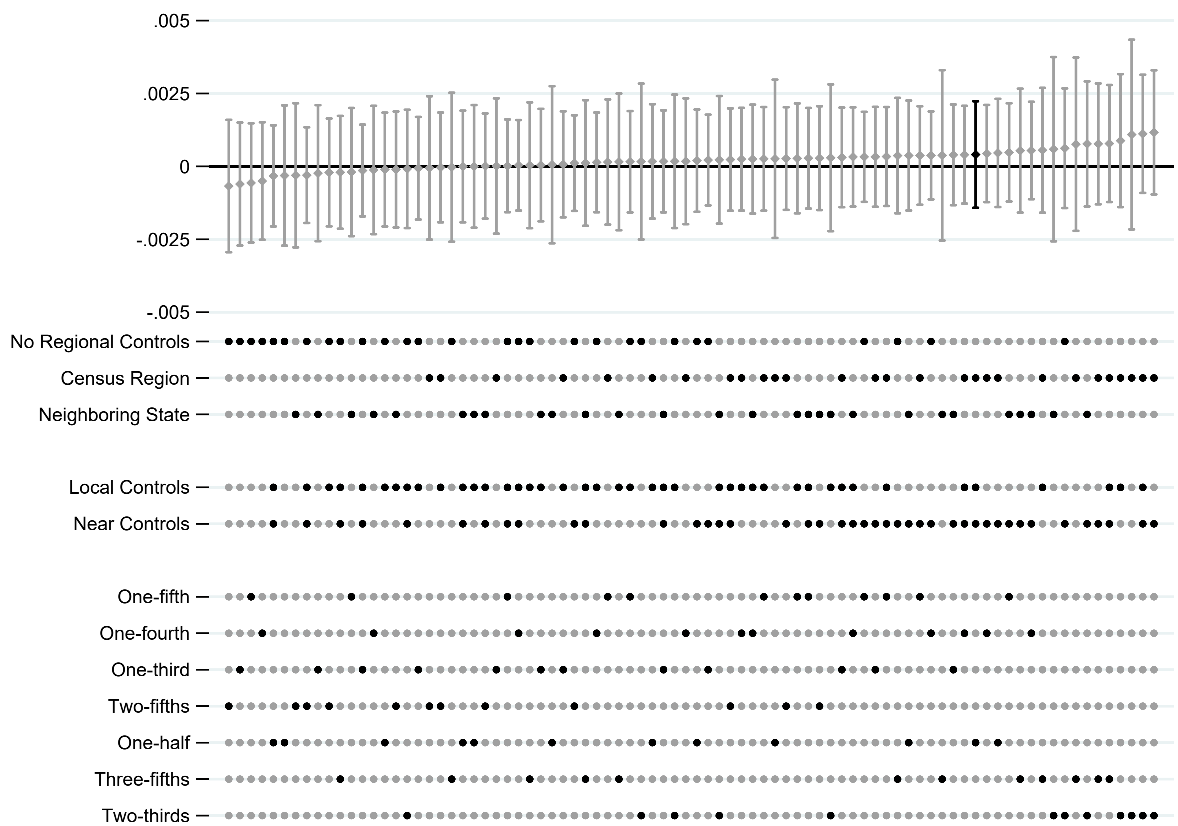


Figure A3: Far Part Specification Curve: Rich-Poor Achievement Gap

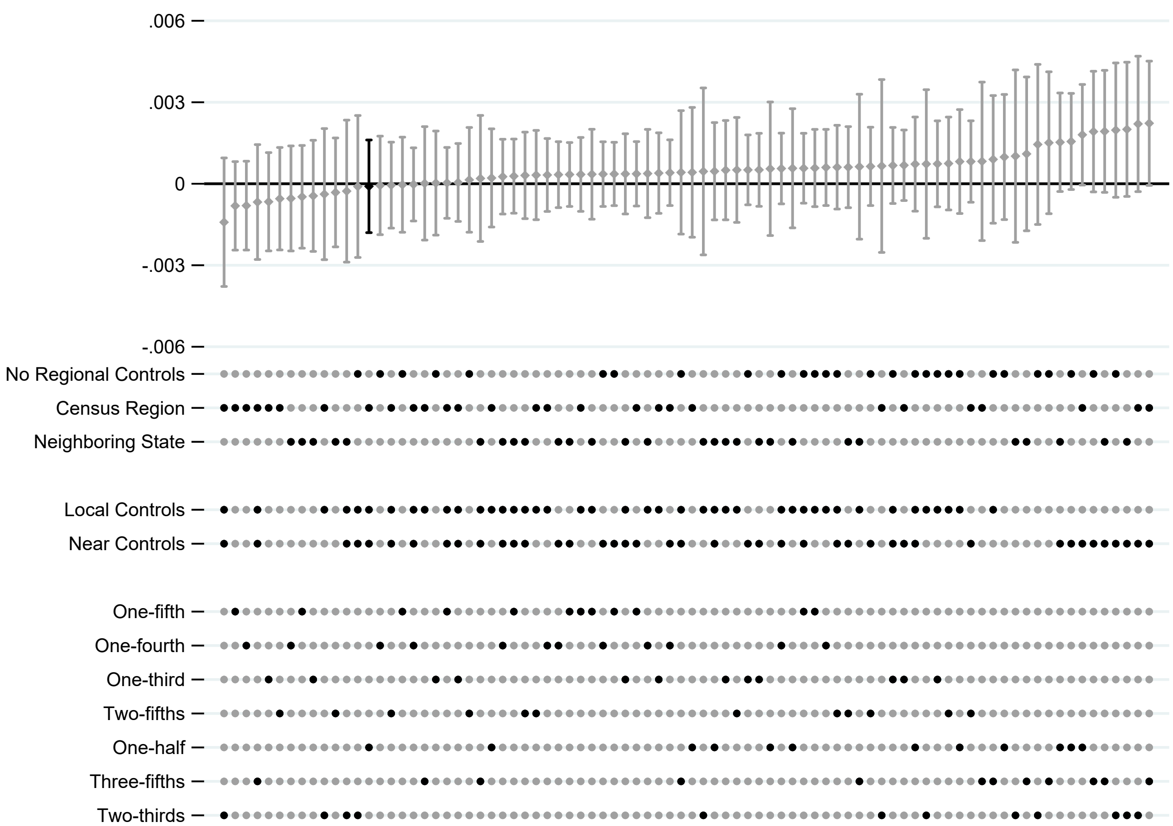


Figure A4: Border County Specification Curve: White-Black Achievement Gap

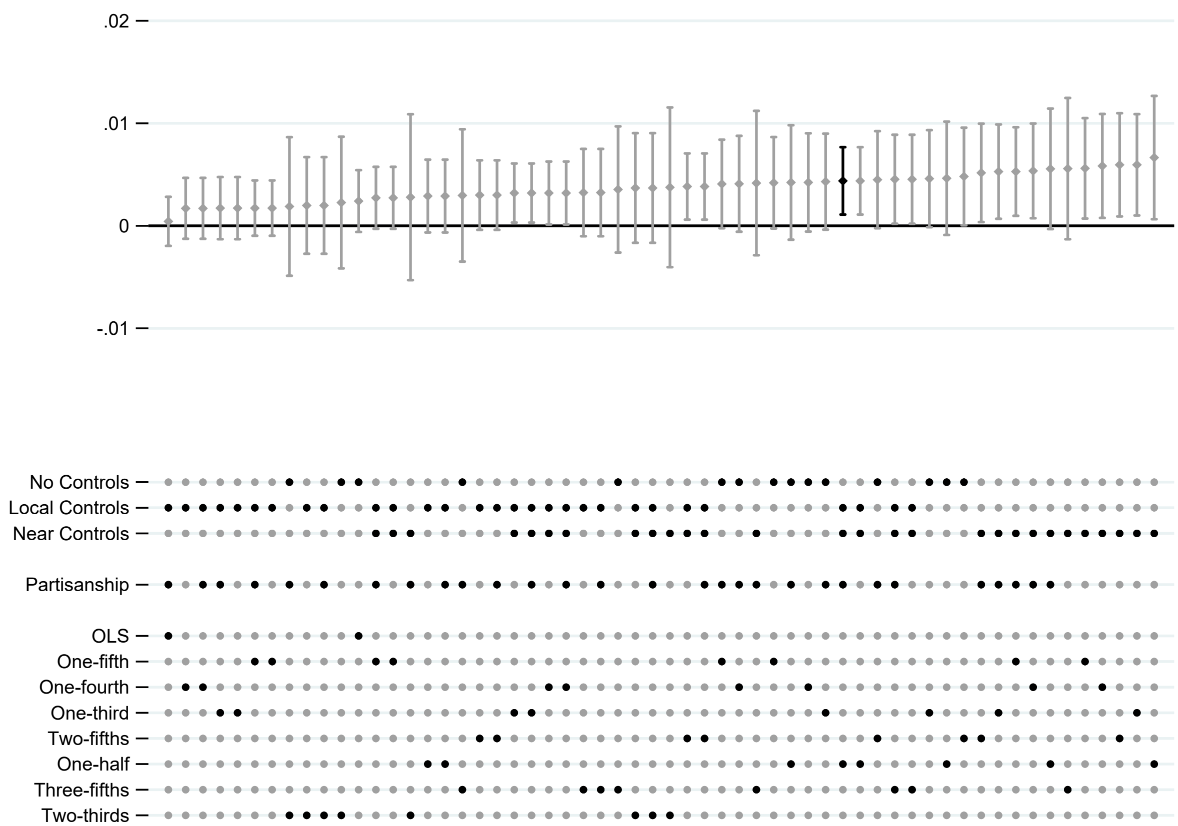


Figure A5: Border County Specification Curve: Male-Female Achievement Gap

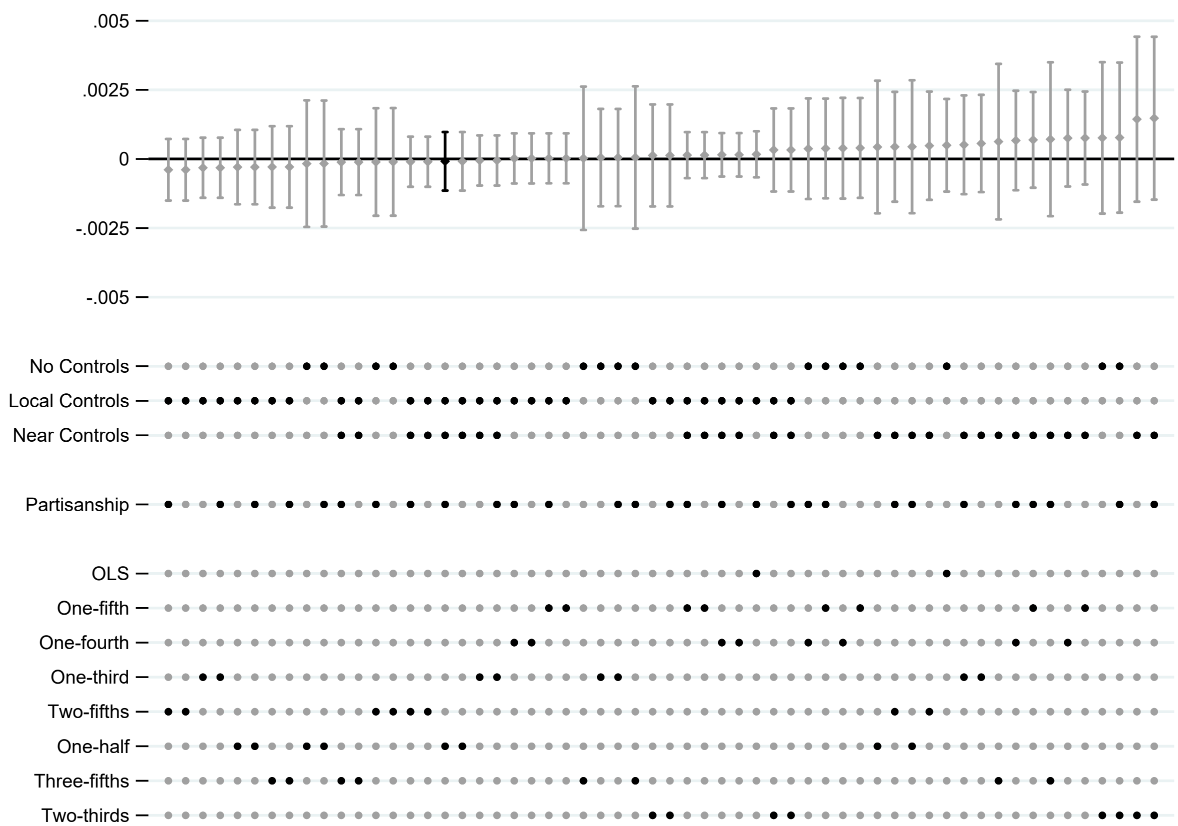


Figure A6: Border County Specification Curve: Rich-Poor Achievement Gap