

# Spending & Achievement Effects of Increased Funding to Rural School Districts: Evidence from Wisconsin\*

Riley K. Acton<sup>†</sup>  
Miami University and IZA

Cody Orr  
Center for Economic Studies  
U.S. Census Bureau

Salem Rogers  
Michigan State University

November 16, 2023

## Abstract

We study the spending and achievement effects of increased state funding to rural American school districts by leveraging the introduction and subsequent expansion of Wisconsin's Sparsity Aid Program. We find that the program, which provides additional state funding to small and isolated school districts, increased spending in eligible districts by 2% annually. Districts mostly allocate the funds toward non-instructional areas, such as hiring additional administrative staff and increasing spending on general operations and food service. As a result, we do not find consistent evidence that the increased funding improved standardized test scores or changed postsecondary enrollment and completion patterns. However, our confidence intervals do not exclude positive effects for rural schools as large as those found elsewhere in the literature.

**JEL Codes:** H75, I21, I22, R51

**Keywords:** School finance, educational attainment, rural schools

---

\*We gratefully acknowledge that this research was made possible through data provided by the Wisconsin Department of Public Instruction (DPI). The results, information, and opinions presented here solely represent the authors' analysis, information, and opinions and are not endorsed by, or reflect the views or positions of the DPI or any employee thereof, Miami University, the U.S. Census Bureau or Michigan State University. We would also like to thank Erica Edwards for her excellent research assistance. We are further grateful for generous financial support for this project provided by the Bill & Melinda Gates Foundation. Finally, we would like to thank Scott Imberman, Peter Nenka, and seminar participants at the Association for Education Finance and Policy Annual (AEFP) and Association for Public Policy Analysis & Management (APPAM) Annual Conferences, the U.S. Department of Education's Rural Education Achievement Program, and Elon University for their helpful comments and suggestions.

<sup>†</sup>Corresponding author. Contact: Department of Economics, Miami University. 800 E. High St., Oxford, OH 45056. actonr@miamioh.edu.

## 1 Introduction

Rural school districts in the United States face unique challenges relative to their urban and suburban counterparts, such as frequent staffing turnover, high transportation costs, and limited economies of scale (Sipple and Brent, 2015; Showalter et al., 2019). These characteristics may reduce how much rural districts can spend on specialized staff (e.g., social workers and guidance counselors) and curriculum (e.g., AP courses and career and technical education), potentially contributing to the well-documented disparities in educational outcomes between rural and non-rural students. For instance, rural students are four percentage points less likely to attend college and seven percentage points less likely to earn a bachelor's degree than their non-rural peers (Wells et al., 2019).

As a potential remedy to these inequalities, 34 states provide additional funding to rural districts through grants and multipliers that account for their low enrollment, low density of students, and/or isolated location (Education Commission of the States, 2021). These funding programs vary widely in terms of their eligibility requirements and generosity (Gutierrez and Terrones, 2023). But despite their prevalence and their relevance to policymakers, there are few attempts in the literature to estimate how school districts use the additional funds provided by these programs and how they influence student outcomes. Understanding the spending and achievement impacts of these state funding programs is important because, while prior literature documents that, on average, increases in school funding improve student outcomes (Jackson, 2020), the heterogeneity in observed effects (Jackson and Mackevicius, 2023) and unique challenges of rural education make the efficacy of increased funding to rural districts less certain. For example, given rural districts' distinct cost structures, they may allocate additional funds differently than their urban or suburban counterparts, generating different effects on student achievement and educational attainment.

In this paper, we evaluate the impact of Wisconsin's Sparsity Aid program, which is one of the largest state-level school finance programs targeting small, rural districts. Currently, the program provides \$28 million in additional, unrestricted funding to 185 districts in the state. Our empirical approach leverages the introduction of the program in 2008 and subsequent expansion in 2010 in

event study and difference-in-differences designs that compare the outcomes of school districts that were eligible and ineligible for sparsity aid, before and after the policy changed. Using comprehensive school finance data from the U.S. Department of Education’s Common Core of Data (CCD), we first show that receiving a sparsity aid payment increases annual spending on elementary and secondary education by approximately \$226 per student, or 2% of average spending.

To further understand how district spending responds to an increase in funding, we analyze detailed, district-level spending data from the Wisconsin Department of Public Instruction (DPI). We document that districts use sparsity aid dollars in a variety of ways and, in general, tend to allocate funds to non-instructional areas: we estimate positive, statistically significant increases in spending on administration, food service, and general operations, as well as non-salary spending on instruction outside of core academic subjects (e.g., extracurricular activities), due to the sparsity aid program. Notably, we find minimal effects on teacher staffing —including student/teacher ratios, average salaries, and experience levels —but find increases in the staffing of administrative positions. Furthermore, we find substantial heterogeneity in how districts allocate funds, with increases in spending in most categories inversely related to districts’ baseline budget shares. This finding suggests that the unrestricted nature of the sparsity aid program allows administrators to put the additional funding towards areas, particularly non-instructional areas, that were relatively underfunded prior to the program’s introduction. In a survey of school district administrators, we confirm that districts used these funds flexibly and rarely earmarked them for specific purposes.

We then assess the impact of this increased spending on educational outcomes using student-level data from the DPI. We find little evidence that the increased spending resulting from the program substantially improved student performance on state standardized tests. Our preferred point estimate for average scores across grades and subjects is statistically indistinguishable from zero, which may explained by the minimal increase in teacher staffing and instructional spending that we note above. We also see little effect of the program on behavioral outcomes, such as attendance and disciplinary incidence, and on postsecondary enrollment and completion rates for the full sample of students. For the subset of students eligible for free or reduced-price lunch (FRL), we find suggestive evidence that the sparsity aid program improved enrollment and completion at

two-year colleges.

Despite our largely null effects on student outcomes, we note that our findings are not inconsistent with the existing school finance literature. In a meta-analysis of 31 studies that causally identify the effects of increased school spending on student outcomes, Jackson and Mackevicius (2023) document that, on average, a policy increasing spending by \$1,000 per student improves test scores by 0.032 standard deviations and increases college-going by 2.8pp. Given that the Wisconsin sparsity aid program increases school spending by about \$250 per student, we would expect test score gains of about 0.008 standard deviations and college-going gains of about 0.7pp if the returns to school spending in rural Wisconsin were similar to the returns of previously-studied policies. Our 95% confidence intervals do not exclude positive effects as large as these. Thus, we cannot rule out the possibility that larger increases in school spending in rural areas can have similar effects to increased spending in non-rural areas. However, our results highlight the importance of understanding how districts use increased funding and the potential for differences in districts' needs and allocation decisions across different contexts.

Our findings contribute to several lines of literature on rural education and public investments in K-12 schools. First, we contribute to a growing set of studies on a variety of education policies targeted at rural schools and students. In recent years, an increasing number of small and rural school districts have adopted four-day school weeks as a cost-saving measure (Thompson et al., 2021). While these adoptions have reduced expenditures (Thompson, 2021a), they have also caused a reduction in student achievement (Thompson, 2021b). Other rural communities have either chosen or been mandated to reign in costs by consolidating school districts (Duncombe and Yinger, 2007). Such consolidations do not necessarily affect districts' economies of scale (Gordon and Knight, 2008), but they may lead to increased student performance (McGee et al., 2022) at the expense of population growth and property values (Smith and Zimmer, 2022). Some states have also begun to allocate funding to rural communities to specifically address teacher shortages, which Tran and Smith (2021) find modestly reduces teacher turnover. Other states have attempted to retain teachers and bolster student success by providing professional development in specific content areas to teachers in rural areas, realizing significant math gains (Barrett et al., 2015). While these stud-

ies consider narrowly prescribed interventions, we examine the efficacy of additional, unrestricted funding that allows rural districts to respond to their unique needs.

We also add to a large literature on how school spending affects student outcomes. Much of this literature addresses the endogeneity of school spending by exploiting variation in court-ordered school finance reforms that weakened the correlation between district wealth and per-student spending. These studies generally find positive effects of increased school spending on test scores (Papke, 2005; Roy, 2011; Lafortune et al., 2018), high school completion (Candelaria and Shores, 2019), educational attainment (Hyman, 2017), adult earnings (Jackson et al., 2016), and income mobility (Biasi, 2021b). These effects are generated by sustained increases in school spending that are much larger than the increases induced by the Wisconsin sparsity aid program or by other grant programs that target rural school districts. For example, Lafortune et al. (2018) estimate that, on average, a school finance reform increases state funding for low-income districts by \$1,225 per student per year and for high-income districts by \$527 per student per year. The sparsity aid program, in contrast, increases funding by \$226 per student per year during the time frame of our analysis. In this way, our findings are more closely aligned with studies of smaller-scale investments in schools, such as funding for new technology purchases (Bass, 2021) or textbooks (Holden, 2016), which have been shown to generate improvements in student achievement. Our paper is distinguished from this prior work by the fact that the sparsity aid program allows for unrestricted spending —along with its focus on rural schools.

To our knowledge, only one existing study considers the effect of a sparsity aid policy like Wisconsin's.<sup>1</sup> Kreisman and Steinberg (2019) exploit two features of Texas' school finance system that provide additional funding to geographically large districts with low enrollment. Using regression discontinuity and regression kink designs, they find that an additional \$1,000 in funding per year over students' schooling years improves reading scores by 0.1 standard deviations, improves math scores by 0.07 standard deviations, decreases high school dropout rates by 1.6 percentage points, and increases college enrollment among students who take college preparatory exams (e.g., SAT, AP exams) by 10 percentage points. Kreisman and Steinberg are not able to fully measure enroll-

---

<sup>1</sup>We note that some other papers, such as Hyman (2017) and Rauscher (2020) consider heterogeneous effects of funding in rural areas, as opposed to urban or suburban setting. However, they do not study policies specifically targeted at rural districts.

ment changes in the two-year sector because many students who enroll in a two-year college do not take these exams.

We build on this prior work by providing new evidence on the impacts of increased education funding to rural communities within a different demographic and policy context. The Wisconsin policy we study serves districts that are, on average, much smaller and less dense than the Texas districts studied by Kreisman and Steinberg. The policy is also structured as a stand-alone grant, rather than being embedded within the state's general aid formula, which may affect how the program is perceived and used by district administrators. In addition, our empirical approach that leverages the introduction and expansion of the program allows us to estimate effects across all eligible districts, rather than those situated at the enrollment and density cutoffs, which are the largest and least sparse of districts receiving additional funding. In doing so, our paper considers how the effects of additional funding to rural school districts may vary across settings and provides new insights into how programs similar to Wisconsin's may affect the outcomes of similarly small and sparse rural districts.

## 2 Policy Background & Data

### 2.1 Policy Introduction

Wisconsin is home to 421 unique school districts, each of which is funded by a combination of state aid (46.1%, on average), local property taxes (42.2%), federal funding (7.2%), and other local revenue sources (4.5%) (Kava and Pugh, 2019). The majority (79%) of state aid is allocated via a “general aid” formula that distributes funds based on districts’ per student value of taxable property to equalize funding across districts with low and high property tax revenues. The remainder (21%) of state aid is allocated via categorical aid programs, which are designed to fund specific costs faced by districts, such as special education, transportation, and limited-English proficiency (LEP) programs. Unlike general aid, categorical aid programs are distributed without regard to the district’s local property tax revenues and are not subject to state revenue limits that cap the

total amount of general state aid and local property tax revenues a district can receive.<sup>2</sup> As such, categorical aid programs can increase a district's resources even if they are not eligible to receive additional general aid.

In 2007, under Wisconsin Act 20, the state legislature added a new categorical aid program called the Sparsity Aid Program. The goal of the program was to provide additional unrestricted funds to rural school districts experiencing small economies of scale.<sup>3</sup> Initially, districts were eligible to receive sparsity aid funds if (1) they had a pupil membership of no more than 725 in the prior year, (2) they had a density of fewer than 10 members per square mile in the prior year; and (3) at least 20% of the district's students in the prior year were eligible for free or reduced-price lunch. The program first became active in the 2008-2009 school year, during which eligible districts whose FRL percentage fell between 20 and 50 percent were slated to receive \$150 per student while those whose FRL percentage exceeded 50 percent received \$300 per student. However, the total program appropriation was not large enough to make these payments, so payments were prorated to \$67 per student and \$134 per student, respectively. Beginning in 2009, the legislature removed the bifurcation and all eligible school districts were eligible to receive \$300 per student. Once again, the program was underfunded and, due to proration, eligible districts only received \$69 per student.

In 2010, the Wisconsin legislature significantly expanded funding for sparsity aid, from \$3.5 million per year to nearly \$15 million per year. Today, the program allocates almost \$28 million per year to 185 districts and is one of the largest categorical aid programs in the state.<sup>4</sup> From the 2010-2011 school year onward, eligible districts received between \$237 and \$400 per student per year, including any necessary prorations. The only other change in program eligibility during our time frame occurred in 2015 when the FRL requirement (which was not binding for any otherwise eligible districts) was removed and the enrollment eligibility threshold increased from 725 to 745.

Figure 1 plots the average sparsity aid amount received by districts, both in total and on a per-

---

<sup>2</sup>For a full discussion of revenue limits in Wisconsin and the impact on students of raising them, see Baron (2022).

<sup>3</sup>See the Wisconsin Sparsity Aid Program website for a full legislative history.

<sup>4</sup>Source: Wisconsin DPI. The 188 count of districts in the 2022-2023 includes two who receive "stop-gap" sparsity aid (introduced in the 2017-2018 school year to provide 50% of the prior year's sparsity aid grant to schools who lose eligibility) and 33 who receive Tier 2 sparsity aid funding (introduced in the 2021-2022 school year to provide a reduced sparsity aid grant to schools with membership between 745 and 1,000).

student basis, that are consistently eligible for sparsity aid from 2008 to 2017.<sup>5</sup> Prior to 2008, districts received no sparsity aid. In 2008 and 2009, districts received an average of about \$32,480 annually, or \$72 per student per year. Since 2010, districts have received an average of \$115,350 annually or \$269 per student per year. For context, this total amount is approximately equal to 2.5 times the average full-time equivalent (FTE) teacher's salary in sparsity-eligible districts. Given that these districts employ an average of 35 teachers, this additional funding —while small in per-student terms relative to previously studied school finance interventions —represents a meaningful increase in districts' available resources.

## 2.2 Data Sources

Our primary data source for student outcomes is the Wisconsin DPI student-level records from 2005-2006 through 2017-2018. These records contain demographic information, enrollment history, attendance data, disciplinary infractions, and standardized test scores for every student who attended a Wisconsin public school in the time period. The state further links these records to post-secondary enrollment and completion records from the National Student Clearinghouse (NSC).<sup>6</sup> We supplement the student-level data with several sources of district-level data. We obtain a rich set of district-level demographics, enrollment, and financial information from the National Center for Education Statistics (NCES) Common Core of Data (CCD), along with annual sparsity aid payments and additional school finance outcomes —such as the revenue districts receive from local, state, and federal sources and the amount they spend on instruction, support, and administration —from the DPI. We also obtain district-level information on teacher and administrator staffing, including full-time equivalent (FTE) staffing levels, average salaries, and average years of experience, from the DPI. In addition, we follow Bayer et al. (2021) to aggregate annual census tract-level house price index data from the Federal Housing Finance Agency (FHFA) to the school district level to track district-level house price indices over time.<sup>7</sup>

---

<sup>5</sup>Of the 106 districts initially eligible for the program in 2008, 104 remain eligible across the entire time series.

<sup>6</sup>Additional information about Wisconsin's use of NSC data is available on the DPI website: <https://dpi.wi.gov/wisedash/districts/about-data/ps-enrollment>.

<sup>7</sup>All indices are measured relative to the first year the FHFA tracts data for a given tract. See Bogin et al. (2018) for more detail on the construction of this dataset.

To validate and expand upon results from these sources of administrative data, we additionally conducted a survey of rural school district leaders throughout Wisconsin. The survey primarily contained questions regarding the usage of sparsity aid funds, but it also measured general awareness of the program and the expected effects of receiving sparsity aid funding. We distributed the survey electronically to all superintendents/district administrators, principals, and financial officers who were employed by a district receiving sparsity aid funding in 2022. The Wisconsin Rural School Alliance (WiRSA) also advertised the survey in an email newsletter. Out of the 409 employees we attempted to contact via email, 39 (9.5%) completed the survey, representing 37 distinct school districts (and one unnamed school district). For our analysis, we drop 3 observations that reported not working in a sparsity aid-eligible district. Appendix B contains the full text of the survey and recruitment email, and we reference the results throughout the text. Appendix Table B.1 further reports baseline summary statistics for the sample of districts represented by the survey respondents and the sample of sparsity aid-eligible districts without a survey respondent. The two samples are similar across a variety of dimensions, including size, finances, and student achievement. As such, we interpret our survey responses as representative of how a typical sparsity aid district perceived and used the sparsity aid program.

### **2.3 Sample Restrictions**

Because the goal of our analysis is to compare the outcomes of similar districts that did and did not receive sparsity aid funding, we limit our sample to school districts that offer all grades K-12 and are either always or never eligible for the sparsity aid program.<sup>8</sup> We drop 13 districts that have poor house price index coverage and 5 districts with implausibly large spikes in either revenue or spending that we believe are due to data reporting errors. We then drop 113 districts that were in the top 30% of the enrollment or density distributions prior to the policy's introduction in 2008. This restriction eliminates Wisconsin's largest cities and suburbs, which differ in multiple dimensions from rural areas, and may provide poor estimates for the counterfactual outcomes of rural districts

---

<sup>8</sup>The majority of Wisconsin school districts offer all grades K-12. In 2007, there were 426 local school districts in the state, 369 (86.6%) of which offered grades K-12. 46 districts only offered grades K-8, while 1 only offered grades 6-12 and 10 only offered only grades 9-12.

had rural districts not received sparsity aid.<sup>9</sup> Finally, because we will consider specifications with flexible region-specific time trends, we drop 14 non-sparsity districts located in regions where no districts in the region both meet the above criteria and receive sparsity aid payments.<sup>10</sup>

Our final sample consists of 89 districts that received sparsity aid payments beginning in 2008 and 99 districts that never received sparsity aid payments. Figure 2 identifies the locations of these districts. Both sparsity-eligible and ineligible districts in our sample are geographically distributed throughout Wisconsin and, often, eligible and ineligible districts are located next to one another. The only area of the state that our sample does not cover is the southeast region, in and around the Milwaukee metropolitan area.

## 2.4 Summary Statistics

Table 1 provides summary statistics on school districts in Wisconsin and in our analysis sample, averaged across the academic years 2003-2007. Panel A provides information on the size and location of sparsity-eligible and ineligible districts. Unsurprisingly given the eligibility guidelines of the program, sparsity-eligible districts are smaller and less dense than the districts in our comparison group. However, the comparison group itself is relatively small and sparse compared to Wisconsin as a whole: the average Wisconsin school district enrolled 2,035 students and 45.9 students per square mile before 2008, whereas our comparison group enrolled an average of 1,231 students and 9.31 students per square mile. Sparsity districts also tend to have fewer school buildings and fewer students per building than their non-sparsity peer districts in the comparison group, with the comparison districts still being smaller than the overall Wisconsin average. 97.8% of school districts in our sample are characterized as “rural” by the NCES defined as an area outside of an urban cluster, as are the majority (70.7%) of districts in our comparison group.<sup>11</sup>

Panel B of Table 1 then provides summary statistics on the demographic characteristics of

<sup>9</sup>In Section 4.1 and Appendix Figure A.10, we consider alternative sample restrictions and show that our effects are similar across different enrollment and density criteria.

<sup>10</sup>Throughout the analysis, we define school district regions using Wisconsin’s Cooperative Educational Service Agency (CESA) definitions. CESAs are collections of adjacent school districts that facilitate communication and cooperation across districts in the same area of the state. More information is available on the Wisconsin DPI website.

<sup>11</sup>28.3% of our comparison districts are located in “towns” (defined as an area within an urban cluster, but outside of the primary urbanized area) and 1% are located in suburban areas. No districts in our comparison group are located in urban areas. In contrast, 7% of Wisconsin school districts statewide are located in urban areas, with an additional 14.7% located in suburban areas.

the two groups of school districts. The racial demographics of our treatment and comparison groups are similar, with both enrolling approximately 94% white students. In contrast, the average Wisconsin district was 88.7% white between 2003 and 2007. Students attending sparsity districts are somewhat more disadvantaged than our comparison districts, with an average FRL rate of 34.7% (vs. 23.7%) and an average local child poverty rate of 14.5% (vs. 9.5%). The house price index in sparsity districts is also about 36 percentage points lower than that in the comparison districts, though the comparison district group average is also lower than the Wisconsin average.

Next, Panel C compares district finances in sparsity-eligible districts to the comparison districts in our analysis sample. Sparsity districts both receive and spend more per student than the comparison group—and the state average—prior to the introduction of the sparsity aid program, which is surprising given that sparsity districts tend to be less wealthy than non-sparsity districts. However, in Appendix Figure A.1 we show that there is a striking non-linear relationship between district size and per-student finances: smaller districts receive and spend much more per student than larger districts do, perhaps due to fixed costs and economies of scale that allow districts to reduce per-student costs as enrollment increases. Thus, because sparsity districts are, by definition, smaller than their peer districts that are not eligible for sparsity aid, they tend to have higher revenues and expenditures on a per-student basis. Sparsity districts also tend to spend a larger share of their budgets on administrative and other operational costs (e.g., transportation, food service), as compared to instruction and support services.<sup>12</sup>

Panel D then compares teacher and administrator staffing across sparsity-eligible and ineligible districts. Due to their small size, sparsity districts employ fewer teachers and administrators (superintendents, principals, and directors/coordinators), but sparsity districts have similar—or a bit higher—staffing levels on a per-student basis. In addition, sparsity and non-sparsity districts employ teachers with similar levels of experience. Despite this similarity in experience, and the fact that sparsity districts spend more per-student overall, teachers in sparsity-eligible districts are, on average, paid roughly \$2,900 (6.7%) *less* than teachers in the comparison group. This disparity suggests that the higher spending levels in sparsity districts are not due to higher investments in

---

<sup>12</sup>We derive the budget shares in Table 1 from detailed, district-level financial data submitted to the Wisconsin DPI. We provide more information on this data source and the construction of budget shares in Section 5.

teacher pay, but potentially a result of the higher per-student operating costs sparsity districts face due to their small size and lack of economies of scale.

Finally, Panel E highlights differences in baseline achievement between sparsity districts and the comparison group. While we might expect sparsity districts to outperform their sparsity-ineligible peers because of their higher levels of spending and smaller school sizes (Kuziemko, 2006; Gershenson and Langbein, 2015; Egalite and Kisida, 2016), prior to the sparsity aid reform, they tended to have lower levels of achievement than their non-sparsity peer districts *and* the state average. A smaller share of students grades 3-8 and grade 10 were rated as “proficient” on state math and reading exams, and a smaller share of students enrolled in college within one year of graduating from high school or completed college by the end of our data’s time frame. These disparities lend credence to the idea that sparse, rural school districts face additional challenges in educating their students and motivate our analysis of how districts utilize increased state funding and whether a policy like the sparsity aid program can improve student outcomes.

### 3 Empirical Strategy

#### 3.1 Difference-in-Differences Framework

Our empirical strategy leverages the introduction and subsequent expansion of the sparsity aid program, which generated exogenous increases in district funding for eligible districts and should not have affected ineligible districts. To demonstrate that the program indeed increased district revenues and expenditures, we begin by estimating the effect of the program on district-level outcomes by estimating equations of the following form:

$$Y_{dt} = \beta \text{SparsityAid}_{dt} + \mathbf{Z}_{dt}\Pi + \theta_d + \delta_t + \varepsilon_{dt} \quad (1)$$

where  $Y_{dt}$  is an outcome (e.g., revenues or expenditures per student) for district  $d$  in year  $t$  and  $\text{SparsityAid}_{dt}$  indicates whether district  $d$  received sparsity funding in year  $t$ . This variable “turns on” for all eligible districts in 2008 and remains zero for all ineligible districts throughout the entire time frame of the sample.  $\mathbf{Z}_{dt}$  are time-varying district covariates (e.g., enrollment, student

demographic composition) that may also affect a district's outcomes over time. We discuss our choice of control variables in the context of our identification assumptions in Section 3.2.  $\theta_d$  are district-level fixed effects that capture any time-invariant characteristics of school districts (e.g., location within the state) and  $\delta_t$  are year fixed effects that capture any state-wide changes in district finances or student outcomes over time.  $\varepsilon_{dt}$  is the error term. Throughout the analysis, we cluster all standard errors at the school district level.

The coefficient of interest in equation (1) is  $\beta$ , the difference-in-differences (DID) estimate of how a school district's outcomes change when it becomes eligible for the sparsity aid program. In order for  $\beta$  to represent the causal effect of the sparsity aid program on outcomes, it must be the case that sparsity-eligible districts' outcomes would have evolved the same as non-sparsity-eligible districts' outcomes had the sparsity aid program never been implemented.<sup>13</sup> While this counterfactual assumption is inherently untestable, we assess its plausibility by extending our DID equation to the following event study specification:

$$Y_{dt} = \sum_{k=2003, k \neq 2007}^{2017} \beta_k \text{SparsityEligible}_d * 1[t = k] + \mathbf{Z}_{dt} \boldsymbol{\Pi} + \theta_d + \delta_t + \varepsilon_{dt} \quad (2)$$

where  $\text{SparsityEligible}_d$  indicates that a district will be eligible for sparsity aid funding when the policy is implemented and  $k$  indexes years. The  $\beta_k$  coefficients, therefore, trace out differences in the trends between sparsity and comparison districts' outcomes before and after the sparsity aid policy was implemented in 2008. If the two groups were trending similarly prior to the policy, we expect that the  $\beta_k$  coefficients will be equal to 0 up until 2006.

We also extend our district-level regression from equation (1) to consider student-level outcomes for students in grades 3-12 by estimating equations of the following form:

$$Y_{igsdt} = \beta \text{SparsityAid}_{dt} + \mathbf{Z}_{dt} \boldsymbol{\Pi}_g + \mathbf{X}_{it} \boldsymbol{\Gamma}_g + \lambda_{sg} + \delta_{tg} + u_{igsdt} \quad (3)$$

where  $Y_{igsdt}$  is an outcome (e.g., standardized test score or college enrollment) for student  $i$ , who

---

<sup>13</sup>Since the treated districts in our sample all receive treatment at the same time and never lose their treated status, we do not face the econometric problems associated with staggered treatment timing identified in recent DID methodological research. See Roth et al. (2022) for a recent literature review.

is enrolled in grade  $g$  in school  $s$  in district  $d$  in year  $t$ .  $\text{SparsityAid}_{dt}$  is equal to 1 if student  $i$ 's district  $d$  receives sparsity aid funding in year  $t$ .  $\mathbf{Z}_{dt}$  are the same time-varying district covariates as equation (1) and  $X_{it}$  are student characteristics that may or may not vary over time, such as their race, gender, FRL status, and special education status. In specifications that include multiple grade levels, we allow the effects of both sets of covariates to vary by grade level.  $\lambda_{sg}$  are school-by-grade fixed effects that capture any time-invariant characteristics of individual schools at each grade level and  $\delta_{tg}$  are year-by-grade fixed effects that capture any secular trends by grade level. When we estimate specifications with only one grade level—for example, postsecondary outcomes for graduating seniors—these fixed effects collapse to the school and year levels, as in our district-level regressions.  $u_{igsdt}$  is the error term. We continue to cluster standard errors at the district level and also extend equation (3) to an event study equation to test for pre-trends.

### 3.2 Identification Assumptions

Our DID empirical framework relies on the assumption that school districts ineligible for the sparsity aid program serve as valid counterfactuals for school districts eligible for the sparsity aid program. Functionally, this assumption can be broken down into two parts. The first part is that the outcomes of school districts eligible and ineligible for sparsity aid were trending similarly prior to the introduction and expansion of the program. The  $\beta_k$  coefficients in the event study specifications from equation (2) allow us to test this assumption directly.

The second part of our identification assumption is the untestable assumption that there are no changes in unobserved determinants of our outcome measures that occur concurrently with the introduction of the sparsity aid program *and* which differentially affect sparsity-eligible and ineligible districts. This assumption could be threatened if there are (1) policy changes surrounding the introduction of the sparsity aid program that differentially affect sparsity eligible or ineligible districts and/or (2) if there are underlying demographic and economic trends that differ between sparsity districts and our comparison group. We address both sets of identification challenges in the sections that follow.

### **3.2.1 Concurrent Policy Changes**

While we are unaware of any policy changes that occurred alongside the introduction of the sparsity aid program and specifically targeted sparsity-eligible or ineligible districts, there were several other education policy changes in Wisconsin during the time frame of our sample that may threaten our empirical approach. One of the largest education-related policy changes in Wisconsin during the past 20 years was the passage of Act 10 in 2011, which discontinued collective bargaining requirements over teachers' salaries. As school districts' existing collective bargaining agreements (CBAs) expired in the years following 2011, they were able to pay teachers outside of standard salary schedules. Biasi (2021a) shows that the end of these CBAs and the subsequent introduction of flexible pay raised salaries of teachers with high value-added (VA) measures, increased cross-district teacher mobility to districts with flexible pay, and improved student achievement. Biasi and Sarsons (2022) further show that the adoption of flexible pay schemes following Act 10 induced a gender wage gap in teacher salaries.

Because Act 10 occurred at the state level and did not target rural school districts, it is not obvious that its introduction would threaten our identification strategy. However, the policy change could have differentially impacted sparsity-eligible districts if they (1) had collective bargaining agreements that expired earlier or later than those in the comparison districts and/or (2) if they employed higher or lower VA teachers, who faced different incentives to move to flexible play districts after Act 10. While we lack the data to answer these questions precisely, we provide evidence in Section 5 that a variety of teacher-related staffing outcomes—including the number of teachers, salary distributions, and experience—trended similarly in sparsity eligible and ineligible districts from 2003 through 2017. Thus, we do not believe that the introduction of Act 10 poses a threat to our identification of the effects of the sparsity aid program.

Besides Act 10, there were two smaller policy changes in Wisconsin during our sample period that may have affected sparsity-eligible and ineligible districts differently. First, beginning in the 2014-2015 academic year, Wisconsin changed its standardized testing regime three times in three years due to a combination of technical troubles in transitioning to online exams and a series of legislative decisions related to the national Common Core curriculum (Mason, 2016). It is

reasonable to expect that sparsity-eligible districts —which are smaller, have fewer specialized staff, and may face additional barriers to internet access —were less equipped to deal with these regime changes than our comparison districts. In addition, it is unclear how to compare exam results over time given the changes in content and modality. As such, we limit our analysis of test scores to those through the 2013-2014 academic year.

The second policy change that may have differentially affected sparsity districts was the addition of a “high cost pupil transportation aid” categorical aid program beginning in 2013-2014.<sup>14</sup> As of 2019, the program stipulates that districts receive additional transportation funding if their transportation cost per student is greater than 145% of the state average in the prior year and their density is less than or equal to 50 students per square mile (Wisconsin Legislative Fiscal Bureau, 2019). The grant is not provided on a per-student basis, but the average per-student amount per school was \$185 in the 2019-2020 school year. While sparsity districts may be more likely to meet these criteria, districts in our comparison group are also relatively sparse and, thus, may also qualify for the program. Indeed, using data from the DPI on eligibility and payments for the program, we find that 86% of sparsity districts received payments from the program in at least one year from 2013-2017 and 33% of comparison districts did. Given this variation, we present specifications that control for districts’ receipt of additional transportation aid. We find that doing so minimally changes our results, indicating that this policy change is not a main driver of our findings.

### **3.2.2 Demographic & Economic Trends**

While we believe our results are robust to the various policy changes we discuss above, we also consider whether our identification assumptions may be threatened by demographic and economic trends over our analysis period. We note that sparsity-eligible districts experience more pronounced decreases in membership —in relative terms —during the time frame of our analysis than their sparsity-ineligible counterparts. Between 2003 and 2017, sparsity-eligible districts saw an average membership decrease of 76.3 students —or 15.3% of their baseline membership. In contrast, membership in sparsity-ineligible districts declined by an average of 61.7 students which,

---

<sup>14</sup> Additional information on the high cost pupil transportation aid program is available on the DPI website: <https://dpi.wi.gov/sfs/aid/categorical/high-cost-pupil-transportation-aid>.

due to their larger size, represents only a 5% decrease in their baseline membership. Appendix Figure A.2 presents these membership trends, both in raw numbers and in relative decreases from districts' 2003 baselines. Panel A of Appendix Figure A.3 then presents event study estimates of districts' log membership before and after the sparsity aid program's introductions, both with year fixed effects and with year-by-region fixed effects to capture the fact that different regions of the state may be experiencing different migration and fertility trends over time. Both sets of estimates show a consistent decline in membership in sparsity districts that begins before the program began and continues after.

Appendix Figures A.2 and A.3 provide little evidence that the decline in membership in sparsity districts differentially changes when the sparsity aid program is introduced. This consistent downward membership trend, combined with the relatively small amount of funding provided to districts —particularly in the first years of the program —makes it unlikely that households re-sorted between school districts in response to the policy. As further evidence against household resorting in response to the policy, Panel B of Appendix Figure A.3 presents event study specifications of districts' retention rates: the share of students in grades K-11 enrolled in the district in year  $t - 1$  that continue to be enrolled in the district in year  $t$ . We see little evidence that districts' retention of students changes differentially across sparsity and non-sparsity districts when the sparsity aid policy is introduced. If anything, we see a slight increase in the retention of students in sparsity districts across our analysis period that does not differentially change when the policy begins. The fact that we see few changes in districts' retention of their students also indicates that the downward membership trends we document in Panel A are *not* driven by increasing rates of students leaving sparsity districts. Rather, the declines in membership are the result of smaller and smaller cohorts entering the districts, which are likely reflective of broader birth rate and population declines in Wisconsin's most rural areas in the 2000s and 2010s (Forward Analytics, 2020).

While it is unlikely that the underlying membership trends we document are related to the sparsity aid program, they could raise two concerns for our empirical strategy. First, larger relative membership declines in sparsity districts may reflect or induce changes in districts' demographic characteristics that are related to academic achievement outcomes. Second, changes in

membership will mechanically affect districts' per-student financial outcomes, such as revenues and spending per student. As such, we control for districts' log membership in all of our empirical specifications. In addition, we directly test whether districts' demographic characteristics change differentially in sparsity and non-sparsity districts over our sample period. The remaining panels of Appendix Figure A.3 present event studies for select characteristics. In Panel C, we see little change in the share of students who qualify for free or reduced-price lunch, indicating that the declines in membership in sparsity districts occur evenly across lower- and higher-income students. Similarly, in Panel D, we see little change in the share of students identified as eligible for special education services. In Panel E, we see a slight increase in the share of students in sparsity districts, as compared to our comparison group, who are white. This trend appears to be the result of somewhat faster racial diversification in our comparison group: in 2003, both sparsity and non-sparsity districts were approximately 95% white, while in 2017, sparsity districts were 89% white and non-sparsity districts were 87% white. To capture these modest compositional changes, our preferred empirical specifications control for districts' racial composition (% white, % Black, % Hispanic, and % Asian), along with their FRL percentage, special education percentage, and the local child poverty rate.

A related concern to declines in membership is the potential for different effects of the Great Recession on sparsity-eligible and ineligible districts. Given the large role of local property taxes in Wisconsin's school finance system, differential changes in local home values during the housing and financial crisis could result in differential changes in school district resources over the same time period. Appendix Figure A.4 plots changes in districts' house price indices (HPIs) over time. Panel A presents averages of the HPIs, while Panel B standardizes each district's index relative to 2003. While home prices in sparsity-eligible and ineligible districts are generally trending similarly prior to the start of the sparsity aid program, sparsity-eligible districts did not experience as large of a decline in the 2007-2012 period as sparsity-ineligible districts, which had higher prices prior to the start of the Great Recession.

Panel A of Appendix Figure A.5 presents event study estimates of districts' log-HPI, which are somewhat attenuated by the inclusion of year-by-region fixed effects. Panel B shows similar ef-

fects for the log of total property values in the district, as reported by the DPI. Panels C and D then provide event study estimates for per-student property values and property taxes, which mechanically capture both the changes in property values and the changes in membership described above. Given the concurrent decline in membership and slight increase in home values, both measures exhibit upward pre-trends which continue after the introduction of the sparsity aid program. While the increase in property taxes per student does not affect eligible districts' receipt of sparsity aid funds, it could affect the total state revenue they receive since Wisconsin's state finance system equalizes resources between districts with low and high property tax revenues. To show that this increasing trend does not contaminate our results, in Appendix Figure A.6 we show that these differential trends largely disappear if we include year-by-region FEs and control for both a district's log membership and log-HPI, which we include in our preferred empirical specifications. Further, in Section 4, we show that our estimates of the effects of the sparsity aid program on districts' finances are robust for controlling directly for districts' property value per student or property tax revenue per student.

In summary, to address potential threats to our identification assumption, our preferred specifications include district-level control variables that capture relevant changes in districts' demographic and economic conditions over time that may be related to their financial and student achievement outcomes. Specifically, we control for a district's log membership, log house price index, the number of school buildings, racial composition, % FRL, % special education, and the local child poverty rate, as well as region-by-year FEs. In the results that follow in Section 4, we show that our estimated effects of the sparsity aid program on districts' finances are generally similar with and without these controls, further validating our choice of the comparison group and difference-in-differences framework.

## 4 Effects of Sparsity Aid Program on District Finances

We begin our analysis by showing how the sparsity aid program affected eligible districts' revenues and overall spending. In Section 5, we investigate districts' allocation of sparsity funds

and changes in school inputs, particularly staffing decisions. Finally, in Section 6, we estimate how these spending changes affected student outcomes.

Figure 3 presents the event study estimates from equation (2) for districts' financial outcomes. First, in Panel A, we consider the relationship between a district's sparsity aid eligibility and the state revenue they receive from sources other than the general aid formula. From 2003 to 2007, there is no differential trend in non-formula state revenue between sparsity-eligible and ineligible districts. Then, beginning in 2008, we see that sparsity eligible districts see an increase in non-formula state revenue per student that is approximately the same size as the sparsity payments. This effect persists when the sparsity aid program is expanded in 2010 and becomes somewhat larger than the sparsity payments beginning in 2015. This shift is due to an expansion of high-cost pupil transportation aid in 2015, for which sparsity aid districts were more likely to be eligible. As discussed in Section 3.2, we present specifications that control for districts' receipt of funding from the high-cost pupil transportation program when evaluating student-level outcomes.

In Panels B and C, we present event study estimates of a district's total revenue per student and total current spending on elementary and secondary education per student. For revenues, we see no evidence of pre-trends prior to the sparsity aid policy and clear increases in total revenues per student after the policy that are consistent with the size of sparsity aid payments. For expenditures, we again see evidence of parallel trends before 2008, but we do not see increases in the first two years of the program. This lack of a spending response could be driven by uncertainties over whether the program would be permanent, or it could be the case that other changes during the height of the Great Recession muted any effects that the sparsity aid program had on spending. Our survey respondents confirmed that uncertainty surrounding sparsity aid was common in the early years of the program; 20 of our 36 survey respondents said they were unaware of the sparsity aid program when it was introduced, and another 8 believed it was unlikely the program would continue into the future. Nevertheless, beginning with the 2010 program expansion, we see increases in spending per student that align with the size of sparsity payments.

Table 2 summarizes these effects using the difference-in-differences specification from equation (1). Column (1) presents estimates only controlling for log membership, while column (2)

adds demographic controls, column (3) interacts the year FEs with twelve different school district region indicators, and column (4) controls for whether a district receives additional transportation funding. The results are similar across specifications, indicating that demographic changes, transportation funding changes, nor regional trends are driving our results. In the most saturated specification in column (4), we find that receiving sparsity aid increases non-formula state revenue by \$217 per student (a 26.6% increase), total revenues by \$252 per student (a 1.9% increase), and current spending on elementary and secondary education by \$226 (a 2% increase). Given that the average sparsity-eligible district enrolled 434 members following the sparsity aid program's implementation, these increases translate to additional funding of approximately \$109,000 per year and additional spending of \$98,000 per year, more than twice the average teacher salary of sparsity-eligible districts during this time period.

We now conduct several robustness checks of these results. First, in Appendix Table A.1, we conduct placebo tests to further verify that these increases in revenue and spending are not driven by changes to other revenue sources or expenditures. In Panel A, we repeat our difference-in-differences specifications for per-student revenues from all sources *other than* non-formula state aid, which includes local property tax revenues and appropriations from the state general aid formula. Across specifications, we find no evidence that revenues from other sources increased differentially in sparsity districts, relative to non-sparsity districts, indicating that the sparsity aid program alone was responsible for increasing districts' revenues. In Panel B, we further consider district spending in all areas other than elementary & secondary education, including capital outlays, community and adult education programs, payments to other government entities, and debt interest payments. Spending in these areas is typically financed via other revenue sources and, as such, we do not find that spending in these areas changed in sparsity districts following the implementation of the sparsity aid program. Together, the results in Appendix Table A.1 bolster our claim that the increases in revenues and expenditures we document in our main results are the result of the sparsity aid program.

Appendix Figure A.7 verifies that our revenue increase is driven by the sparsity aid program by plotting the difference-in-differences coefficients for all 35 revenue sources included in the CCD

dataset. While we see some substitution between state general aid revenues and local revenues—which is consistent with declining membership and increased per-student property tax revenue we document in Section 3.2—the increase in total revenues is primarily driven by state revenue for other programs, which contains sparsity aid payments. In Appendix Figure A.8 we show that our total revenue and current spending event study estimates hardly change if we include additional controls for a district’s total property value per student or local property tax revenue per student. Moreover, Appendix Figure A.9 further shows that our difference-in-differences estimates for total revenues and current spending are robust to controlling for districts’ per-student revenue from local, state formula, or federal sources. Thus, the increased revenue and spending in sparsity-eligible districts appears to come from the sparsity aid program and not other changes in revenue sources during the time frame of the data.

Finally, we provide evidence that our estimates are not driven by our sample selection criteria. Recall that our preferred sample removes districts that were in the top 30% of the enrollment or density distribution prior to the start of the sparsity aid program in 2008. In Appendix Figure A.10, we repeat the estimation of  $\beta$  from column (4) in Table 2, varying the percentage of districts dropped from 0% (meaning we do not drop any districts based on their pre-2008 enrollment or density) to 50% (meaning we drop all districts in the top half of the density or enrollment distributions). Across our four outcomes, the estimates vary only slightly across different sample definitions and in no case are statistically different from our preferred specification.

## 5 Allocation of Spending and Staffing

We now investigate how the sparsity aid program affected districts’ spending across budget categories and how these changes in budget allocation are reflected in staffing levels. These results provide important insights into how districts used the increased state funding they received under the sparsity aid program, which may generate different predictions of how the program affected student achievement outcomes.

## 5.1 Budget Categories

To examine how districts allocated their sparsity aid dollars, we leverage annual financial reports submitted by Wisconsin districts to the DPI that summarize all transactions occurring in a district in a fiscal year.<sup>15</sup> To structure our analysis, we bundle spending in eight distinct areas tracked by DPI: (1) general instruction in core curricular areas, (2) instruction in all other curriculum areas (e.g., physical education and co-curricular activities), (3) pupil support (e.g., health, guidance), (4) instructional staff support (e.g., curriculum development, training), (5) administration, (6) transportation, (7) food service operations, and (8) general operations (e.g., maintenance, fiscal services).<sup>16</sup>

Panel A of Table 3 repeats the specification from column (4) in Table 2 for each of the above spending categories. Overall, we find that districts allocated a larger share of their additional spending to non-instructional areas than instructional areas. Specifically, receiving sparsity aid increased districts' general instructional spending by \$56.96, general operations spending by \$56.71, administration spending by \$45.01, and food service spending by \$23.46.<sup>17</sup> The latter three estimates are statistically significant at the 5% level, and these categories received the largest relative increases, with the estimates each representing 4-6% of sparsity-eligible districts' pre-program means. Panels B and C separate the changes in spending in each category into spending on employee salaries and benefits and all non-personnel spending. We find that districts increased salary and benefit spending related to administration and general operations by statistically significant amounts, whereas they increased non-personnel spending related to other instruction (e.g., extracurriculars), student transportation, and food service.

As a whole, the results in Table 3 show that districts did not primarily allocate sparsity aid funding to instruction and most likely did not use sparsity aid funds for a single use. Instead, they allocated the increased funding to a wide variety of areas. Our survey data further confirm this

---

<sup>15</sup>These annual reports are available publicly on the DPI website: <https://dpi.wi.gov/sfs/reporting/safr/annual/data-download>.

<sup>16</sup>Consistent with measures of current elementary and secondary spending in the NCES Common Core of Data (CCD), we exclude capital outlays, debt service payments, inter-fund transfers, and the purchase of investment assets from our spending measures. We also follow Kelly and Farrie (2023) and exclude payments to other governmental entities and schools (e.g., charter schools), except for payments to other Wisconsin public school districts for special education services. The correlation between per-student revenues in the CCD and Wisconsin annual report data is 0.992 and, for expenditures, it is 0.982.

<sup>17</sup>It is possible that this increase in food service spending could be driven in part by changes to the federal nutrition program following the passage of the Healthy, Hunger-Free Kids Act of 2010. However, in Appendix Figure A.11, we show that our estimated effects of the sparsity aid program on spending allocation are robust to controlling for districts' per-student revenues from local, state formula, or federal sources.

finding. 24 of 36 respondents said the sparsity dollars were rarely or never set aside for a specific purpose, and only 4 respondents said they were always earmarked for a specific purpose. Given this finding, and the fact that districts are unrestricted in how they spend sparsity aid dollars, the average effects presented in Table 3 may mask important differences in how different districts use the funds. To explore heterogeneity across districts, we augment our main difference-in-difference specification with an interaction term that allows the effect of receiving sparsity aid to vary based on a district's average budget share in a given spending category in the pre-program period (2003-2007). We define these budget shares as the total spending in a category divided by a district's total revenue and standardize them to have a mean of 0. We scale our effects such that the coefficients represent the change in the sparsity receipt effect per 1pp increase in pre-period budget share.

Table 4 presents these results and uses the linear interaction terms to estimate how spending effects vary across the budget share distribution of each spending category. For the categories of general instruction, other instruction, pupil support, instructional staff support, and food service, we estimate negative and statistically significant interaction terms that indicate that districts' spending allocations differ based on their baseline budget shares. Specifically, districts increase their spending more when they have a low baseline budget share in a given category. For example, districts at the 25th percentile of the general instruction budget share distribution increase spending on general instruction by a statistically significant \$109.40, whereas districts at the 75th percentile do not increase their spending in this category. In addition, while there are no effects on spending on instructional or pupil support services on average, districts at the bottom of the budget share distributions for these categories increase their spending by statistically significant and economically meaningful amounts. An opposite pattern emerges for student transportation spending, where the interaction term is positive and statistically significant, indicating that districts with *high* baseline transportation budget shares further increase their transportation spending when they receive sparsity aid funds. As a whole, these heterogeneous effects provide evidence that the unrestricted nature of Wisconsin's sparsity aid program allows districts to allocate funds toward areas that were relatively underfunded prior to the program's introduction.

## 5.2 District Staffing

In Table 3, we see that receiving sparsity aid increases spending on salary and employee benefits, particularly in the administration budget category. Specifically, we find that districts increased administrative personnel spending by \$41.26 per student, or approximately \$18,000 for the average-sized district. To quantify how this spending increase affected the number and type of staff employed by sparsity-eligible districts, we estimate our difference-in-differences and event study specifications for the number of administrative FTEs per 100 students in three categories: superintendents, principals, and other administrative staff members. In interpreting these results, it is important to note that sparsity-eligible districts frequently employ *less* than one FTE in administrative positions and/or employ a single staff member across multiple positions. For example, prior to 2007, 35.7% of sparsity-eligible districts employed less than 1 FTE principal and 91.2% employed less than 1 FTE in other administrative positions, such as curriculum and special education directors.

Table 5 presents difference-in-difference results for our measures of administrative staff.<sup>18</sup> Panel A presents our main results, while Panel B adds an interaction term with districts' standardized baseline administrative budget share, analogous to the specifications in Table 4. In column (1), we find that receiving sparsity aid increased total district administrators —inclusive of superintendents and assistant superintendents, principals and assistant principals, and other directors and coordinators —by 0.021 per 100 students, or 9.1% of an FTE for the average-sized district. This effect was equal to approximately 4.5% of baseline staffing and, in Panel B, we show that it was larger in districts with low baseline administrative spending: districts at the 25th percentile of the baseline administrative budget share distribution increased staffing by 0.036 FTEs per 100 students (15.6% of an FTE for the average-sized district), while districts at the 75th percentile of the distribution did not meaningfully increase their administrative staffing.

Columns (2) through (6) of Table 5 estimate the effects of sparsity aid receipt on staffing increases across different administrative positions. In column (2) we find that sparsity aid receipt has

---

<sup>18</sup>In Appendix Figure A.12, we present event study estimates of all outcomes in Table 5, none of which indicate that the results are driven by differential pre-trends between sparsity and non-sparsity districts.

little effect on the number of superintendents and assistant superintendents per 100 students. This finding is not surprising as, at baseline, over 98% of sparsity-eligible districts report employing a superintendent and only 1.1% of districts report having more than one. Thus, it is unlikely that districts used sparsity aid funds to hire additional superintendent positions.

In columns (3) through (6) we consider sparsity aid effects on principal and other administrator staffing. For each, we consider both the likelihood that a district reports employing non-zero FTEs and the total number of FTEs per 100 students. For principals, we find a statistically insignificant but positive effect on the likelihood that districts employ a principal (which 91.2% report at baseline), as well as on the number of principals per 100 students. Consistent with our spending patterns in Table 3, these effects are larger for districts with low baseline administrative spending. Districts at the 25th percentile of the baseline administrative budget share distribution are 4.8pp more likely to employ non-zero principal FTEs and employ 0.021 more FTEs per 100 students after receiving sparsity aid. The latter estimated effect is statistically significant at the 5% level and represents an increase of 8.9% of the baseline mean.

We find even larger effects for other administrative positions. In column (5), we find that receiving sparsity aid funds increases the likelihood that a district employs non-zero FTEs in other administrative positions by 14.9pp. This effect is highly statistically significant and represents an effect size of over 50% of the baseline mean. This effect is slightly larger for districts with lower baseline administrative spending but remains statistically significant at the 75th percentile of the baseline distribution. In column (6), we find an increase of 0.013 FTEs per 100 students, which is less precise, but similarly large, representing 38% of the baseline mean. While we lack the precision to estimate these effects across more granular positions, the types of administrative staff that sparsity districts are most likely to employ in the post-2008 period include special education directors, business managers, and instruction/curriculum coordinators. Thus, it is reasonable to expect that sparsity aid funds allowed districts to hire staff in these positions.

In Appendix Table A.2 and Appendix Figure A.13, we estimate similar regressions for the number of teacher FTEs per 100 students and teacher salaries, benefits, and experience. Consistent with our imprecise and relatively small effect on teacher-related salary and benefit spending

found in Table 3, we find little effect of receiving sparsity aid funds on teacher staffing, salaries, benefits, or experience. These results indicate that the sparsity aid program did not substantially change instructional inputs in eligible districts. Further, they help us rule out that Wisconsin Act 10 differentially affected sparsity and non-sparsity districts and, thus, is unlikely to be driving our results.

Taken together, our results indicate that sparsity aid funding allowed districts to increase spending on a variety of non-instructional areas, particularly those with low baseline budget shares. Districts used a portion of these additional funds to hire non-instructional staff, such as administrative positions. It is possible that these spending patterns may not meaningfully change academic outcomes, such as test scores and college enrollment, which we consider in the next section.

## 6 Effects of Increased Spending on Student Outcomes

To estimate the impact of increased spending from the sparsity aid program on student outcomes, we rely on student-level administrative records from the Wisconsin DPI. We limit our sample to students in grades 3-12 who have non-missing demographic information and who continuously enroll in Wisconsin public schools. These restrictions produce a final sample of 308,630 unique students and 1,484,856 unique student-year observations, of which approximately one-quarter are enrolled in sparsity-eligible districts and three-quarters are not.

### 6.1 K-12 Outcomes

Table 6 presents estimates of  $\beta$  in equation (3) for student test score outcomes. Because of changes in Wisconsin's testing regime over time, our analysis is limited to math and reading test scores among students in grades 3-8 and grade 10 from 2005 to 2013, along with science, social studies, and writing scores for students in grades 4, 8, and 10 in the same years. We standardize all test scores at the year, grade, and subject level across the universe of test-takers to have a mean of zero and a standard deviation of one. Thus, our  $\beta$  estimates can be interpreted as the percent of a standard deviation change due to the sparsity aid program. We estimate effects for each grade

level and test subject, as well as average effects across grade levels and across test subjects.

Panels A through E present our estimated effects for each test subject. For reading, science, social studies, and writing exams, we estimate small and statistically insignificant effects across all grade levels. In addition, our average effects across grade levels are close to zero and not statistically significant. However, for math exams, our average effect is negative and statistically different from zero at the 10% level, mostly driven by a large negative effect among 6th graders. Panel F then presents average effects across all test subjects taken by a grade level, and across all grades and test subjects. For each grade level, our effects are small and statistically insignificant at conventional levels. The point estimates are particularly small and close to zero for grades 7, 8, and 10. Overall, we do not detect a statistically significant effect on test scores and, with 95% confidence, can rule out that the sparsity aid program increased test scores by more than 0.75% of a standard deviation. Moreover, our confidence intervals generally include the effect size we would expect from the Jackson and Mackevicius (2023) meta-analysis given the size of the spending increase in the sparsity aid program, suggesting that our estimates are not inconsistent with the school finance literature as a whole.<sup>19</sup>

In Appendix Figure A.14 we present analogous event study estimates for each test subject to test whether our effects are driven by existing differential trends in test scores between students in sparsity-eligible and ineligible districts. While the pre-trends are generally flat, the availability of only three pre-treatment periods limits our ability to determine whether the negative effects we estimate —particularly for math test scores —may be due to a longer-run decline in performance in sparsity districts. To further assess the role of pre-trends in our estimates, we obtain a longer panel of school-level test score data for grades 4, 8, and 10 from the Wisconsin DPI. Appendix Figure A.15 plots the average school-level test scores for these grades for schools in sparsity-eligible and ineligible districts from 2002 to 2013 and Appendix Figure A.16 estimates event study specifications over this time frame. While the estimates are quite noisy, we do not see strong evidence of declining math scores prior to treatment years. In addition, we see little evidence

---

<sup>19</sup>Jackson and Mackevicius document that, on average, an increase in school spending of \$1,000 per student increases test scores by 0.31 standard deviations. Given that the typical sparsity aid payment is about one-quarter of this size (\$250 per student), we would expect test scores impacts of about 0.008 (0.8%) standard deviations if the returns to this increased school spending were similar to that of previously studied policies and could be scaled linearly.

of changes in reading test scores for sparsity districts before or after the sparsity aid program began, which aligns with our small, statistically insignificant results in Table 6. Finally, despite the substantially smaller size of the sparsity aid grant during the first two years of the program, we do not observe significantly different effects on math and reading test scores when looking at 2010 and onward as opposed to 2008 and 2009.

As a whole, we take our test score results to suggest that the spending patterns induced by the sparsity aid program did not meaningfully improve academic achievement in sparsity districts. If anything, test scores declined somewhat in sparsity districts, relative to non-sparsity districts, during the 2008-2013 time frame. These effects are not surprising given that districts did not increase instructional investments in response to the program's funding. In addition, despite our robust set of control variables, we can not rule out that our effects are driven by differential impacts of the Great Recession on sparsity and non-sparsity districts. Stated differently, our results indicate that increased, unrestricted spending to sparse, rural school districts during the Great Recession did not improve their standardized test scores.

A null effect on test scores does not rule out the possibility that the increased funding improves students' non-cognitive and/or behavioral outcomes, particularly since districts appear to use their increased funds to hire administrative positions that may oversee these sorts of student outcomes —such as special education directors. In Appendix Table A.3 we consider how sparsity aid funding affects a variety of these outcomes, including students' annual attendance rate, the likelihood they are involved in a disciplinary incident, the likelihood they repeat a grade level, and, for 10th-12th graders, the likelihood they dual-enroll in a college course while enrolled in a Wisconsin public high school.<sup>20</sup> Across the different outcomes and grade levels, we estimate precise null effects. Appendix Figure A.17 presents event study estimates of these outcomes. The estimates are noisy but do not suggest that the main results are driven by differential pre-trends between sparsity-eligible and ineligible districts. As such, we interpret our findings as indicating that the sparsity aid program also had little effect on students' behavior in schools.

---

<sup>20</sup>We consider outcomes for grades 6-12 in this table, as there is little variation in attendance and disciplinary incidence in elementary grades.

## 6.2 Postsecondary Enrollment & Completion

We now turn to estimating how exposure to the sparsity aid program affects students' longer-run educational attainment by estimating effects on both postsecondary enrollment and completion. While we do not observe positive effects on student achievement or behavioral outcomes, it is still possible that the spending patterns we document in Section 5 could improve postsecondary outcomes. For example, the administrative positions that districts hire may oversee college and career preparation activities.

Table 7 presents estimates of  $\beta$  from equation (3) on the sample of all seniors in our sample from 2005 to 2017. We estimate effects for the entire sample of students and separately for students who are and are not eligible for free and/or reduced-price lunch (FRL) to test whether additional resources boosts college attendance and completion for low-income students who, at baseline, are less likely to attend and complete college.

Panel A of Table 7 presents our estimated effects for the full sample of students. Columns (1) to (3) show effects for enrollment in college within 12 months of high school graduation.<sup>21</sup> Overall, we estimate that the sparsity aid program increased college enrollment by 0.3pp, with a larger effect in two-year colleges (0.6pp) than in four-year colleges. These effects are not statistically different from zero, but similar to our test score impacts, our confidence intervals contain effect sizes that we would expect from the prior literature.<sup>22</sup> Columns (4) to (6) then estimate the effects for college completion at any point in our data's time frame. We similarly see about a 0.7pp increase in college completion, which is again not statistically different than zero.<sup>23</sup>

Panels B and C then estimate separate effects for FRL eligible and ineligible students. In Panel B, we find large point estimates of the sparsity aid program on college enrollment and completion for FRL eligible (lower-income) students, especially for the two-year sector, but none of the estimated effects are statistically different from zero at conventional levels. In Panel C, we find

<sup>21</sup>Due to changes in how Wisconsin reported high school graduation data during the time period of our analysis, we only observe high school graduation dates for students who enroll in college and are not able to consider graduation as an outcome directly.

<sup>22</sup>Jackson and Mackevicius (2023) document that, on average, an increase in school spending of \$1,000 per student increases test scores by 2.7pp. Given that the typical sparsity aid payment is about one-quarter of this size (\$250 per student), we would expect test scores impacts of about 0.7pp if the returns to this increased school spending were similar to that of previously studied policies and scaled linearly.

<sup>23</sup>Because later cohorts in our data have had fewer years to enroll in and complete college, we also estimate effects only on the 2005-2013 cohorts. Appendix Table A.4 presents these results, which are very similar to our main results.

even less evidence that the sparsity aid program improved college enrollment and completion for non-FRL eligible students —all the point estimates are practically and statistically indistinguishable from zero. In Appendix Figures A.18 and A.19, we present the corresponding event study estimates for post-secondary enrollment and completion. The estimated coefficients on the few periods we have available prior to the sparsity aid program’s implementation do not reveal any clear violations of our parallel trends assumption, and we see similar effect sizes across the post-treatment period. Thus, overall, our results do not provide strong evidence that the sparsity aid program increased college enrollment and completion for affected students overall, but we find suggestive evidence that there may have been modest increases for low-income students.

## 7 Conclusion

Rural schools and school districts in the United States face a myriad of distinct challenges compared to their urban and suburban peers, including high per-student costs in areas like transportation and frequent staffing turnover. States often recognize these challenges and many provide additional funding to rural districts as a result. However, there is limited work on how districts use these funding sources, nor how increased spending generated by them affects student outcomes like test scores and postsecondary enrollment.

We provide new evidence on the returns to school funding in rural districts by exploiting policy variation from Wisconsin’s sparsity aid program —one of the largest state-level funding streams geared towards rural school districts. We find that the introduction and subsequent expansion of the program increased school spending by about 2% annually. Using detailed school finance data from the Wisconsin DPI, we show that the sparsity aid program increased spending more in non-instructional areas than instructional areas. Moreover, we find that districts increased spending the most in areas where, at baseline, they had low budget shares compared to other districts, suggesting that districts were able to use the sparsity aid funds flexibly to supplement areas that were relatively underfunded prior to the introduction of sparsity aid.

We generally find that the additional funding did not change standardized test scores, behavioral

outcomes, college enrollment, nor college completion, but we find suggestive evidence that the program may have boosted college attainment for low-income students, particularly at two-year colleges. Our largely null effects on academic outcomes are consistent with how districts allocated sparsity aid funds toward non-instructional areas. These results thus underscore the importance of understanding how districts allocate increased funding to contextualize achievement effects, particularly when policies provide districts flexibility in how funds are used.

Finally, we highlight that, despite our largely null results, our results are broadly consistent with the existing school finance literature. Across the outcomes we study, we generally cannot rule out that our effect sizes are statistically different than the effect sizes we would expect if the returns to school spending in rural districts were the same as in previously studied contexts (Jackson and Mackevicius, 2023). Thus, while the relatively small revenue increases districts received due to the sparsity aid program did not meaningfully affect student outcomes, it is possible that larger increases to rural school districts' budgets would generate positive effects on student achievement and postsecondary outcomes. Future work that considers policy interventions with larger increases to rural school districts' budgets would be a valuable contribution to the literature and could inform the structure of sparsity aid policies across states.

## References

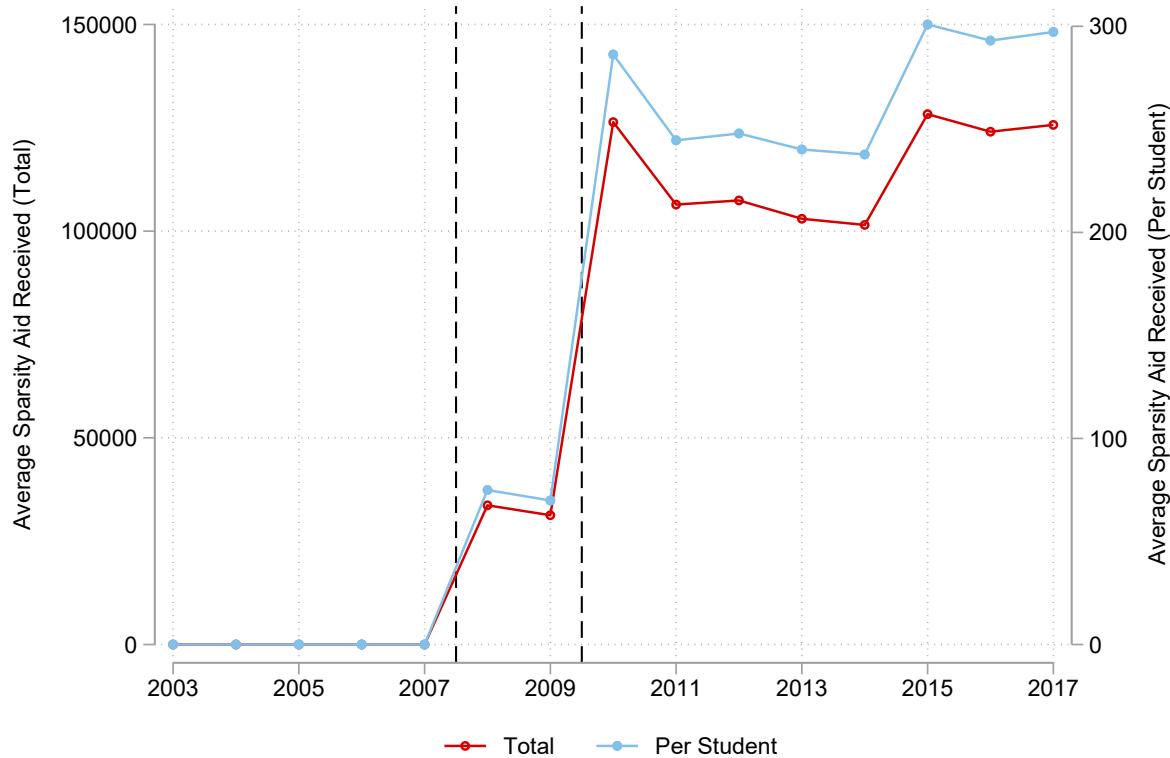
- Baron, E. J. (2022). School Spending and Student Outcomes: Evidence from Revenue Limit Elections in Wisconsin. *American Economic Journal: Economic Policy* 14(1), 1–39.
- Barrett, N., J. Cowen, E. Toma, and S. Troske (2015). Working with What They Have: Professional Development as a Reform Strategy in Rural Schools. *Journal of Research in Rural Education* 30(10), 1–18.
- Bass, B. (2021). The effect of technology funding on school-level student proficiency. *Economics of Education Review* 84.
- Bayer, P. J., P. Q. Blair, and K. Whaley (2021). Are we spending enough on teachers in the U.S.? Working Paper 28255, National Bureau of Economic Research.
- Biasi, B. (2021a). The labor market for teachers under different pay schemes. *American Economic Journal: Economic Policy* 13.
- Biasi, B. (2021b). School Finance Equalization Increases Intergenerational Mobility. *Journal of Labor Economics*, forthcoming.
- Biasi, B. and H. Sarsons (2022). Flexible wages, bargaining, and the gender gap. *Quarterly Journal of Economics* 137.
- Bogin, A., W. Doerner, and W. Larson (2018). Local house price dynamics: New indices and stylized facts. *Real Estate Economics* 47.
- Candelaria, C. A. and K. A. Shores (2019). Court-Ordered Finance Reforms in the Adequacy Era: Heterogeneous Causal Effects and Sensitivity. *Education Finance and Policy* 14(1).
- Duncombe, W. and J. Yinger (2007). Does school district consolidation cut costs? *Education Finance & Policy* 2(4), 341–375.
- Education Commission of the States (2021). K-12 and Special Education Funding. <https://reports.ecs.org/comparisons/k-12-and-special-education-funding-08>.
- Egalite, A. J. and B. Kisida (2016). School size and student achievement: a longitudinal analysis. *School Effectiveness and School Improvement* 27(3), 406–417.
- Forward Analytics (2020). The Rural Challenge: Depopulation and Its Economic Consequences. <https://www.forward-analytics.net/research/the-rural-challenge-depopulation-and-its-economic-consequences/>.
- Gershenson, S. and L. Langbein (2015). The effect of primary school size on academic achievement. *Educational Evaluation and Policy Analysis* 37(1S), 135S–155S.
- Gordon, N. and B. Knight (2008). The Effects of School District Consolidation on Educational Cost and Quality. *Public Finance Review* 36.
- Gutierrez, E. and F. Terrones (2023). Small and sparse: Defining rural school districts for k-12 funding. Research Paper, Urban Institute.
- Holden, K. (2016). Buy the Book? Evidence on the Effect of Textbook Funding on School-Level Achievement. *American Economic Journal: Applied Economics* 8(4).
- Hyman, J. (2017). Does money matter in the long run? Effects of school spending on educational attainment. *American Economic Journal: Economic Policy* 9.
- Jackson, C. K. (2020). Does school spending matter? The new literature on an old question. In L. Tach, R. Dunifon, and D. Miller (Eds.), *Confronting inequality: How policies and practices shape children's opportunities*, pp. 165–186. American Psychological Association.

- Jackson, C. K., R. C. Johnson, and C. Persico (2016). The effects of school spending on educational and economic outcomes: Evidence from school finance reforms. *Quarterly Journal of Economics* 131(1).
- Jackson, C. K. and C. Mackevicius (2023). What Impacts Can We Expect from School Spending Policy? Evidence from Evaluations in the U.S. *American Economic Journal: Applied Economics*, forthcoming.
- Kava, R. and C. Pugh (2019). State Aid to School Districts. Informational Paper 24, Wisconsin Legislative Fiscal Bureau.
- Kelly, M. G. and D. Farrie (2023). Misrepresented Funding Gaps in Data for Some States. *Educational Researcher*, forthcoming.
- Kreisman, D. and M. P. Steinberg (2019). The effect of increased funding on student achievement: Evidence from Texas's small district adjustment. *Journal of Public Economics* 176.
- Kuziemko, I. (2006). Using shocks to school enrollment to estimate the effect of school size on student achievement. *Economics of Education Review* 25(1), 63–75.
- Lafortune, J., J. Rothstein, and D. W. Schanzenbach (2018). School Finance Reform and the Distribution of Student Achievement. *American Economic Journal: Applied Economics* 10(2), 1–26.
- Mason, K. C. (2016). Wisconsin's Second New State Test In 2 Years Rolls Out Quietly. *Wisconsin Public Radio*. <https://www.wpr.org/wisconsins-second-new-state-test-2-years-rolls-out-quietly>.
- McGee, J. B., J. N. Mills, and J. S. Goldstein (2022). The Effect of School District Consolidation on Student Achievement: Evidence From Arkansas. *Educational Evaluation and Policy Analysis*.
- Papke, L. A. (2005). The effects of spending on test pass rates: evidence from Michigan. *Journal of Public Economics* 89.
- Rauscher, E. (2020). Does money matter more in the country? Education funding reductions and achievement in Kansas, 2010–2018. *AERA Open* 6(4), 1–38.
- Roth, J., P. H. C. Sant'Anna, A. Bilinski, and J. Poe (2022). What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature. arXiv Pre-print arXiv:2201.01194.
- Roy, J. (2011). Impact of School Finance Reform on Resource Equalization and Academic Performance: Evidence from Michigan. *Education Finance and Policy* 6.
- Showalter, D., S. L. Hartman, J. Johnson, and B. Klein (2019). Why Rural Matters 2018-2019. Report, Rural School and Community Trust.
- Sipple, J. W. and B. O. Brent (2015). Challenges and Strategies Associated with Rural School Settings. In H. F. Ladd and M. E. Goertz (Eds.), *Handbook of Research in Education Finance and Policy*, pp. 607–622.
- Smith, S. A. and R. Zimmer (2022). The Impacts of School District Consolidation on Rural Communities: Evidence from Arkansas Reform. EdWorkingPaper 22-530, Annenberg Institute for School Reform at Brown University.
- Thompson, P. N. (2021a). Does a day lost equal dollars saved? The effects of four-day school weeks on school district expenditures. *National Tax Journal* 74.
- Thompson, P. N. (2021b). Is four less than five? Effects of four-day school weeks on student achievement in Oregon. *Journal of Public Economics* 193.
- Thompson, P. N., J. M. Schuna Jr., K. Gunter, and E. J. Tomayko (2021). Are all four-day school weeks created equal? A national assessment of four-day school week policy adoption and implementation. *Education Finance and Policy* 16.
- Tran, H. and D. A. Smith (2021). How Hard-to-Staff Rural School Districts Use State Funds to Address Teacher Shortages. *Journal of Education Finance* 47.

Wells, R. S., C. A. Manly, S. Kommers, and E. Kimball (2019). Narrowed Gaps and Persistent Challenges: Examining Rural-Nonrural Disparities in Postsecondary Outcomes over Time. *American Journal of Education* 126.

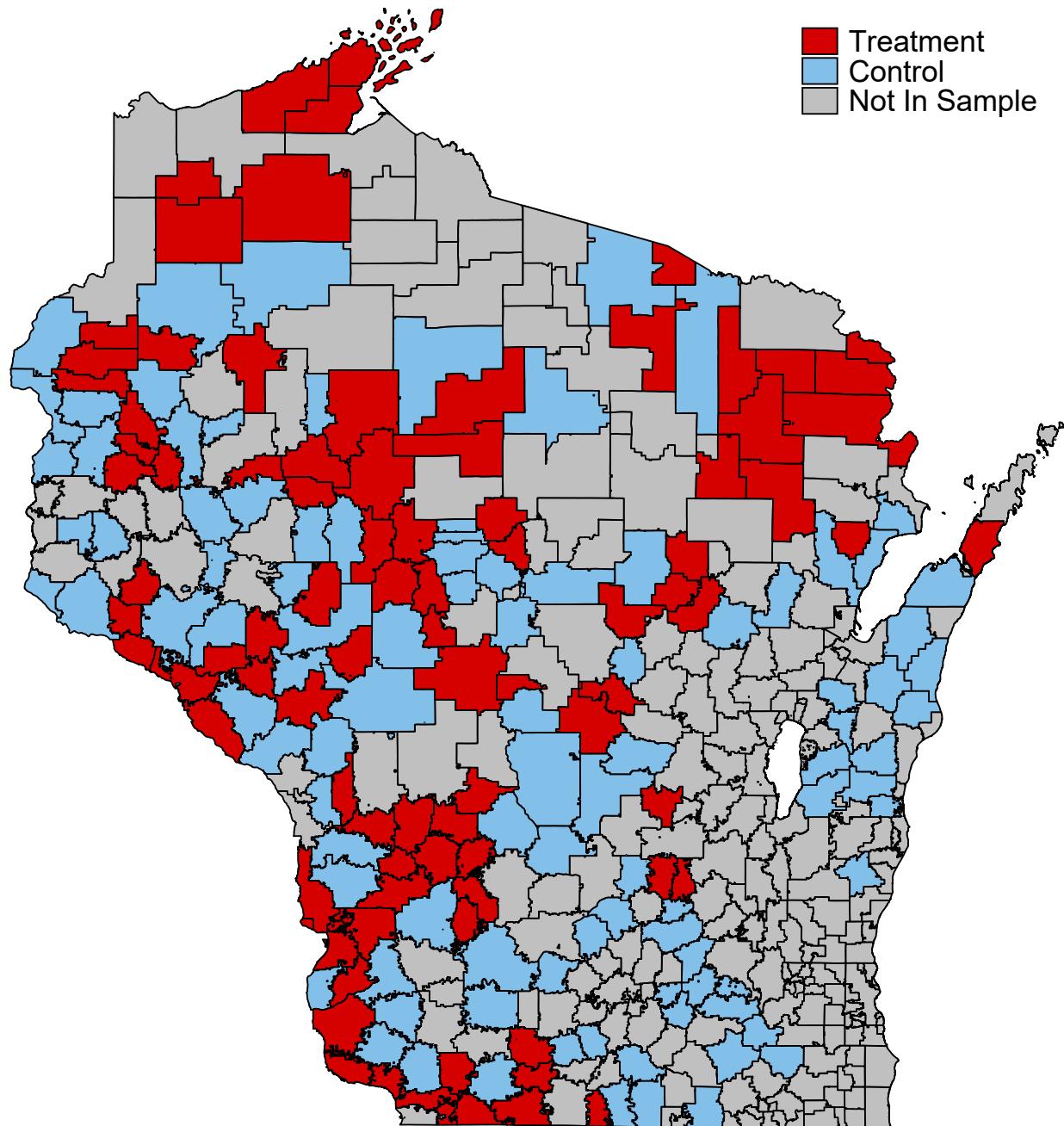
Wisconsin Legislative Fiscal Bureau (2019). High Cost Transportation Aid (DPI – Categorical Aids). [https://docs.legis.wisconsin.gov/misc/lfb/jfcmotions/2019/2019\\_05\\_23/001\\_public\\_instruction/019\\_paper\\_580\\_high\\_cost\\_transportation\\_aid](https://docs.legis.wisconsin.gov/misc/lfb/jfcmotions/2019/2019_05_23/001_public_instruction/019_paper_580_high_cost_transportation_aid).

Figure 1: Introduction & Expansion of Sparsity Aid Program



*Notes:* This figure shows the average sparsity aid funding received each year, both in total and per student, among districts in our sample that are always eligible for sparsity aid funding from 2008 to 2017.

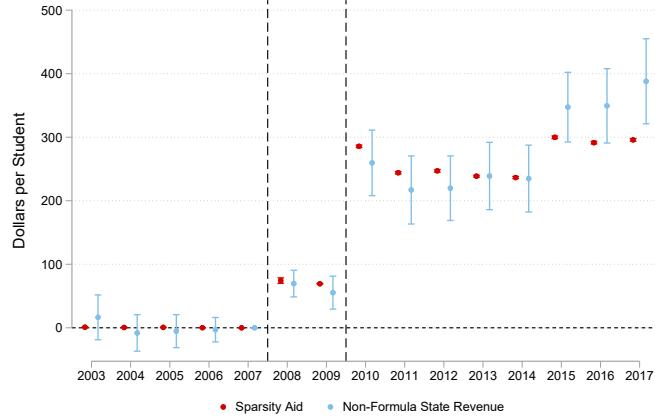
Figure 2: School Districts in Analytic Sample



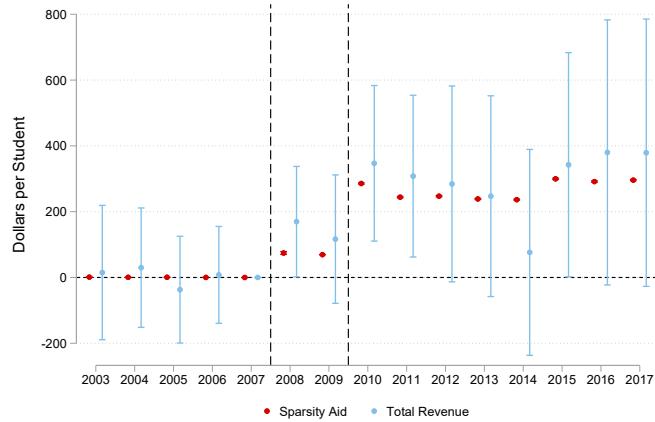
*Notes:* This figure shows the sparsity-eligible (treatment) and ineligible (comparison) districts in our sample.

Figure 3: Event Study Estimates of Sparsity Aid Program on District Finances

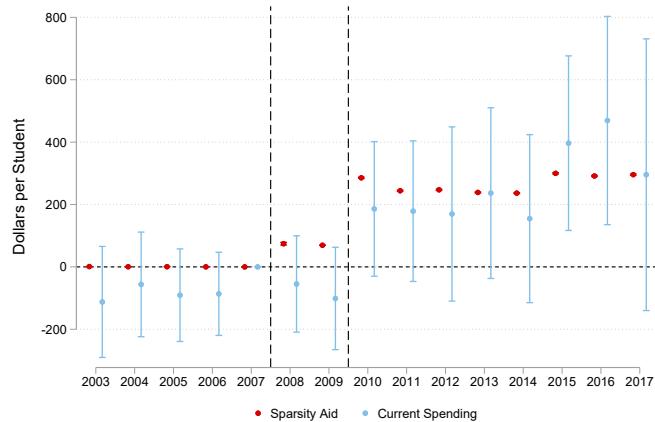
(a) Non-Formula Revenue from State



(b) Total Revenue



(c) Current Spending on Elementary & Secondary Education



*Notes:* Each figure presents estimates of the  $\beta_k$  coefficients from equation (2). All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, and year-by-region (CESA) fixed effects. All standard errors are clustered at the school district level.

Table 1: Baseline District Characteristics

	Wisconsin Average (1)	Analysis Sample Sparsity (2)	Comparison (3)	p-value (4)
<b>Panel A. Size &amp; Location</b>				
Membership	2035	480.1	1231.4	0.000
Membership per Square Mile	45.94	3.809	9.312	0.000
Number of Schools	4.941	2.544	3.889	0.000
Avg. Membership per School	355.9	201.1	332.9	0.000
NCES Rural Classification	0.580	0.978	0.707	0.000
<b>Panel B. Demographics</b>				
% White	0.887	0.940	0.940	0.979
% FRPL	0.239	0.347	0.237	0.000
% Special Education	0.145	0.157	0.144	0.000
Local Child Poverty Rate	0.098	0.145	0.095	0.000
District House Price Index	207.586	163.024	198.858	0.000
<b>Panel C. Finances</b>				
Revenue per student	11,789	12,502	11,122	0.000
Spending per student	9,966	10,354	9,408	0.000
% Instruction	0.698	0.669	0.689	0.000
% Support	0.073	0.064	0.073	0.000
% Administration	0.068	0.072	0.065	0.000
% Other	0.176	0.182	0.179	0.007
<b>Panel D. Staffing</b>				
Number of Teachers (FTE)	131.4	37.71	86.54	0.000
Teachers per 100 Members	7.324	8.027	7.045	0.000
Average Teacher Salary	44,087	40,396	43,305	0.000
Average Teacher Experience	15.476	16.029	15.946	0.589
Number of Administrators (FTE)	7.933	2.336	5.523	0.000
Administrators per 100 Members	0.467	0.496	0.450	0.000
<b>Panel E. Educational Outcomes</b>				
Math Proficiency Rate	0.439	0.393	0.418	0.001
Reading Proficiency Rate	0.361	0.324	0.346	0.000
College Enrollment Rate	0.542	0.518	0.538	0.028
College Completion Rate	0.403	0.386	0.405	0.021
Observations	2,310	445	495	940
Districts	462	89	99	188

*Notes:* Each column summarizes district-level characteristics over the 2003-2007 academic years. The test score and postsecondary outcomes are averaged over the 2005-2007 academic years. The college enrollment rate is defined as the share of high school seniors who enroll in a postsecondary institution within one year of graduating from high school and the college completion rate is defined as the share of high school seniors in the 2005-2007 cohorts who completed a postsecondary credential within the time frame of our data.

Table 2: Effect of Sparsity Aid on District Revenues &amp; Spending

	(1)	(2)	(3)	(4)
<b>Panel A. Sparsity aid dollars</b>				
Received sparsity aid	223.6*** (1.9)	222.2*** (2.2)	221.6*** (2.3)	219.1*** (2.5)
Observations	2,820	2,820	2,820	2,820
<b>Panel B. Non-formula revenue from state</b>				
Received sparsity aid	253.7*** (23.4) [31.1%]	259.7*** (22.1) [31.9%]	229.9*** (20.6) [28.2%]	217.1*** (20.4) [26.6%]
Observations	2,820	2,820	2,820	2,820
<b>Panel C. Total revenue</b>				
Received sparsity aid	261.6** (114.4) [1.96%]	263.8** (104.6) [1.97%]	257.6** (118.9) [1.93%]	252.4** (118.6) [1.89%]
Observations	2,820	2,820	2,820	2,820
<b>Panel D. Current spending</b>				
Received sparsity aid	301.5*** (103.1) [2.70%]	291.6*** (94.6) [2.61%]	247.7** (99.4) [2.22%]	226.3** (101.6) [2.03%]
Observations	2,820	2,820	2,820	2,820
Membership control	X	X	X	X
Demographic controls		X	X	X
Year-by-CESA FE			X	X
Transportation funding control				X

*Notes:* Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (1), the effect of receiving sparsity aid funding. Column (1) controls for a district's log membership, column (2) adds controls for a district's log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, and the local child poverty rate, column (3) adds year-by-region (CESA) fixed effects, and column (4) further controls for whether a district receives funding from the state's high-cost pupil transportation aid program. All standard errors are clustered at the district level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table 3: Effect of Sparsity Aid on Spending Allocations

	General Instruc. (1)	Other Instruc. (2)	Pupil Supp. (3)	Instruc. Staff Supp. (4)	Admin (5)	Student Transp. (6)	Food Service (7)	General Ops. (8)
<b>Panel A. Effects on Total Spending</b>								
Received sparsity aid	56.96 (50.71)	24.08 (35.01)	-0.354 (14.25)	6,404 (18.24)	45.01** (18.94)	5.772 (9.290)	23.46*** (8.453)	56.71* (26.686)
Observations	2,820	2,820	2,820	2,820	2,820	2,820	2,820	2,820
Baseline Mean	4185.3	1990.4	385.88	416.28	895.57	584.90	417.21	1282.27
<b>Panel B. Effects on Salary &amp; Employee Benefit Spending</b>								
Received sparsity aid	75.12 (48.25)	-5.047 (34.79)	-11.99 (12.12)	2,976 (14.17)	41.26** (16.26)	-16.42* (9.871)	9.731 (7.382)	35.01* (18.09)
Observations	2,820	2,820	2,820	2,820	2,820	2,820	2,820	2,820
Baseline Mean	3981.4	1810.13	272.87	282.40	778.20	174.83	221.74	662.73
<b>Panel C. Effects on Other Spending</b>								
Received sparsity aid	-18.16 (12.27)	29.13*** (10.75)	11.64 (8.914)	3,428 (8.052)	3.747 (7.012)	22.19* (13.27)	13.73* (8.126)	21.70 (21.85)
Observations	2,820	2,820	2,820	2,820	2,820	2,820	2,820	2,820
Baseline Mean	203.86	180.27	113.00	133.89	117.37	410.07	195.47	619.54

Notes: Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (1), the effect of receiving sparsity aid funding. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. All standard errors are clustered at the school district level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 4: Heterogeneous Effects of Sparsity Aid on Spending Allocations

	<b>General Instruc.</b> <b>(1)</b>	<b>Other Instruc.</b> <b>(2)</b>	<b>Pupil Supp.</b> <b>(3)</b>	<b>Instruc. Staff Supp.</b> <b>(4)</b>	<b>Admin</b> <b>(5)</b>	<b>Student Transp.</b> <b>(6)</b>	<b>Food Service</b> <b>(7)</b>	<b>General Ops.</b> <b>(8)</b>
Received sparsity aid	43.605 (50.087)	17.34 (34.819)	-4.052 (14.879)	-7.235 (20.088)	54.56*** (18.759)	3.833 (9.081)	22.41*** (8.341)	60.12** (26.399)
Received sparsity aid x budget share	-28.640*** (11.192)	-23.37*** (10.149)	-36.03*** (16.193)	-34.65*** (15.332)	-27.15*** (13.321)	13.66*** (6.901)	-25.99*** (12.888)	19.53 (13.598)
Baseline Mean Spending \$	4185.3	1990.4	385.88	416.28	895.57	584.9	417.21	1282.27
Baseline Mean Share	0.342	0.163	0.032	0.037	0.068	0.044	0.033	0.104
Observations	2,820	2,820	2,820	2,820	2,820	2,820	2,820	2,820
Effect at 10th Percentile	198.3***	121.7***	37.41**	54.21**	91.15***	-14.4	36.96***	21.38
Effect at 25th Percentile	109.4**	64.52	26.48*	37.63*	66.06***	-4.62	31.65***	35.64
Effect at 50th Percentile	54.25	21.90	5.305	6.751	42.72**	5.813	23.01***	55.85**
Effect at 75th Percentile	-6.66	-5.96	-21.9	-21.4	21.60	17.20	14.96*	73.44**
Effect at 90th Percentile	-55.3	-54.7	-37.1	-42.4	4.132	34.12*	3.147	100.7**

Notes: The coefficients in each column are estimated from a separate regression and represent  $\beta$  in equation (1), the effect of receiving sparsity aid funding, with interaction effects based on districts' pre-2008 budget shares. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. All standard errors are clustered at the school district level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 5: Effects of Sparsity Aid on Administrator Staffing

	Total Admin FTEs per 100 Students (1)	Superintendent FTEs per 100 Students (2)	Principals Non-Zero FTEs (3)	Principals FTEs per 100 Students (4)	Non-Zero FTEs (5)	All Other FTEs per 100 Students (6)
<i>Panel A. Main Specification</i>						
Received sparsity aid	0.021* (0.012)	-0.005 (0.006)	0.030 (0.020)	0.014 (0.010)	0.149*** (0.046)	0.013 (0.008)
Baseline Mean	0.465	0.193	0.912	0.237	0.283	0.034
Observations	2,820	2,820	2,820	2,820	2,820	2,820
<i>Panel B. Interaction with Baseline Admin Budget Share</i>						
Received sparsity aid	0.028** (0.012)	-0.003 (0.006)	0.038* (0.023)	0.017* (0.009)	0.152*** (0.046)	0.014* (0.008)
Received sparsity aid x budget share	-0.019** (0.008)	-0.006 (0.004)	-0.023 (0.017)	-0.010* (0.006)	-0.007 (0.023)	-0.003 (0.004)
Baseline Mean	0.465	0.193	0.912	0.237	0.283	0.034
Observations	2,820	2,820	2,820	2,820	2,820	2,820
Effect at 25th Percentile	0.036*** 0.005	-0.001 -0.010	0.048* 0.010	0.021** 0.005	0.155*** 0.143***	0.015* 0.011
Effect at 75th Percentile						

*Notes:* The coefficients in each column are estimated from a separate regression and represent  $\beta_1$  in equation (1), the effect of receiving sparsity aid funding, with interaction effects based on districts' pre-2008 budget shares. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. All standard errors are clustered at the school district level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 6: Effect of Sparsity Aid on Standardized Test Scores

	<b>3rd Grade (1)</b>	<b>4th Grade (2)</b>	<b>5th Grade (3)</b>	<b>6th Grade (4)</b>	<b>7th Grade (5)</b>	<b>8th Grade (6)</b>	<b>10th Grade (7)</b>	<b>All Grades (8)</b>
<b>Panel A. Reading</b>								
Received sparsity aid	-0.010 (0.024)	-0.018 (0.021)	-0.020 (0.021)	-0.007 (0.020)	0.021 (0.019)	-0.022 (0.020)	-0.010 (0.020)	-0.009 (0.012)
Observations	90,631	91,595	92,516	95,059	98,256	100,523	110,142	678,722
Mean	0.047	0.046	0.027	0.057	0.049	0.045	0.039	0.044
<b>Panel B. Math</b>								
Received sparsity aid	-0.015 (0.031)	-0.036 (0.028)	-0.034 (0.028)	-0.062** (0.028)	-0.026 (0.026)	-0.017 (0.024)	-0.026 (0.020)	-0.030* (0.015)
Observations	90,896	91,720	92,612	95,125	98,328	100,574	110,164	679,419
Mean	0.016	0.013	-0.014	-0.006	0.011	0.040	0.046	0.016
<b>Panel C. Science</b>								
Received sparsity aid		0.007 (0.022)				-0.019 (0.022)	-0.008 (0.018)	-0.007 (0.013)
Observations		91,757				100,556	110,096	302,409
Mean		0.079				0.086	0.085	0.083
<b>Panel D. Social Studies</b>								
Received sparsity aid		-0.014 (0.022)				-0.020 (0.021)	0.003 (0.019)	-0.010 (0.013)
Observations		91,731				100,407	110,061	302,199
Mean		0.082				0.100	0.079	0.087
<b>Panel E. Writing</b>								
Received sparsity aid		-0.010 (0.021)				0.002 (0.022)	-0.012 (0.018)	-0.007 (0.014)
Observations		91,607				100,457	109,935	301,999
Mean		0.032				0.025	0.022	0.026
<b>Panel F. Average</b>								
Received sparsity aid	-0.012 (0.025)	-0.015 (0.020)	-0.028 (0.022)	-0.035 (0.022)	-0.002 (0.020)	-0.015 (0.019)	-0.011 (0.016)	-0.016 (0.012)
Observations	90,619	91,578	92,495	95,036	98,231	100,470	110,025	678,454
Mean	0.032	0.044	0.007	0.026	0.031	0.050	0.045	0.034

*Notes:* Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (1), the effect of receiving sparsity aid funding on standardized test scores. Average test scores are calculated for students with non-missing math and reading scores. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level.  
 \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 7: Effect of Sparsity Aid on Postsecondary Enrollment &amp; Completion

	Enrollment			Completion		
	Any (1)	Two-Year (2)	Four-Year (3)	Any (4)	Two-Year (5)	Four-Year (6)
<b>Panel A. All Students</b>						
Received sparsity aid	0.003 (0.009)	0.006 (0.008)	-0.002 (0.007)	0.007 (0.009)	0.001 (0.006)	0.007 (0.007)
Observations	165,442	165,442	165,442	165,442	165,442	165,442
Mean	0.558	0.237	0.340	0.345	0.161	0.209
<b>Panel B. FRL Eligible Students</b>						
Received sparsity aid	0.021 (0.018)	0.020 (0.017)	0.002 (0.012)	0.014 (0.013)	0.011 (0.011)	0.004 (0.011)
Observations	37,017	37,017	37,017	37,017	37,017	37,017
Mean	0.381	0.208	0.183	0.209	0.128	0.092
<b>Panel C. FRL Ineligible Students</b>						
Received sparsity aid	-0.003 (0.010)	0.003 (0.008)	-0.006 (0.008)	0.004 (0.010)	-0.000 (0.007)	0.005 (0.008)
Observations	128,419	128,419	128,419	128,419	128,419	128,419
Mean	0.610	0.246	0.386	0.385	0.170	0.243

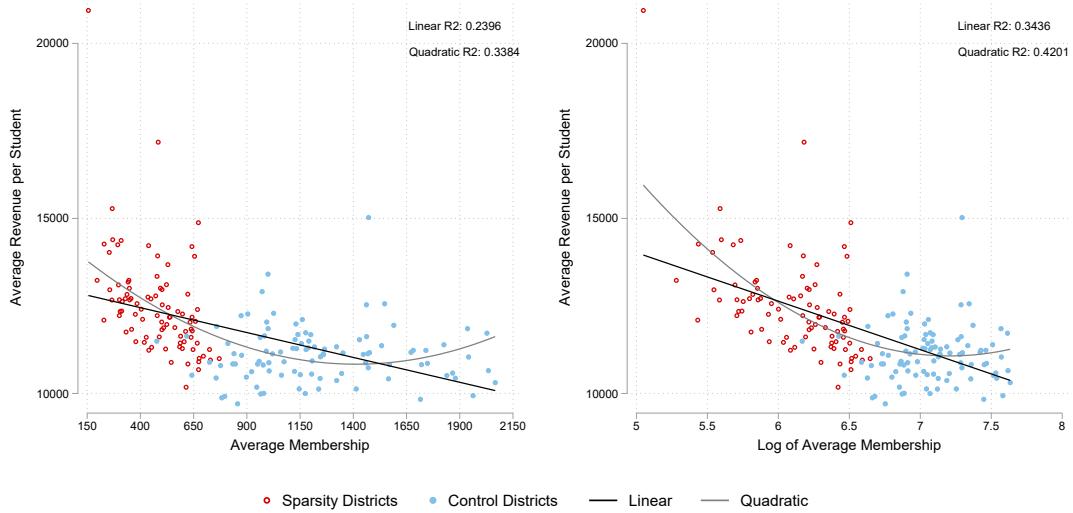
*Notes:* Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (3), the effect of receiving sparsity aid funding. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

# Online Appendix: Not for Publication

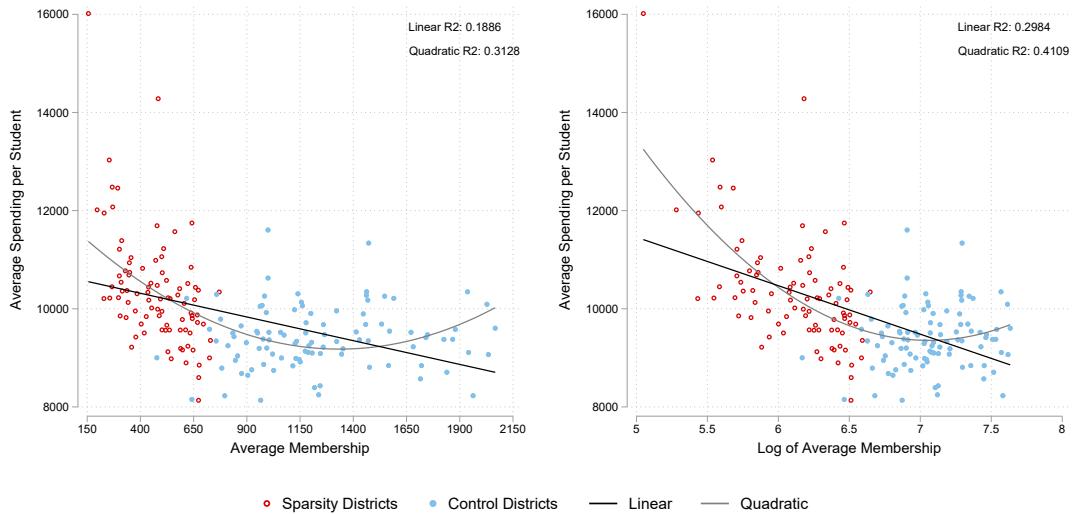
## A Additional Figures & Tables

Figure A.1: Relationship Between District Size & Finances, 2003-2007

(a) Total Revenue

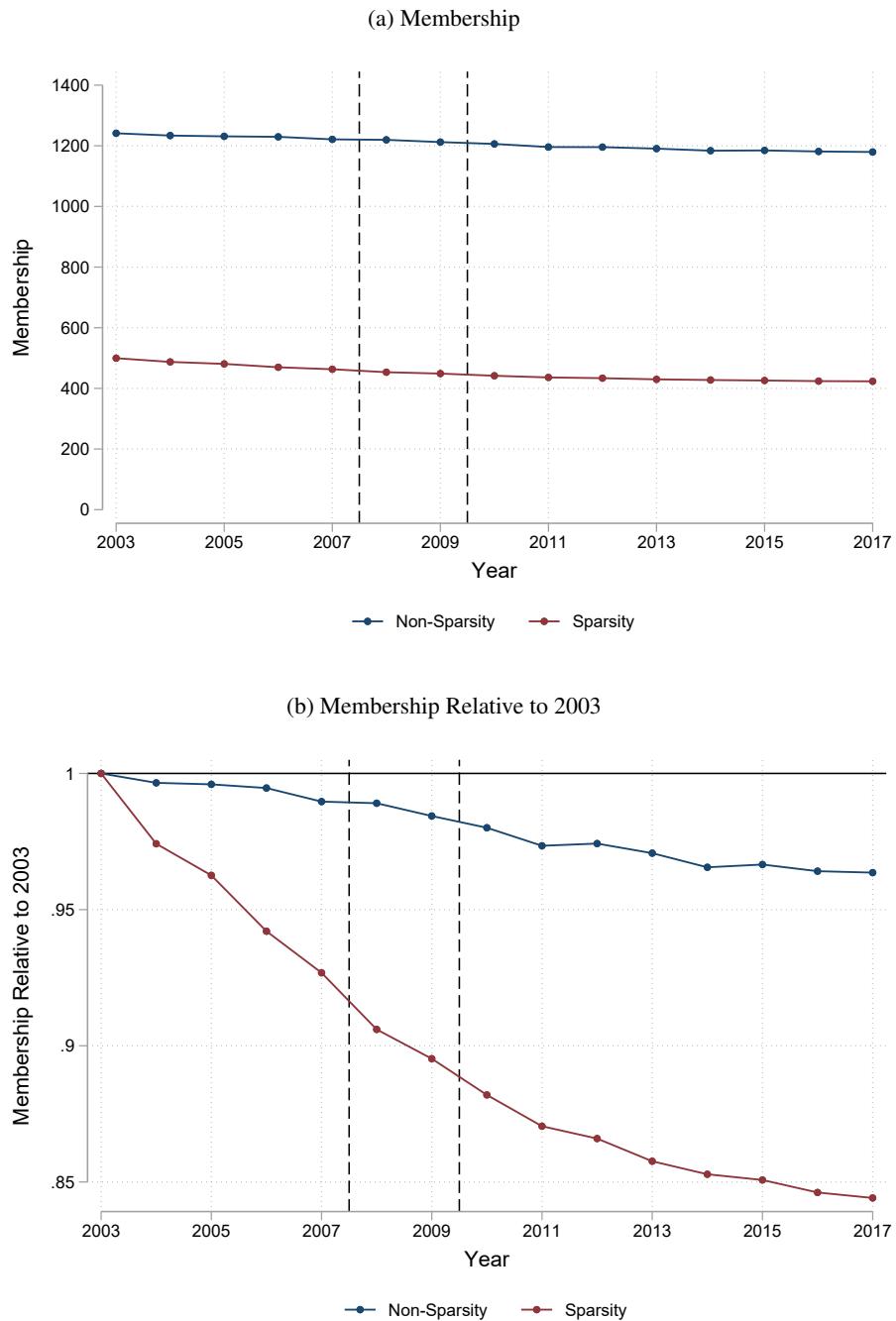


(b) Spending on Elementary & Secondary Education



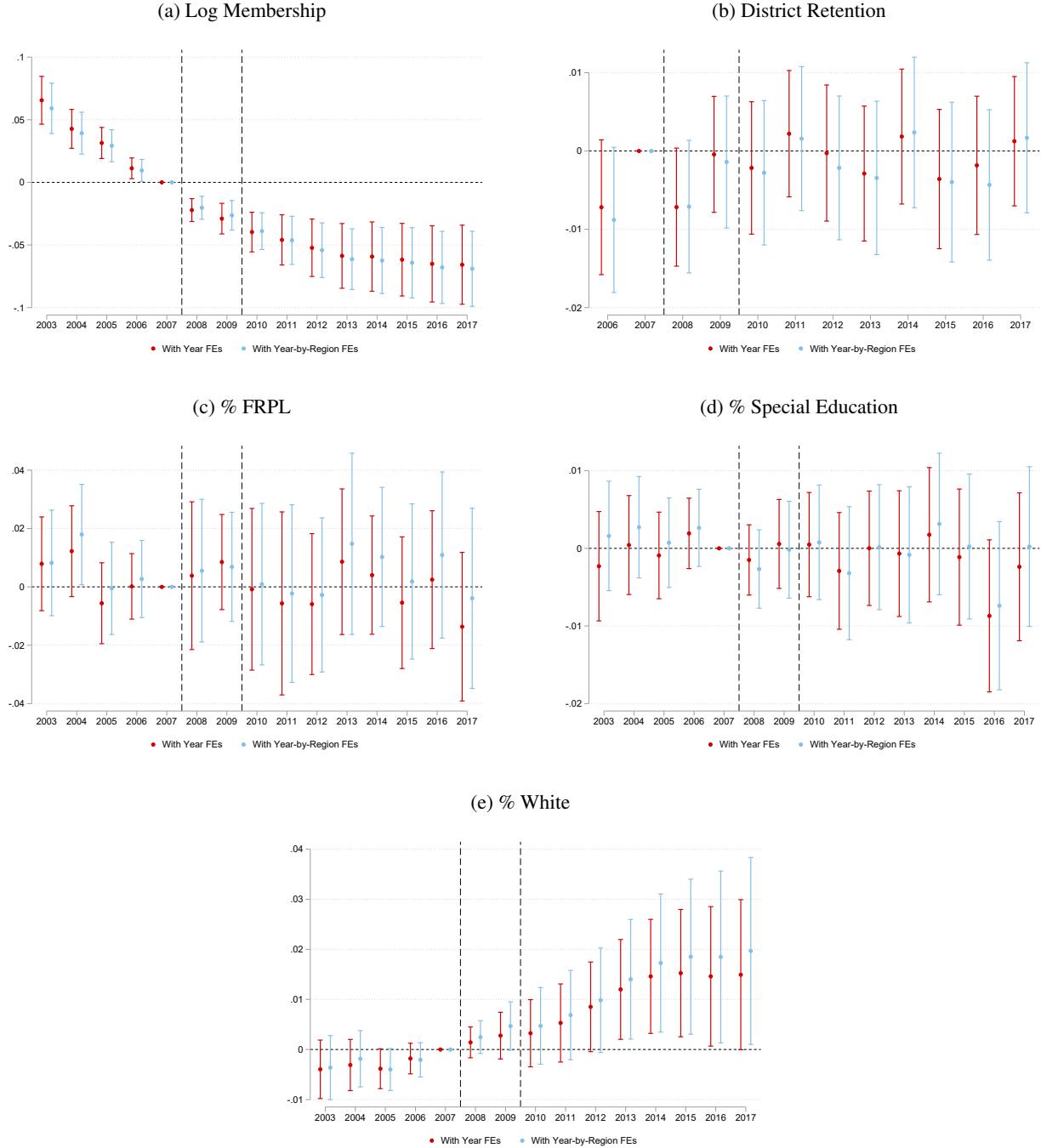
*Notes:* Each figure presents the relationship between districts' average resources per student and average membership in academic years 2003-2007. Districts that become eligible for the sparsity aid program in 2008 are shaded red, while districts that are never eligible for the sparsity aid program are shaded blue.

Figure A.2: Membership in Sparsity-Eligible & Ineligible Districts, 2003-2017



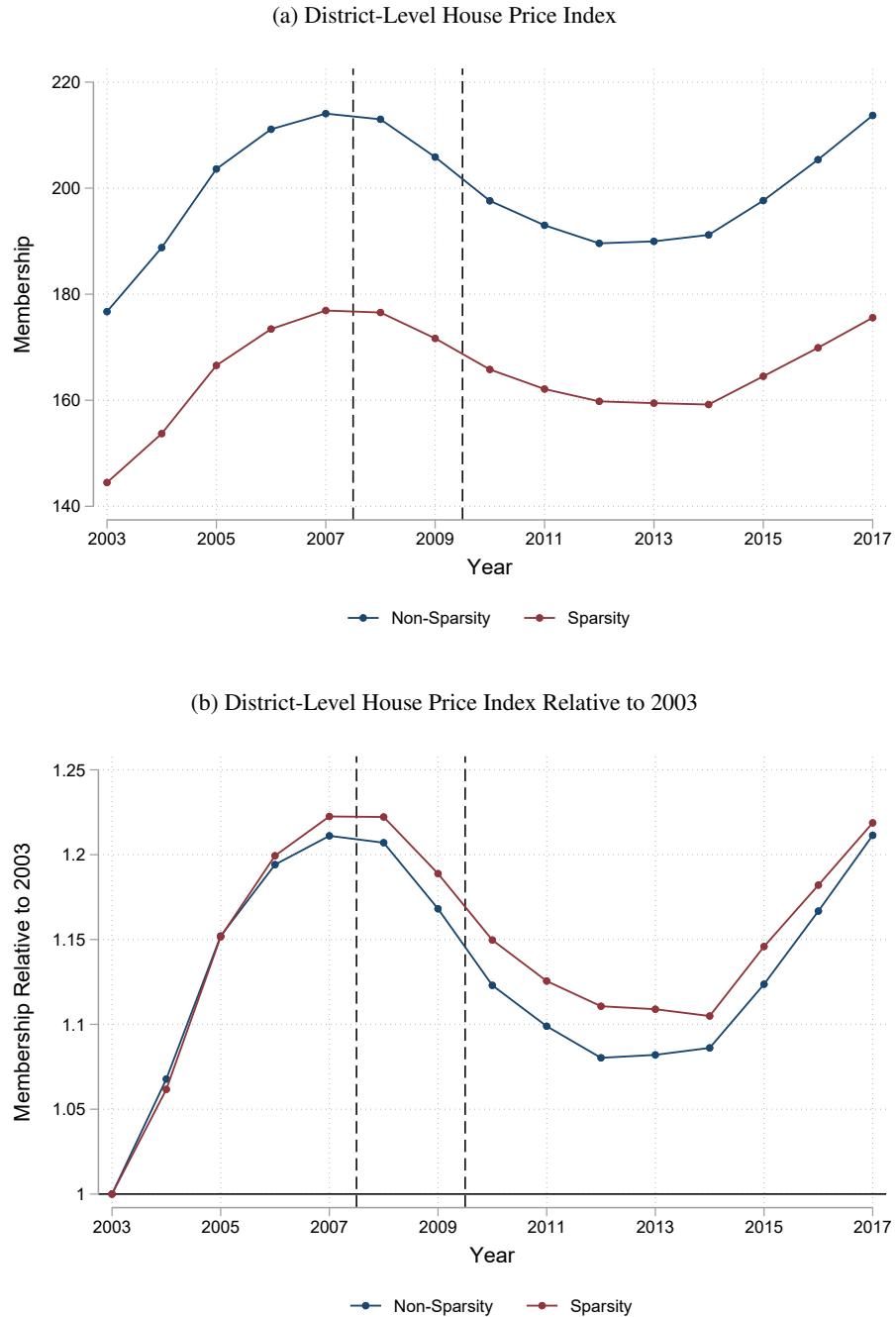
Notes: Panel A plots the average membership in sparsity-eligible and ineligible districts across academic years 2003-2017. Panel B repeats this plot measuring districts' membership relative to 2003.

Figure A.3: Event Study Estimates of Sparsity Aid Program on District Demographics



*Notes:* Each figure presents estimates of the  $\beta_k$  coefficients from equation (2), including either district and year FEs or district and year-by-region FEs. All standard errors are clustered at the school district level.

Figure A.4: House Price Index in sparsity-eligible & Ineligible Districts, 2003-2017



Notes: Panel A plots the average district-level house price index in sparsity-eligible and ineligible districts across academic years 2003-2017. Panel B repeats this plot measuring districts' house price indices relative to 2003.

Figure A.5: Event Study Estimates of Sparsity Aid Program on Local Resources

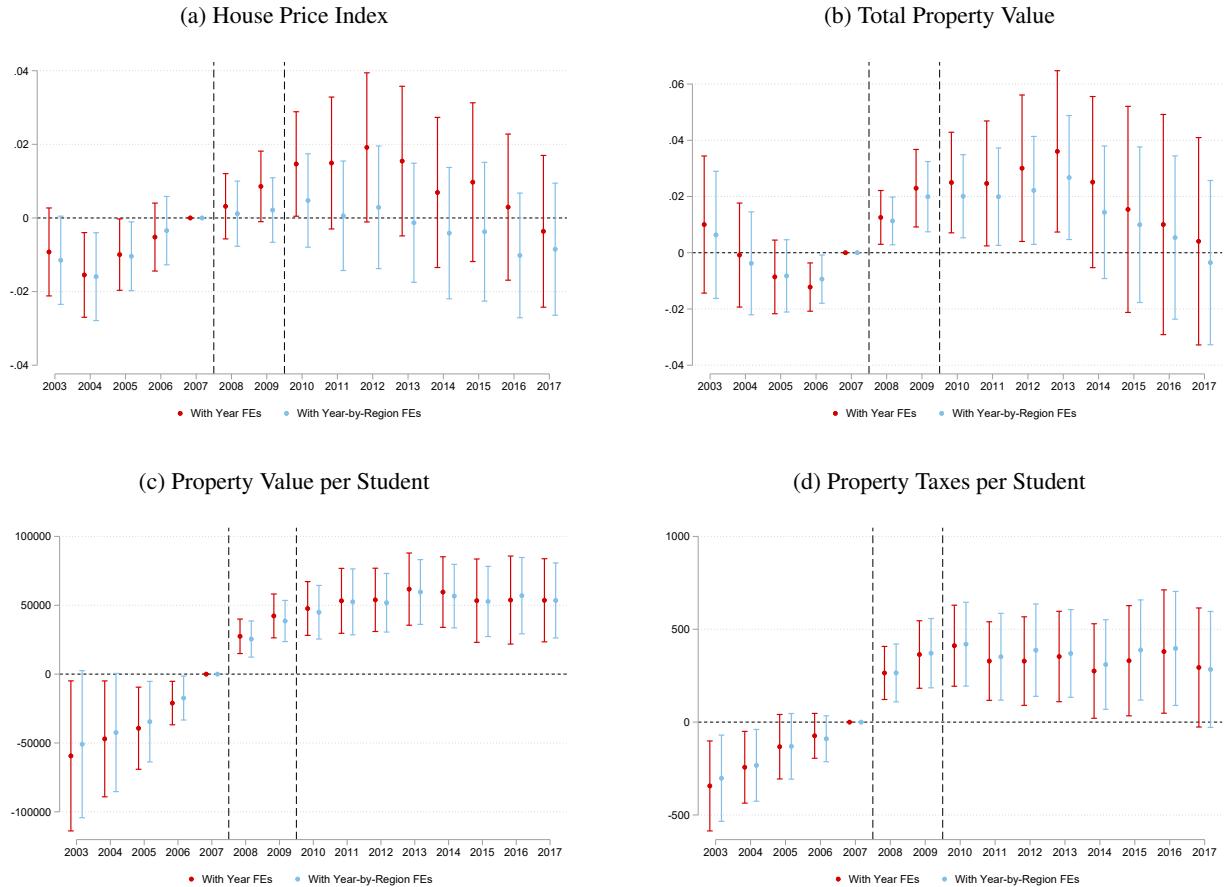
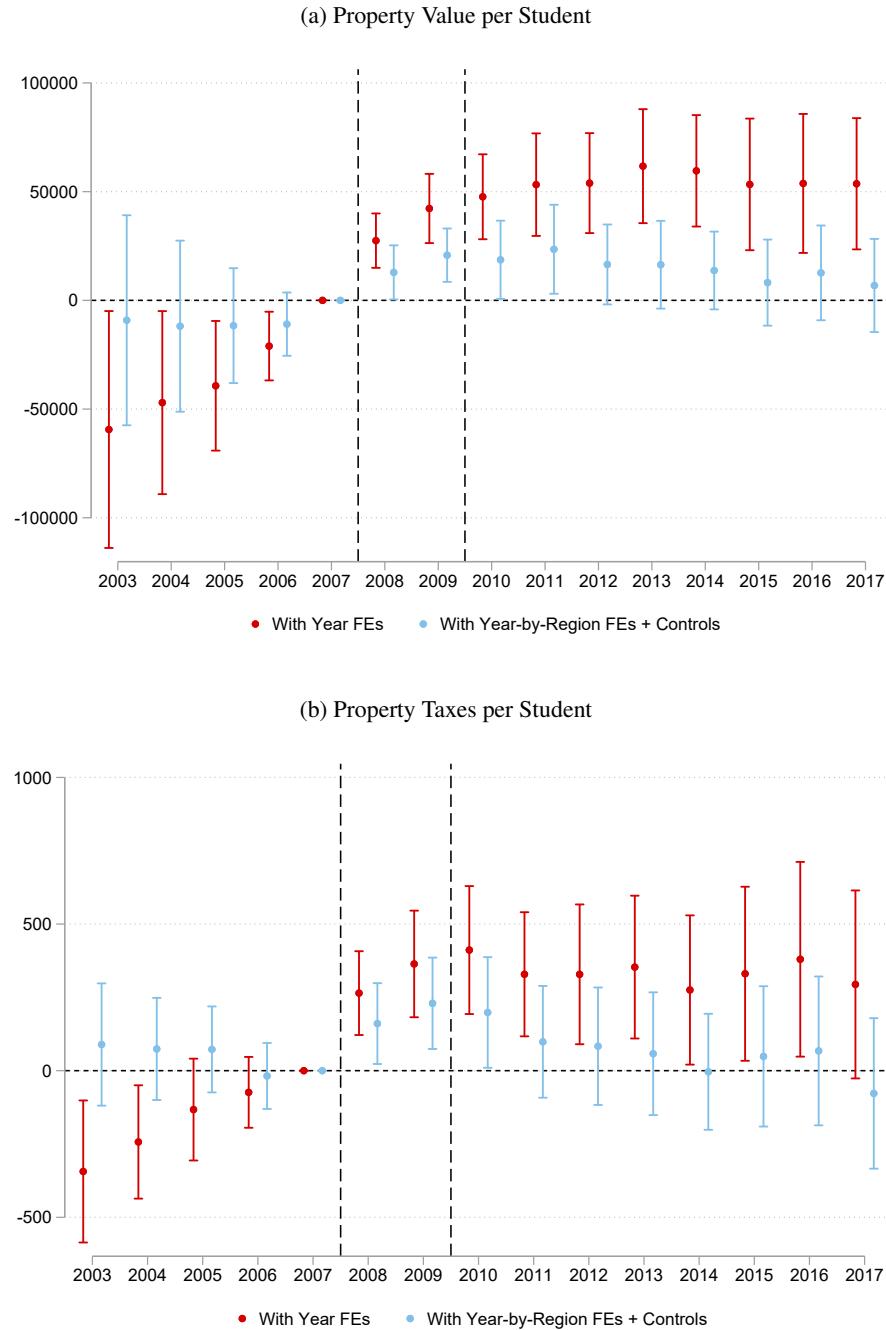
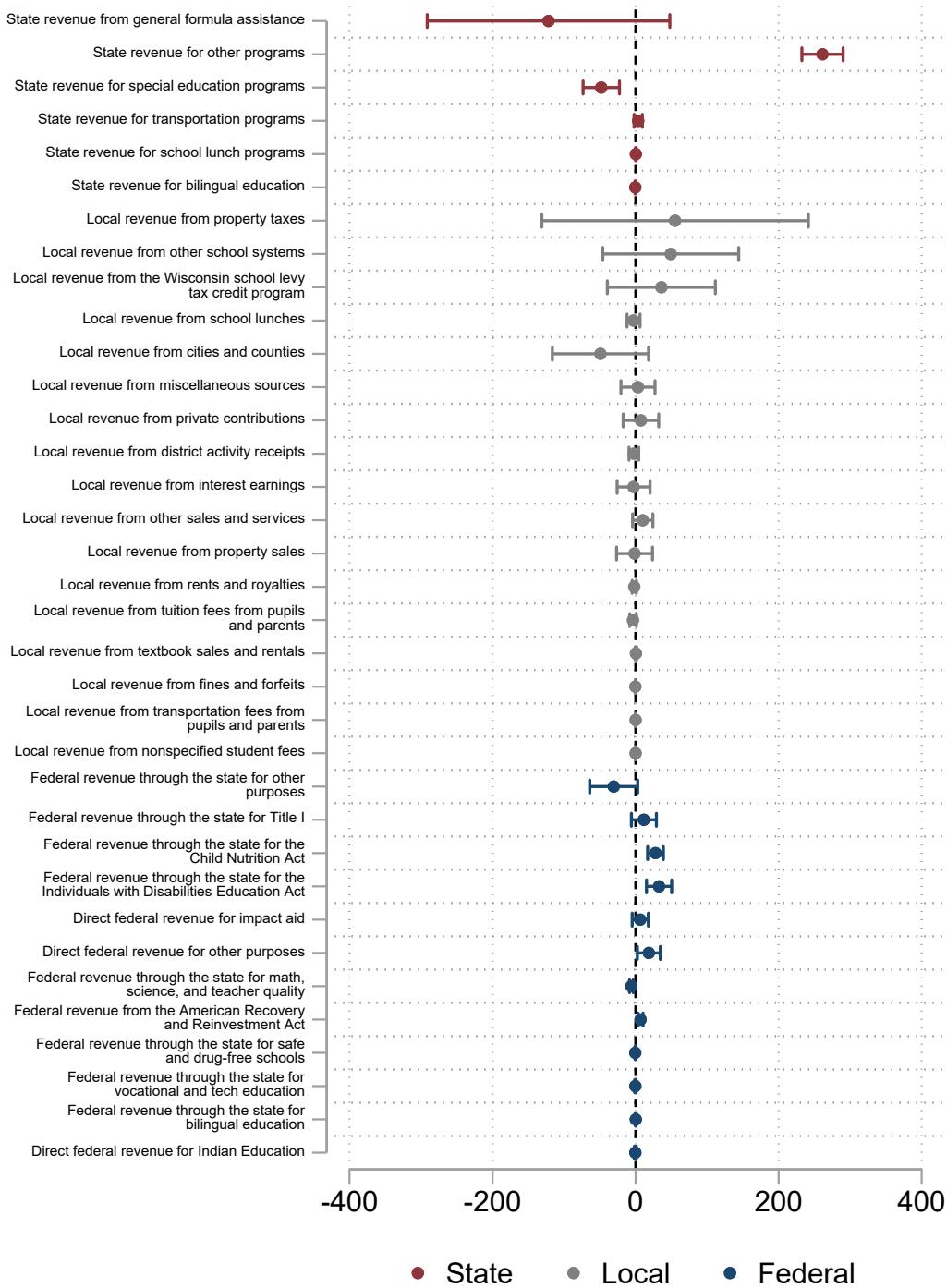


Figure A.6: Event Study Estimates of Sparsity Aid Program on Local Resources, With Additional Controls



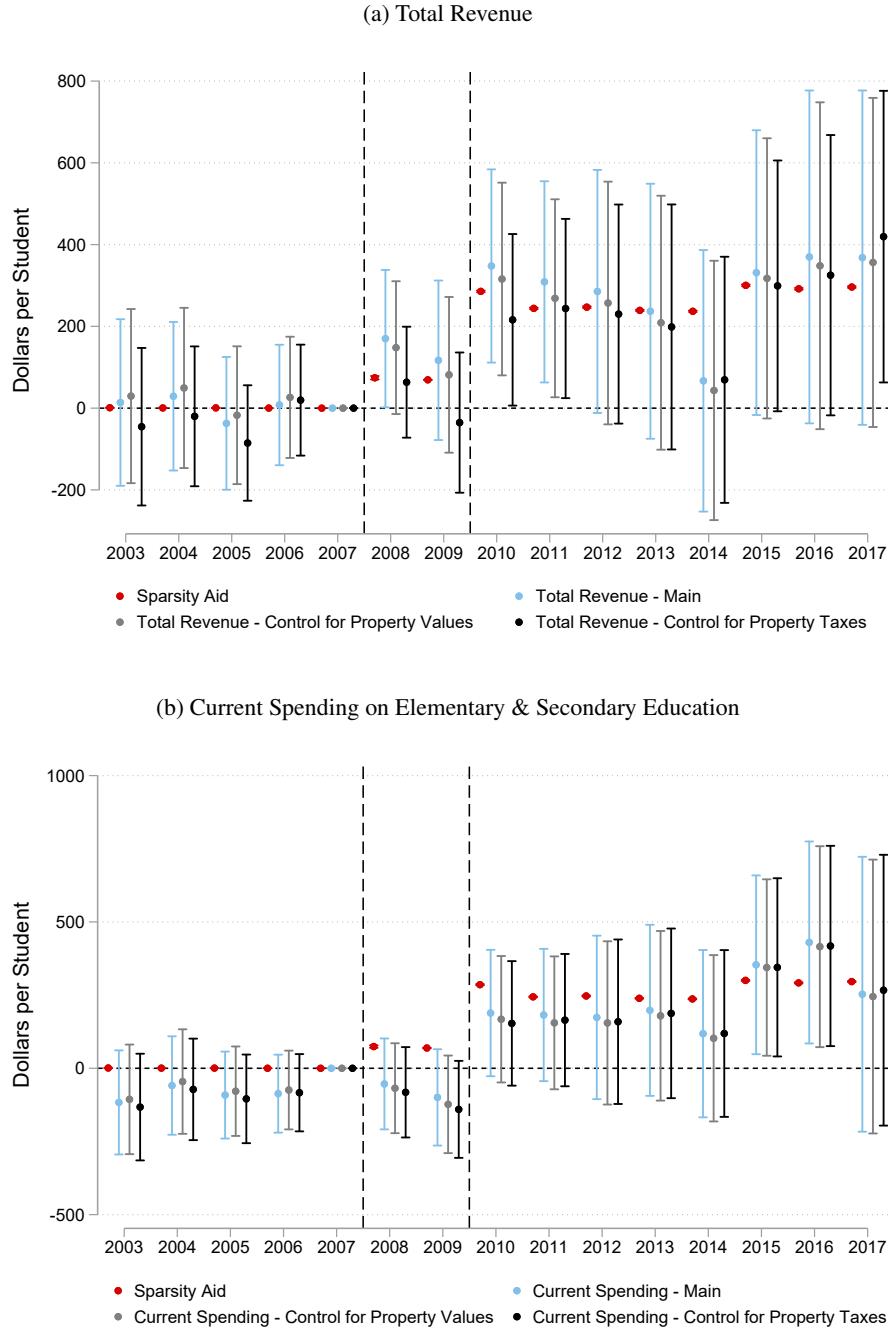
Notes: Each figure presents estimates of the  $\beta_k$  coefficients from equation (2), including either district and year FEs or district and year-by-region FEs, along with districts' log membership and log house price index. All standard errors are clustered at the school district level.

Figure A.7: Effects of Sparsity Aid on District Revenues, by Source



*Notes:* Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (1), the effect of receiving sparsity aid funding. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. All standard errors are clustered at the school district level.

Figure A.8: Event Study Estimates of Sparsity Aid Program on District Finances, With Additional Controls



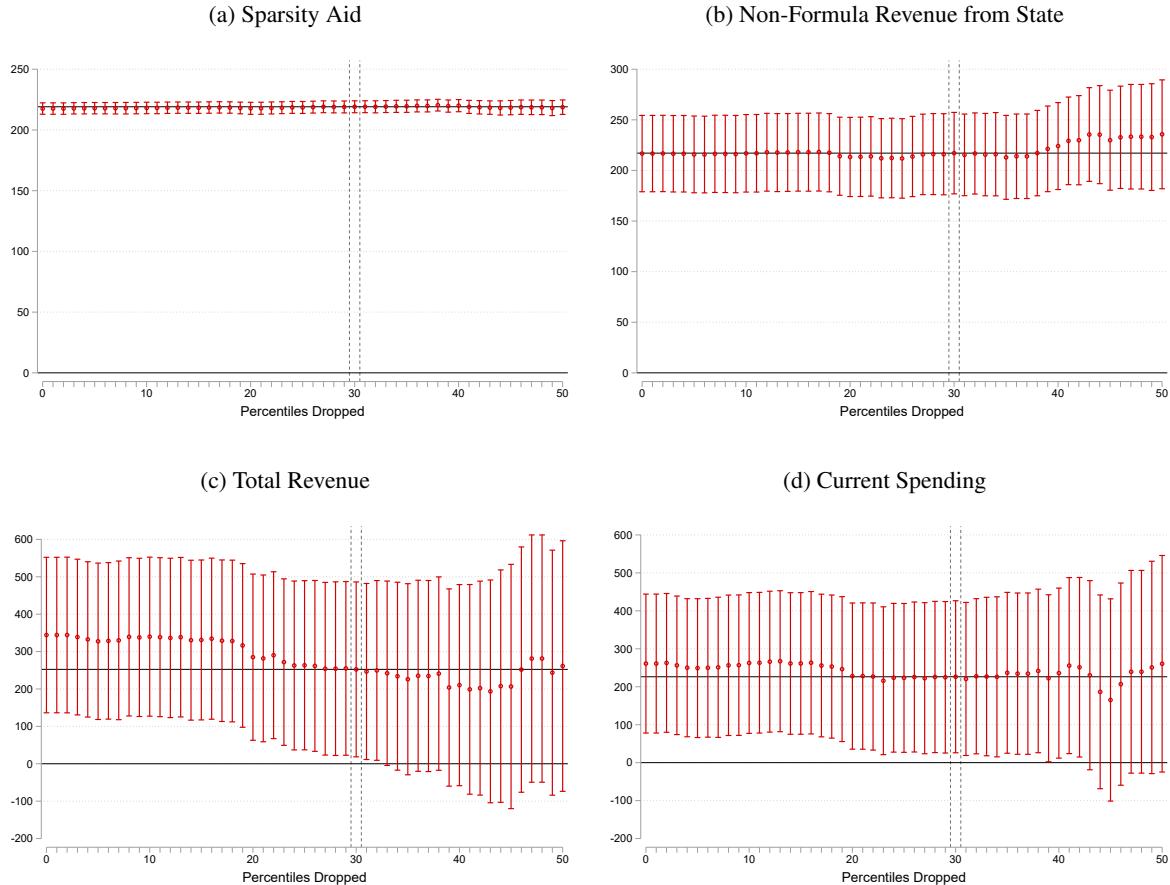
*Notes:* Each figure presents estimates of the  $\beta_k$  coefficients from equation (2). All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. Additional specifications control for a district's total property value per student or total property tax revenue per student, as indicated. All standard errors are clustered at the school district level.

Figure A.9: Effect of Sparsity Aid Program on District Finances, With Additional Revenue Controls



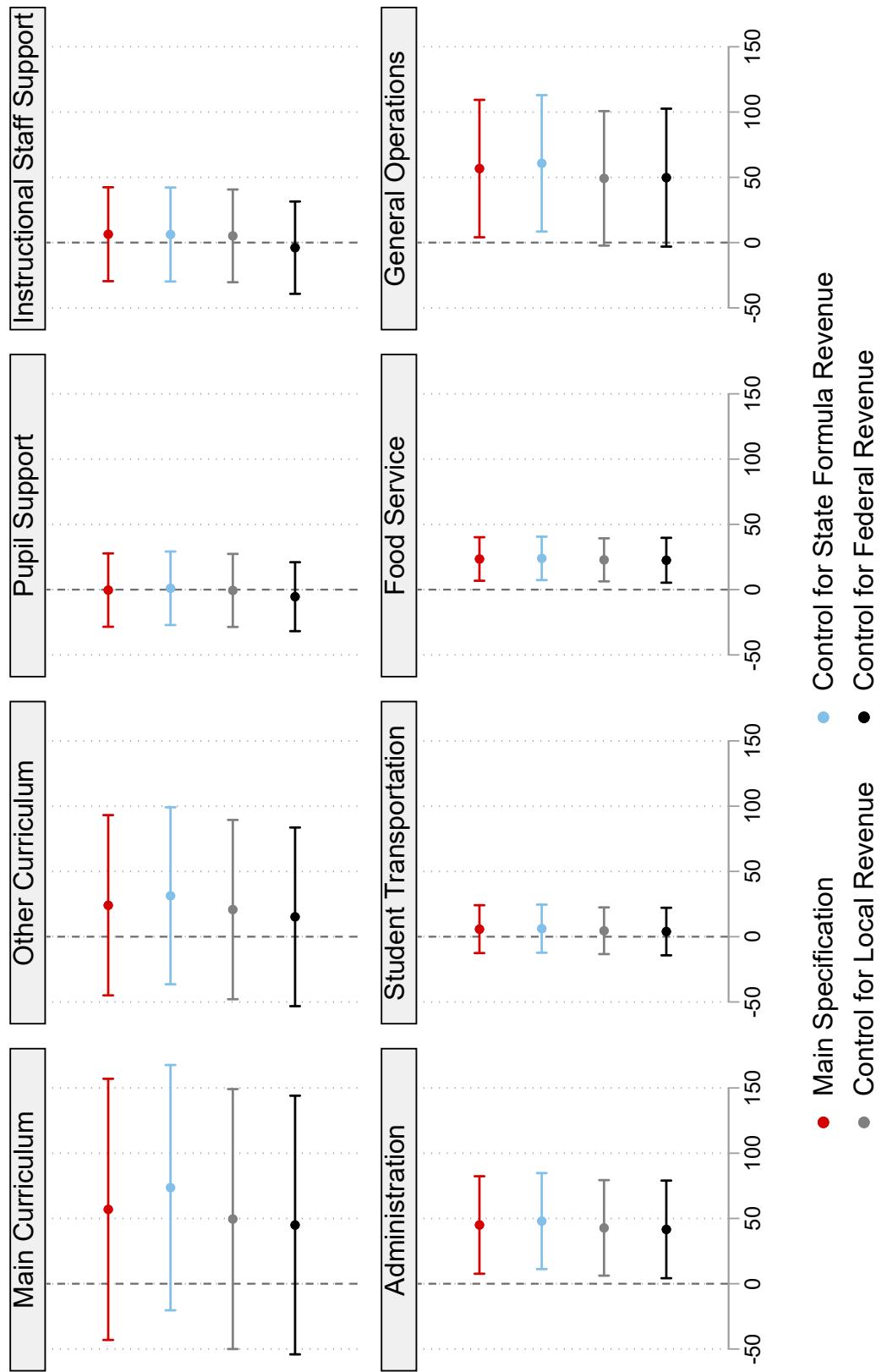
*Notes:* Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (1), the effect of receiving sparsity aid funding. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. Additional specifications control for a district's state formula revenue per student, total local revenue per student, or total federal revenue per student, as indicated. All standard errors are clustered at the school district level.

Figure A.10: Sensitivity of School Finance Estimates to Density & Membership Bandwidth Selection



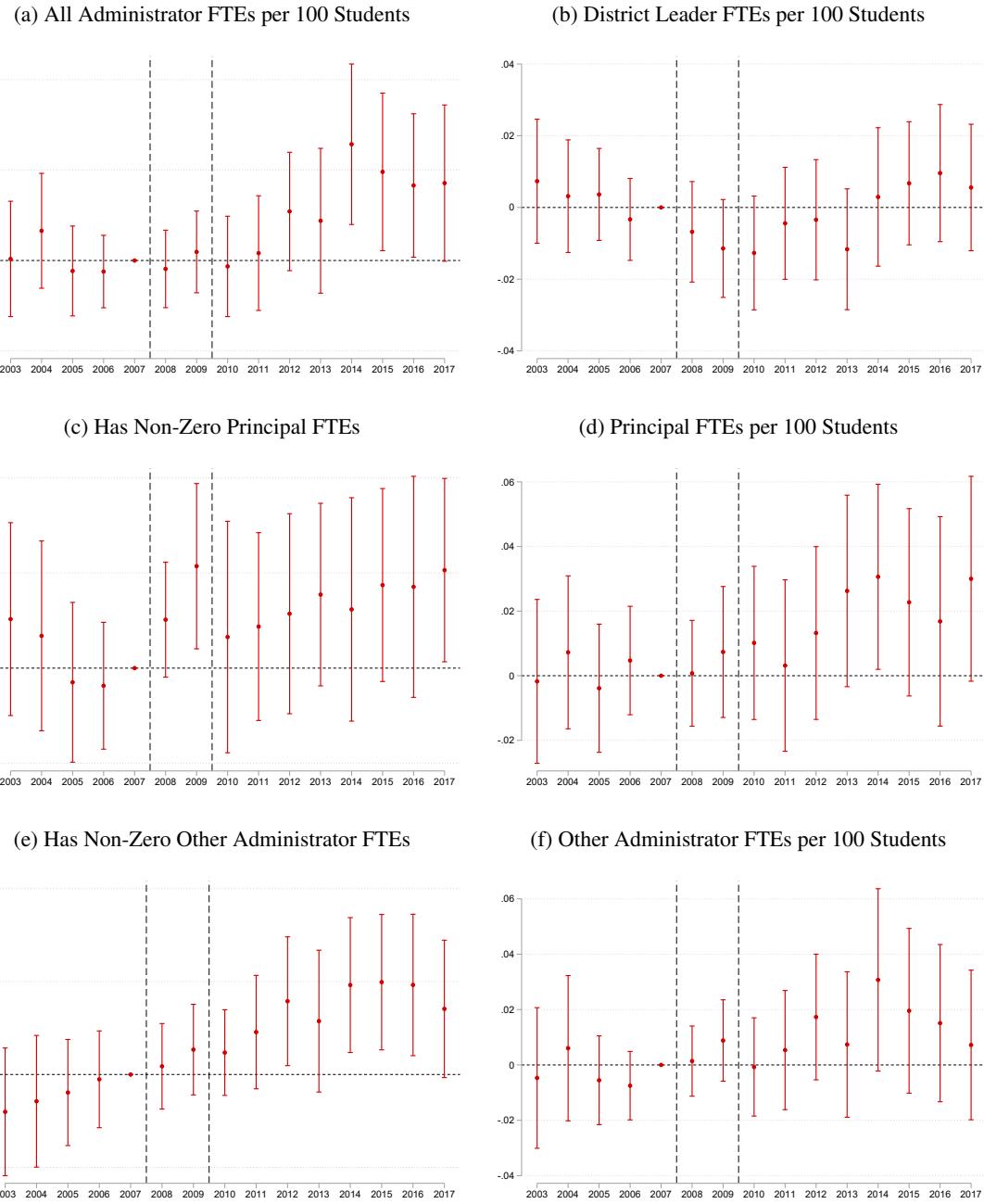
*Notes:* Each figure presents estimates of  $\beta$  in equation (1), the effect of receiving sparsity aid funding. Each coefficient is estimated from a separate regression, where we restrict the sample by dropping districts at the top of the pre-2008 density and membership distributions. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. All standard errors are clustered at the school district level. The grey dashed lines highlight our baseline bandwidth of the 30th percentile.

Figure A.11: Effect of Sparsity Aid Program on Spending Allocations, With Additional Revenue Controls



*Notes:* Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (1), the effect of receiving sparsity aid funding. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. Additional specifications control for a district's state formula revenue per student, total local revenue per student, or total federal revenue per student, as indicated. All standard errors are clustered at the school district level.

Figure A.12: Event Study Estimates of Sparsity Aid Program on Administrator Staffing



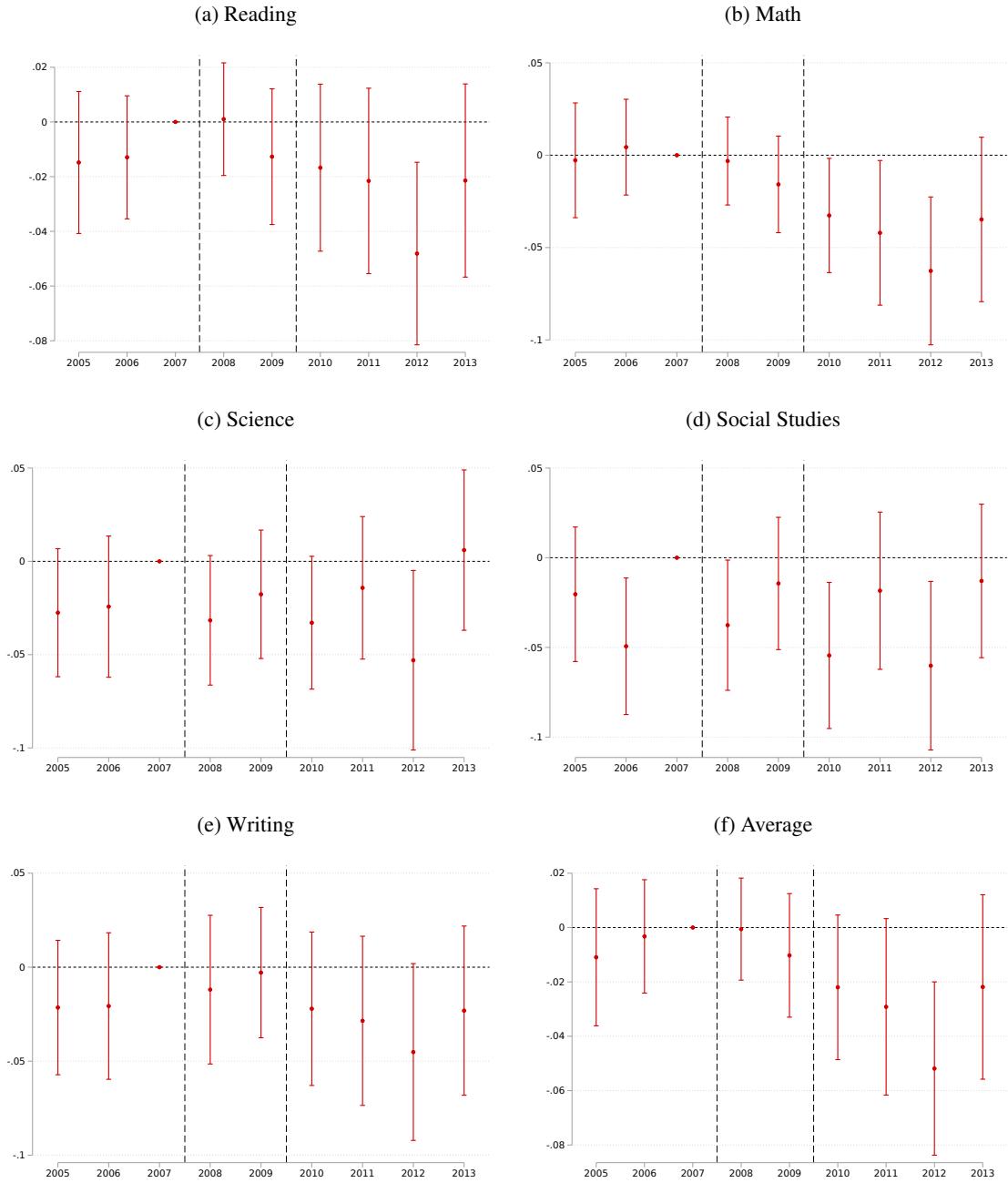
*Notes:* Each figure presents estimates of the  $\beta_k$  coefficients from equation (2). All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level.

Figure A.13: Event Study Estimates of Sparsity Aid Program on Teacher Staffing



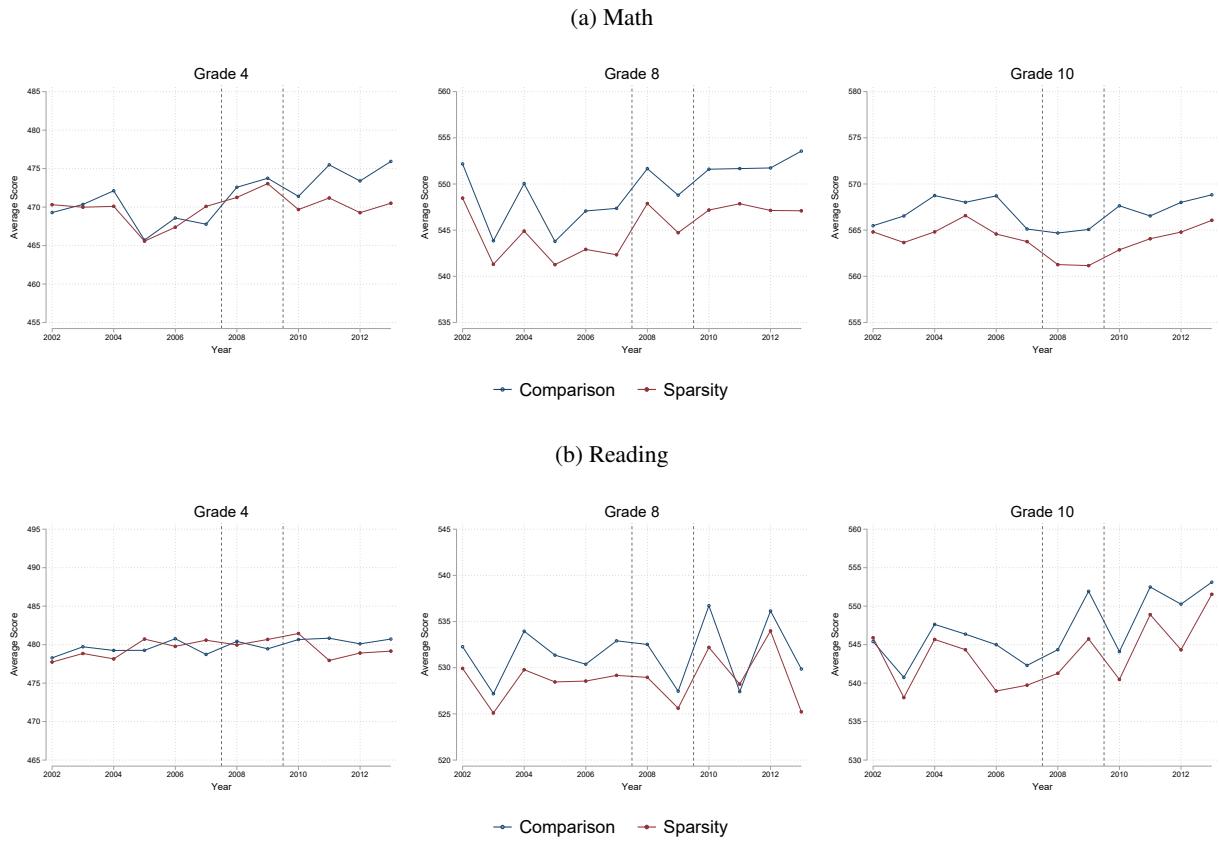
*Notes:* Each figure presents estimates of the  $\beta_k$  coefficients from equation (2). All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level.

Figure A.14: Event Study Estimates of Sparsity Aid Program on Test Scores



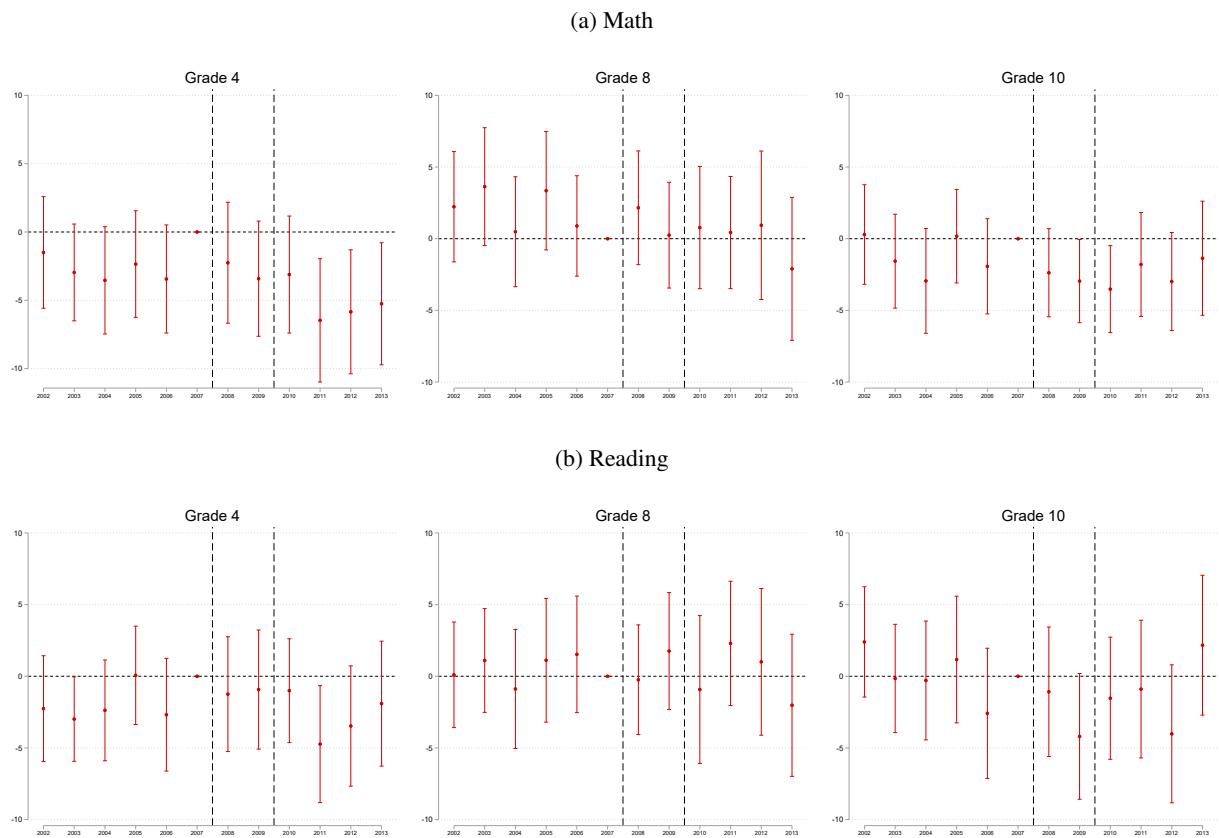
*Notes:* Each figure presents event study estimates for student-level outcomes. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level.

Figure A.15: School-Level Test Scores, 2002-2013



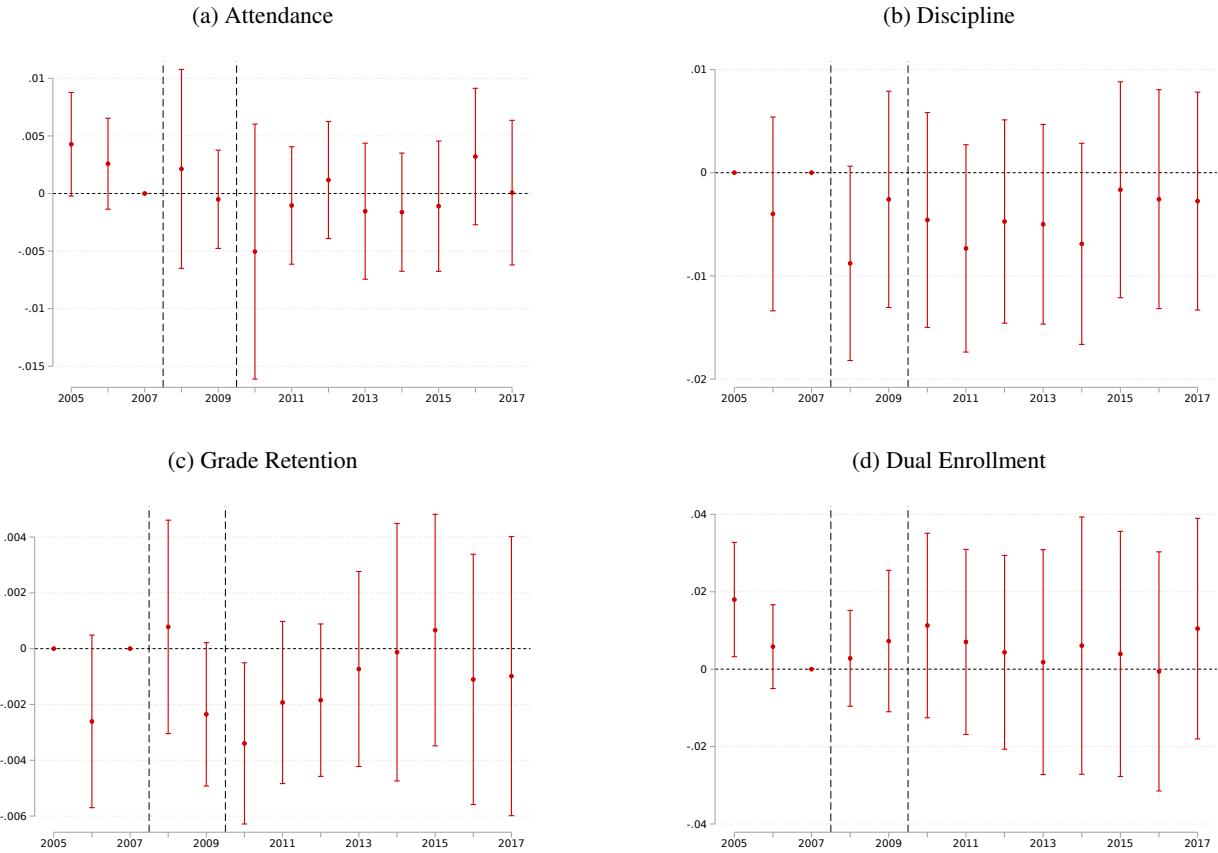
Notes: Panel A plots the average school-level math test scores in sparsity-eligible and ineligible districts across academic years 2002-2013 and grades 4, 8, and 10. Panel B repeats this plot measuring school-level reading test scores.

Figure A.16: Event Study Estimates of Sparsity Aid Program on School-Level Test Scores



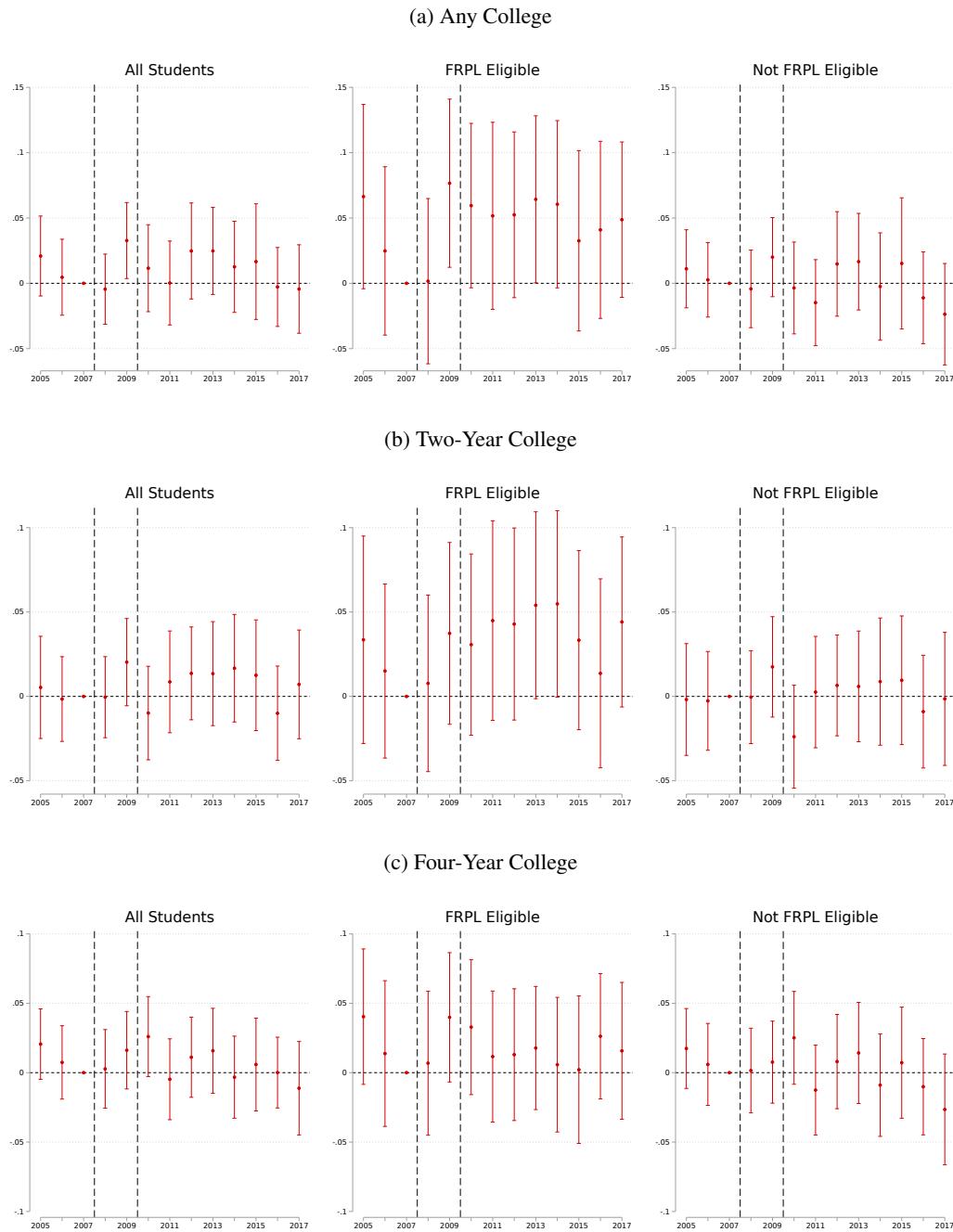
*Notes:* Each figure presents event study estimates for school-level outcomes. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. All standard errors are clustered at the school district level.

Figure A.17: Event Study Estimates of Sparsity Aid Program on Behavioral Outcomes



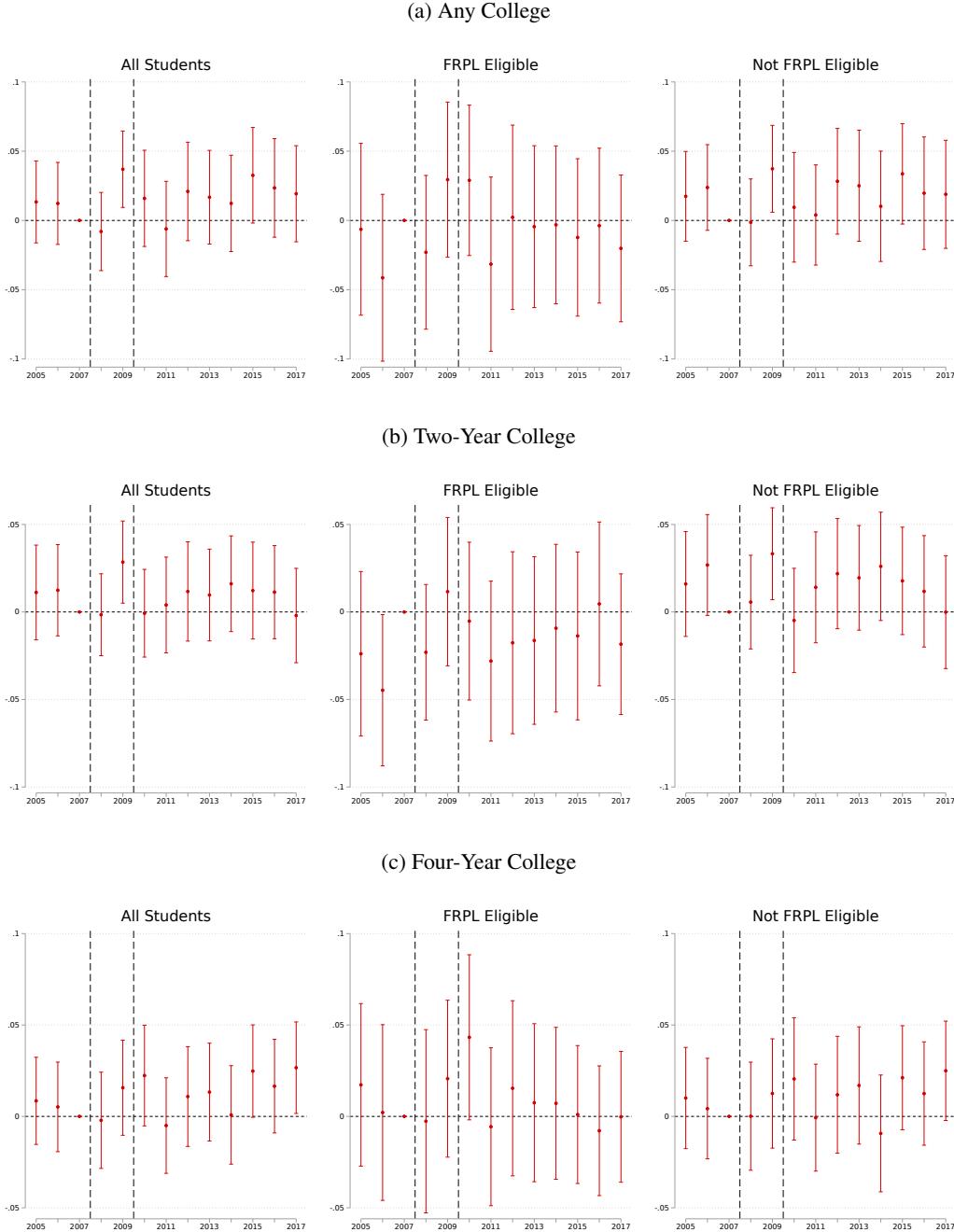
*Notes:* Each figure presents event study estimates for student-level outcomes. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level.

Figure A.18: Event Study Estimates of Sparsity Aid Program on Postsecondary Enrollment



*Notes:* Each figure presents event study estimates for student-level outcomes. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level.

Figure A.19: Event Study Estimates of Sparsity Aid Program on Postsecondary Completion



*Notes:* Each figure presents event study estimates for student-level outcomes. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, and the local child poverty rate, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level.

Table A.1: Effect of Sparsity Aid on Placebo Finance Outcomes

	(1)	(2)	(3)	(4)
<b><i>Panel A. Revenue other than state non-formula</i></b>				
Received sparsity aid	7.91 (108.4)	4.13 (101.2)	27.72 (117.5)	35.31 (117.1)
Observations	2,820	2,820	2,820	2,820
<b><i>Panel B. Spending other than elementary &amp; secondary education</i></b>				
Received sparsity aid	58.41 (161.01)	64.51 (163.38)	73.74 (183.64)	77.53 (188.18)
Observations	2,820	2,820	2,820	2,820
Membership control	X	X	X	X
Demographic controls		X	X	X
Transportation funding control				X
Year-by-CESA FEs			X	X

*Notes:* Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (1), the effect of receiving sparsity aid funding. Column (1) controls for a district's log membership, column (2) adds controls for a district's log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, and the local child poverty rate, column (3) further controls for whether a district receives additional transportation funding, and column (4) adds year-by-region (CESA) fixed effects. All standard errors are clustered at the district level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table A.2: Effects of Sparsity Aid on Teacher Staffing

	FTEs per 100 Students (1)	Avg. Salary (2)	High Salary (3)	Low Salary (4)	Ratio of High/Low (5)	Avg. Fringe (6)	Avg. Local Experience (7)	Avg. Total Experience (8)
<b>Panel A. Main Specification</b>								
Received sparsity aid	0.085 (0.082)	-337.4 (325.9)	98.16 (476.4)	-243.70 (461.4)	0.115 (0.158)	-220.6 (315.3)	0.080 (0.313)	0.103 (0.328)
Observations	2,820	2,820	2,820	2,820	2,820	2,820	2,820	2,820
<b>Panel B. Interaction with Baseline General Instruction Budget Share</b>								
Received sparsity aid	0.066 (0.080)	-338.2 (328.0)	28.29 (488.1)	-294.0 (462.7)	0.132 (0.160)	-226.9 (312.0)	0.125 (0.314)	0.162 (0.331)
Received sparsity aid x budget share	-0.041** (0.020)	-1.906 (68.45)	-149.8* (77.09)	-107.8 (91.28)	0.037 (0.032)	-13.48 (67.87)	0.095 (0.074)	0.126* (0.066)
Observations	2,820	2,820	2,820	2,820	2,820	2,820	2,820	2,820
Effect at 25th Percentile	0.160*	-333.8	373.03	-45.86	0.047	-195.8	-0.094	-0.129
Effect at 75th Percentile	-0.006	-341.5	-234.7	-483.2	0.198	-250.5	0.291	0.384

Notes: The coefficients in each column are estimated from a separate regression and represent  $\beta$  in equation (1), the effect of receiving sparsity aid funding, with interaction effects based on districts' pre-2008 budget shares. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRI, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects. All standard errors are clustered at the school district level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table A.3: Effect of Sparsity Aid on Behavioral Outcomes

	<b>6th Grade (1)</b>	<b>7th Grade (2)</b>	<b>8th Grade (3)</b>	<b>9th Grade (4)</b>	<b>10th Grade (5)</b>	<b>11th Grade (6)</b>	<b>12th Grade (7)</b>	<b>All Grades (8)</b>
<b>Panel A. Attendance</b>								
Received sparsity aid	0.001 (0.002)	-0.001 (0.002)	-0.000 (0.002)	-0.003 (0.003)	-0.004 (0.003)	-0.005 (0.003)	-0.005 (0.003)	-0.003 (0.002)
Observations	140,113	143,606	146,055	156,705	158,689	161,880	165,120	1,072,168
Mean	0.960	0.957	0.954	0.953	0.947	0.940	0.934	0.949
<b>Panel B. Disciplinary Incidence</b>								
Received sparsity aid	-0.005 (0.004)	-0.007 (0.005)	-0.006 (0.006)	-0.002 (0.005)	0.004 (0.005)	-0.003 (0.006)	-0.004 (0.005)	-0.003 (0.004)
Observations	128,662	131,674	133,521	142,583	144,734	148,048	151,400	980,622
Mean	0.018	0.027	0.033	0.039	0.042	0.039	0.030	0.033
<b>Panel C. Grade Retention</b>								
Received sparsity aid	0.001 (0.001)	-0.004 (0.002)	-0.000 (0.001)	0.001 (0.004)	0.003 (0.002)	-0.001 (0.002)	0.001 (0.004)	0.000 (0.001)
Observations	125,457	128,167	131,059	134,258	142,107	143,975	147,888	952,911
Mean	0.001	0.003	0.002	0.009	0.004	0.008	0.031	0.009
<b>Panel D. Dual Enrollment</b>								
Received sparsity aid					-0.005 (0.004)	-0.005 (0.014)	0.003 (0.013)	-0.002 (0.009)
Observations					158,779	162,010	165,442	486,231
Mean					0.008	0.155	0.115	0.042

*Notes:* Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (3), the effect of receiving sparsity aid funding. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level.  
<sup>\*</sup> $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table A.4: Effect of Sparsity Aid on Postsecondary Enrollment & Completion, 2005-2013 Sample

	<b>Any (1)</b>	<b>Enrollment</b>		<b>Completion</b>		
		<b>Two-Year (2)</b>	<b>Four-Year (3)</b>	<b>Any (4)</b>	<b>Two-Year (5)</b>	<b>Four-Year (6)</b>
<b><i>Panel A. All Students</i></b>						
Received sparsity aid	0.010 (0.010)	0.008 (0.008)	0.005 (0.007)	0.006 (0.009)	0.001 (0.007)	0.006 (0.008)
Observations	119,730	119,730	119,730	119,730	119,730	119,730
Mean	0.552	0.237	0.335	0.416	0.174	0.272
<b><i>Panel B. FRL Eligible Students</i></b>						
Received sparsity aid	0.029 (0.020)	0.021 (0.019)	0.011 (0.013)	0.022 (0.014)	0.016 (0.012)	0.007 (0.013)
Observations	24,435	24,435	24,435	24,435	24,435	24,435
Mean	0.374	0.204	0.182	0.256	0.142	0.129
<b><i>Panel C. FRL Ineligible Students</i></b>						
Received sparsity aid	0.004 (0.010)	0.005 (0.008)	0.002 (0.009)	0.003 (0.011)	0.000 (0.008)	0.006 (0.009)
Observations	95,291	95,291	95,291	95,291	95,291	95,291
Mean	0.598	0.246	0.374	0.456	0.183	0.309

*Notes:* Each coefficient is estimated from a separate regression and represents  $\beta$  in equation (3), the effect of receiving sparsity aid funding. All specifications control for a district's log membership, log house price index, number of school buildings, racial composition (% white, % Black, % Hispanic, and % Asian), % FRL, % special education, the local child poverty rate, a dummy variable indicating whether a district receives funding from the state's high-cost pupil transportation aid program, and year-by-region (CESA) fixed effects, along with student-level race, gender, FRL, special education, and limited English proficiency indicators. All standard errors are clustered at the school district level. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## B Survey of Sparsity Aid Eligible Districts

### B.1 Email to Wisconsin Association of School District Administrators (WASDA)

#### **Subject: Interview request for research on Wisconsin rural school districts**

Dear [Insert Name],

I hope this email finds you well. My name is Dr. Riley Acton and I am an Assistant Professor of Economics at Miami University. I research the economics of education and education policy and am currently working with a team of researchers to study Wisconsin's sparsity aid program. Our work is funded by the Bill & Melinda Gates Foundation and aims to develop a richer understanding of the various challenges that rural school districts face, as well as the ways in which the sparsity aid program helped districts address these challenges. Our ultimate goal is to inform state and district policymakers on a national scale about how state investments in rural schools affect students, districts, and communities.

My research team and I would love to have an opportunity to speak with you or one of your WASDA colleagues about the history of the sparsity aid program and how it has been perceived among school district administrators. Is there a time in the coming weeks when you would be available for a phone or Zoom call? I am cc'ing my collaborator, Salem Rogers, who can coordinate with you or someone from your office to find a time that is most convenient. Thank you for your consideration, and we look forward to hearing back from you!

All the best,

Riley Acton, Ph.D.

### B.2 Survey Text

#### **Sparsity Aid Research Survey**

#### **Research Consent Information:**

You are invited to participate in a research project being conducted by Dr. Riley Acton from Miami University. The purpose of this research is to examine the unique challenges of small, rural school districts and how Wisconsin's sparsity aid program has helped districts address these challenges. Participation in this research is restricted to persons 18 years of age or older.

Completing the survey should take about 10 minutes. Your participation is voluntary, you may skip any questions you do not want to answer, and you may stop at any time. Foreseeable risks and/or discomforts associated with your participation are minimal and you will receive no direct benefit from your participation. However, we hope our study will benefit Wisconsin students, district leaders, and national education policymakers by uncovering how school districts and policymakers can effectively support student success with increased funding, specifically in the

rural context. To achieve this goal, we plan on broadly disseminating our findings to the academic community and interested parties in the general public.

Only the research team will have access to individual responses and we will not attribute the name of your school district to any of your answers in any presentations or publications without first receiving your permission, in writing, to do so. Unless you provide this permission, the results of the research will be presented publicly only as aggregate summaries. The research data will be retained until June 30, 2027.

Funding agencies or journal policies may require that individual participant data be made available to other researchers. Sharing data in this way advances the field by allowing the data to be used beyond this study. No personally identifying information will be included in the shared data.

Our research team is not associated with Wisconsin's Department of Public Instruction, and we have no conflicts of interest to disclose. The research project is supported by a non-renewable grant from the Bill & Melinda Gates Foundation (INV-036567).

If you have any questions about this research or you feel you need more information to determine whether you would like to volunteer, you can contact the principal investigator (PI), Dr. Riley Acton, at actonr@miamioh.edu or at (513) 529-2865. If you have questions or concerns about the rights of research subjects, you may contact the Miami University Research Ethics and Integrity Office at (513) 529-3600 or humansubjects@miamioh.edu.

Please keep a copy of this information for future reference.

**1. Do you consent to participate in this study?**

- I consent.
- I do not consent.

**2. Have you ever worked for a school district that received funding from Wisconsin's Sparsity Aid program?**

- Yes
- No
- I don't know

*General Background: For these questions, please think about the most recent school district that you worked for that received sparsity aid funding. This can be your current school district.*

**3. What school district did you work for?**

**4. What title best described your highest position in this district**

- District Administrator/Superintendent

- District Treasurer/Business Official
- School Board Member
- Teacher
- Other [open-ended]

**5. During what years did you work for this district? Please select all that apply.**

- Before 2008
- 2008
- 2009
- ...
- 2020
- 2021
- 2022/Present

*Sparsity Aid Funds: For these questions, please continue to think about the most recent school district that you worked for that received sparsity aid funding. This can be your current school district.*

**6. When your district received sparsity aid funding, how often were the funds set aside for a specific purpose?**

- Never
- Rarely
- Often
- Always
- I don't know

**7. To the best of your knowledge, for what purposes were sparsity aid funds used? Please select all that apply.**

- Instruction in core academic subjects (e.g., math, reading)
- Supplemental instruction (e.g., tutoring)
- Electives (e.g., art, music) or co-curricular activities (e.g., athletics, speech & debate)
- Pupil Support (e.g., guidance, health, social work)

- Instructional Staff Support (e.g., curriculum development, training)
- Administration (e.g., general district administration, school building administration)
- Operations and/or maintenance (e.g., site and building repairs)
- Pupil Transportation
- Food Service
- I don't know

**8. To the best of your knowledge, were sparsity aid funds spent on specific grade levels? Please select all that apply.**

- Elementary
- Middle/junior high
- High school
- District-wide
- I don't know

*Perceptions: For these questions, please continue to think about the most recent school district that you worked for that received sparsity aid funding. This can be your current school district.*

**9. Thinking back to the early years of the sparsity aid program (2008-2010), how likely did you think it was that the program would continue long-term?**

- Very unlikely
- Unlikely
- Likely
- Very likely
- Do not remember
- Was not aware of the sparsity aid program in 2008-2010

**10. If all other funding sources were held constant, but your district no longer had access to sparsity aid funding, how likely do you think each of the following scenarios would be? [Options: Very Unlikely, Unlikely, Likely, Very likely, No opinion]**

- My district would employ fewer staff members.

- Staff retention in my district would worsen.
- Student achievement (e.g., test scores) in my district would decline.
- Graduation rates in my district would decline.
- Fewer students in my district would pursue postsecondary education.
- My district would consolidate with a neighboring district.
- My district would implement a four-day school week.

11. **In your opinion, how has the sparsity aid program most affected your district, staff, and students since it began in 2008? Please include as much detail as you are able. [Open-ended response]**

### B.3 Respondent Characteristics

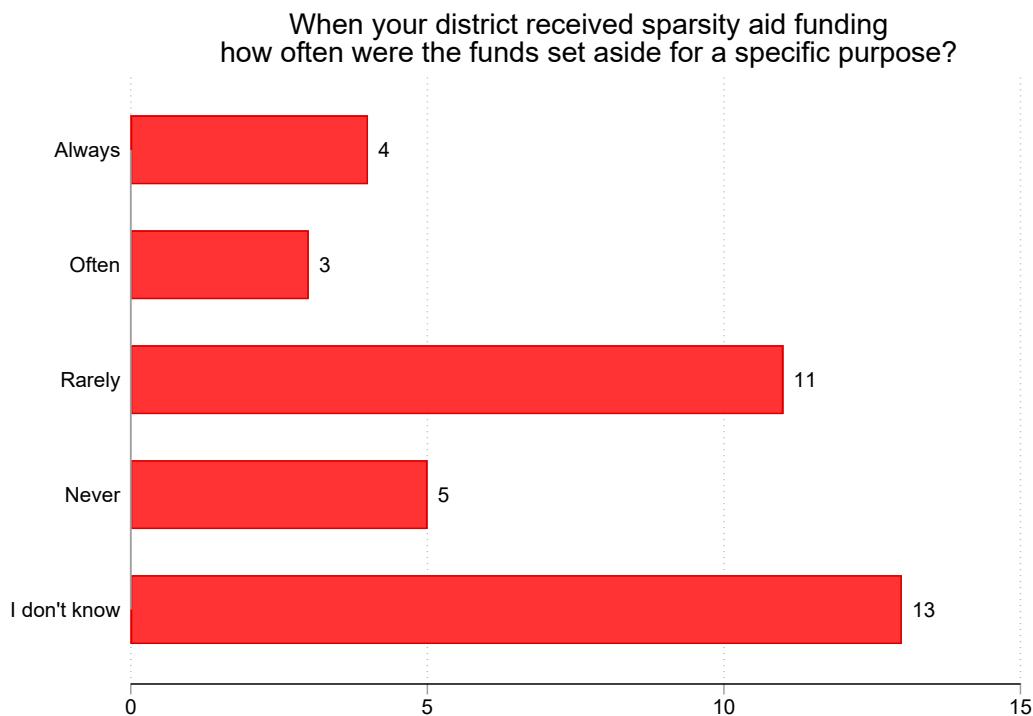
Table B.1: Survey Respondent Characteristics at Baseline

	Respondents (1)	Non-respondents (2)	p-value (3)
<b><i>Panel A. Size &amp; Location</i></b>			
Membership	468.2	477.0	0.708
Membership per Square Mile	3.777	3.831	0.567
Number of Schools	2.553	2.465	0.135
Avg. Membership per School	195.1	207.7	0.237
NCES Rural Classification	1.000	0.968	0.024
<b><i>Panel B. Demographics</i></b>			
% White	0.918	0.952	0.000
% FRPL	0.326	0.345	0.563
% Special Education	0.153	0.159	0.027
Local Child Poverty Rate	0.133	0.148	0.012
District House Price Index	172.8	164.2	0.377
<b><i>Panel C. Finances</i></b>			
Revenue per student	12,638	12,517	0.435
Spending per student	10,460	10,392	0.980
% Instruction	0.685	0.668	0.561
% Support	0.064	0.065	0.890
% Administration	0.072	0.073	0.151
% Other	0.178	0.183	0.759
<b><i>Panel D. Staffing</i></b>			
Number of Teachers (FTE)	36.568	37.575	0.417
Teachers per 100 Members	8.099	8.053	0.558
Average Teacher Salary	40,610	40,446	0.932
Average Teacher Experience	15.97	15.92	0.729
Number of Administrators (FTE)	2.378	2.298	0.256
Administrators per 100 Members	0.542	0.496	0.042
<b><i>Panel E. Educational Outcomes</i></b>			
Math Proficiency Rate	0.403	0.389	0.673
Reading Proficiency Rate	0.342	0.321	0.182
College Enrollment Rate	0.532	0.515	0.759
College Completion Rate	0.398	0.386	0.989
Observations	170	310	465
Districts	34	62	96

*Notes:* Each column summarizes district-level characteristics over the 2003-2007 academic years. The test score and postsecondary outcomes are averaged over the 2005-2007 academic years. The college enrollment rate is defined as the share of high school seniors who enroll in a postsecondary institution within one year of graduating from high school and the college completion rate is defined as the share of high school seniors in the 2005-2007 cohorts who completed a postsecondary credential within the time frame of our data. The sample of respondent districts does not adhere to the same sample restrictions as in our analytic sample, so the total district count exceeds that from Table 1.

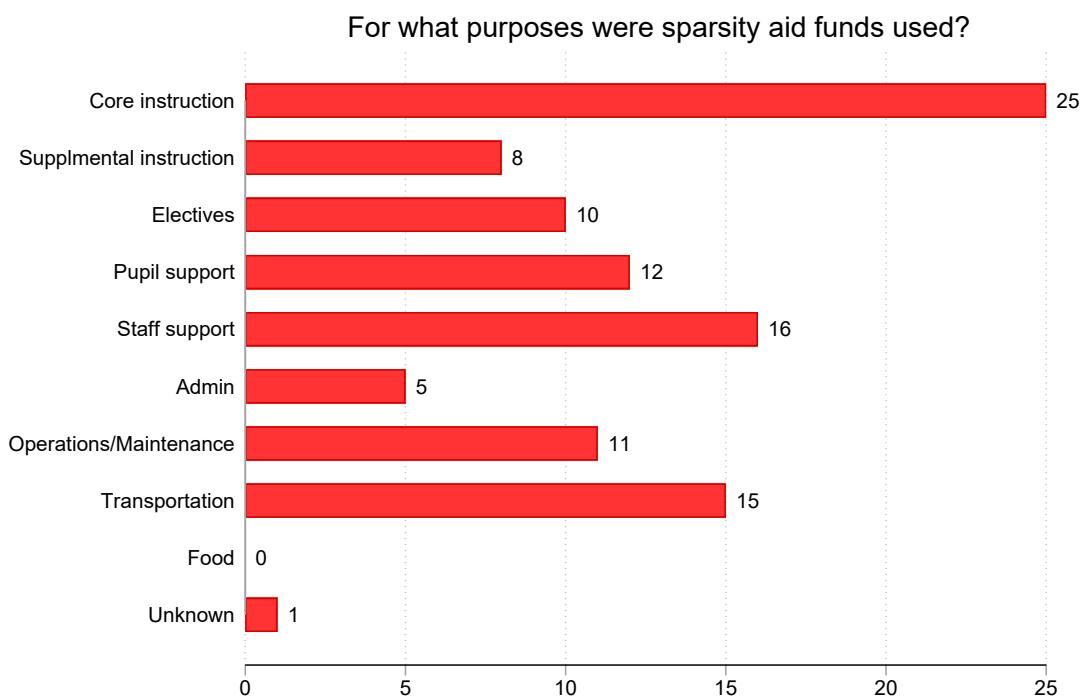
## B.4 Survey Results

Figure B.1: Distribution of responses for Q6



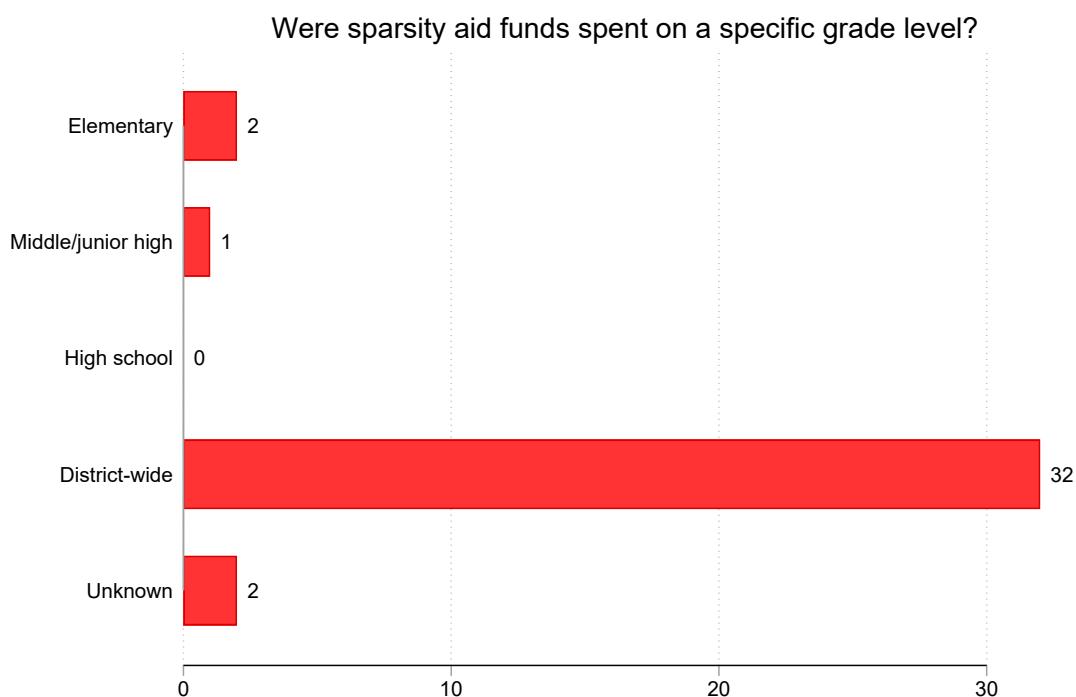
*Notes:* Each bar represents the number of survey respondents (out of 36) who selected the corresponding answer to, "When your district received sparsity aid funding, how often were the funds set aside for a specific purpose?"

Figure B.2: Distribution of responses for Q7



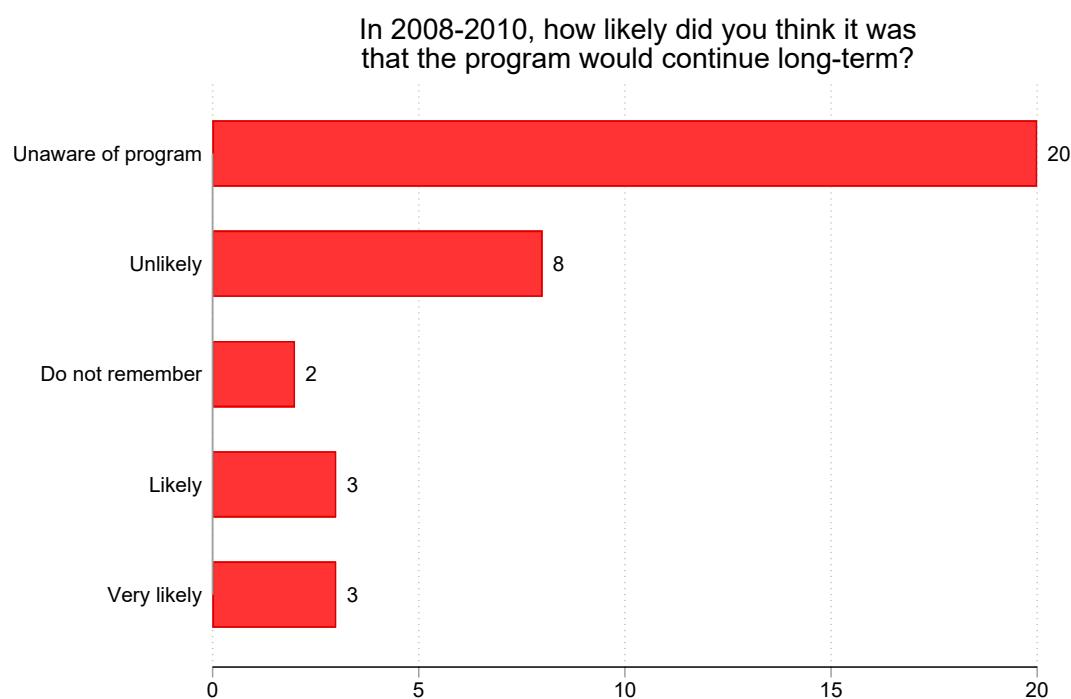
*Notes:* Each bar represents the number of survey respondents (out of 36) who selected the corresponding answer to, "To the best of your knowledge, for what purposes were sparsity aid funds used? Please select all that apply."

Figure B.3: Distribution of responses for Q8



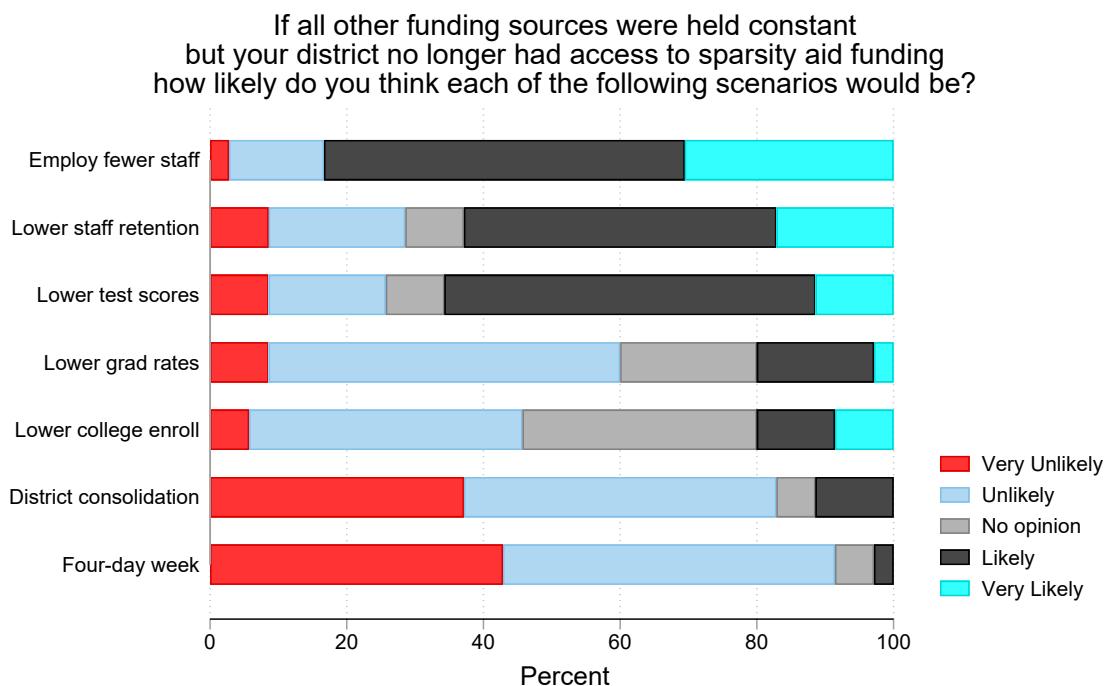
*Notes:* Each bar represents the number of survey respondents (out of 36) who selected the corresponding answer to, "To the best of your knowledge, were sparsity aid funds spent on specific grade levels? Please select all that apply. Note, the sum of responses equal 37 because one respondent answered with both Elementary and Middle/junior high."

Figure B.4: Distribution of responses for Q9



*Notes:* Each bar represents the number of survey respondents (out of 36) who selected the corresponding answer to, "Thinking back to the early years of the sparsity aid program (2008-2010), how likely did you think it was that the program would continue long-term?"

Figure B.5: Distribution of responses for Q10



*Notes:* Each colored bar segment represents the proportion of survey respondents (out of 36) who selected the corresponding answer to, "If all other funding sources were held constant, but your district no longer had access to sparsity aid funding, how likely do you think [scenario] would be?"