

The Effects of Strong Oversight on Education Spending: Evidence from Michigan*

Matthew Guzman[†]

September 2026

Abstract

This paper estimates the effects of lump sum categorical grants on school district spending with and without strong oversight. Using a 22-year panel of Michigan Intermediate School Districts, I find that lump sum categorical funding for special education without strong oversight increases spending for special education by \$0.67 per dollar of grant funding. In contrast, categorical funding for special education with strong oversight increases spending by \$0.94 per dollar of grant funding. Heterogeneity analyses indicate that the difference in the effects of oversight are primarily driven by low-income ISDs where strong oversight has a strong effect on spending in aligned areas.

1 Introduction

Categorical or conditional grants comprise a substantial portion of funding for local governments, and these grants have strong stimulatory effects on spending. A categorical grant represents funding for a narrowly defined purpose, and these grants may be lump sum grants or matching grants (Smart, 2005). Grants from the federal and state governments to local governments comprised approximately 35% of total local revenues in 2022, and more than 80% of this grant funding was provided through a categorical program (Levin, 2025; Rich, 2006).

*This research result used data structured and maintained by the MERI-Michigan Education Data Center (MEDC). MEDC data is modified for analysis purposes using rules governed by MEDC and are not identical to those data collected and maintained by the Michigan Department of Education (MDE), Michigan's Center for Educational Performance and Information (CEPI), or Michigan's Department of Lifelong Education, Advancement, and Potential (MiLEAP). Results, information and opinions solely represent the analysis, information and opinions of the author(s) and are not endorsed by, or reflect the views or positions of, grantors, MDE, CEPI, MiLEAP or any employee thereof.

[†]Michigan State University. Email: guzman27@msu.edu

Categorical grants comprise a central aspect of public finance, and these grants support the equitable allocation of public resources across localities. Grants from federal and state governments to local governments support the efficient allocation of resources via redistribution to localities (Musgrave, 1959; Oates, 1968). Further, research demonstrates that under some conditions, grant funding can increase local expenditures by more than the size of the grant (Gramlich, 1977; Grossman, 1990; Hines & Thaler, 1995). These findings suggest that categorical grant funding can influence local spending priorities and stimulate public expenditures (Levaggi & Zanola, 2003).

In contrast to categorical grants in other sectors, many education federal and state grants for education comprise lump sum categorical grants to support specific educational functions. For example, major federal education grants include Title I for economically disadvantaged students, Perkins for career and technical education, and IDEA for special education. Further, 30 states now distribute state categorical funding using a lump sum per pupil amount for special student populations (Fischer & Duncombe, 2024).¹

While lump sum categorical grants in education are common, limited research has considered differences in the structure, oversight, and efficacy of these grants. This paper begins to address this gap by comparing the effects of conditional grant programs for special education in Michigan. Michigan Intermediate School Districts (ISDs) receive lump sum categorical funding for special education via a dedicated local property tax for special education and federal categorical funding via the Individuals with Disabilities in Education Act (Individuals with Disabilities Education Act, 2019). Like state grants for special education, revenues generated by special education property taxes are categorical in nature and earmarked for special education by state law. However, these revenues are not subject to strong oversight or regulation at the ISD-level. In contrast, IDEA revenues are subject to strict maintenance of effort provisions which require that ISD-level special education expenditures not decrease year-over-year. If spending falls or if revenues are not spent within 27 months of receipt, ISDs are subject to claw backs from the federal government. These revenues face strong oversight at the federal level.

Using difference-in-differences models with continuous treatments, I estimate the effects of adopting local property taxes for special education (increased local grant funding without strong oversight) and the effects of additional IDEA funds (federal grant funding with strong oversight) on special education spending. I find that federal grants with strong oversight induce a \$0.94 increase in special education spending per dollar of grant funding whereas local

¹Under these systems, funding is provided based on the characteristics of the underlying student population and states provide funding in alignment with the predicted needs of special populations including low-income students (Duncombe & Yinger, 2005), English learners (Bartlett et al., 2026), and students with disabilities (Guzman, 2026).

grants induce a \$0.67 increase in special education spending per dollar of additional grant funding. Comparing these estimates, I find that strong oversight increases the stimulatory effects of grant funding on special education spending by \$0.27 per dollar of additional grant funding.

In addition, I also explore heterogeneity of the effects of strong oversight by ISD characteristics. I find that strong oversight is the most effective for inducing special education spending for smaller, lower-income ISDs. In contrast, strong oversight for special education funding has a negligible or potentially negative effect on special education spending in wealthier ISDs relative to providing funding without strong oversight. Policymakers aiming to support special education or other education functions should be cognizant of the stimulatory effects of strong oversight on spending, however, these may also induce inefficiencies if districts serve high needs populations.

This paper builds on substantial research related to school district responses to increases in grant funding (Fisher & Papke, 2000). Considering unconditional grants, Fisher and Papke (2000) find that “general unrestricted state grants for education increase local spending, but not dollar-for-dollar,” (Fisher & Papke, 2000, p. 160). For example, Duncombe and Yinger (1998) find that a \$1 increase in state aid is associated with a \$0.33 increase in school spending. Similarly, Cascio et al. (2013) also find that an increase in federal grant aid to school districts induced a \$0.50 dollar increase per dollar of aid to southern school districts in the 1960s, and local school districts decreased local tax effort by \$0.33 per dollar of grant aid as well. While the authors in this paper are not able to account for every cent of the effects of the grant increase, they conclude that the increase in spending was practically meaningful for districts.²

Given that unconditional grant funding has limited stimulatory effects on spending, some studies have also explored the effects of conditional grants to school districts. In Michigan, Addonizio (1997) finds that increased state funding for economically disadvantaged students increased school spending for those students by \$0.61 per dollar of grant funding, and the remaining expenditures “leaked” to other general fund expenditures. Similarly, Craig and Inman (1982) explore federal categorical grants for education, and they find that federal grants tend to increase local school district spending by \$0.73 per dollar of grant aid. Summarizing this literature, Fisher and Papke (2000) find that, like unconditional grants, conditional grants are also effective for increasing in education, although spending increases are again less than the full value of the grant.

This paper corroborates these findings in a quasi-experimental framework, and I build

²See also Dee and Levine (2004), Evans et al. (1997), Goertz and Natriello (1999), Gordon (2004), Hoxby (2001), and Tsang and Levin (1983).

on these results by comparing the stimulatory effects of grants with and without strong oversight. Section 2 presents the theory of the stimulatory effects of categorical grants for school district spending, Section 3 describes the context of Michigan special education context and data sources, Section 4 describes the difference-in-differences framework with continuous treatment, Section 5 presents main estimates of grant effects and robustness checks, and Section 6 concludes.

2 Theory of Categorical Grants for School Spending

To illustrate the effect of this policy change on special education spending, Figure 1 presents the ISD’s budget constraint following an increase in special education grant funding with and without strong oversight.³ In these simplified examples, the ISD is assumed to be an individual decision maker with convex preferences, and these preferences are defined over bundles of special education and non-special education goods.

The first panel of this figure illustrates the predicted effect of a lump sum increase in a non-matching categorical grant for special education. Initially, the ISD has the black budget constraint with a grant equal to \$1,500 per pupil that may only be spent on special education, and it has \$1,000 additional dollars that may be spent for any purpose. In this case, the budget constraint has a kink where special education expenditures equal \$1,500 because an ISD cannot use any of this funding for non-special education purposes. The dashed black line in this figure illustrates what the budget constraint would be if the \$1,500 grant were unconditional, although the ISD cannot access any of the bundles on this line due to the grant conditions. In this example, the ISD’s indifference curve is plotted such that the ISD spends the entire amount of the grant on special education and all unrestricted funding on non-special education purposes illustrated by the black indifference curve and the bundle at point A.

Following a lump-sum increase of \$500 in conditional grant funding for special education, an ISD would shift to the blue budget constraint in panel (a) of Figure 1. This budget constraint extends the flat section of the budget constraint as the ISD now has a \$2,000 non-matching categorical grant for special education, and it may select any bundle along the blue line. As before, the ISD cannot access any bundle on the dashed blue line due to the constraints of the categorical grant.

Panel (a) of Figure 1 presents the theoretical predictions of this change in the presence of strong oversight. In this case, the grant provider includes strong oversight of the grant funds to deter recipients from spending funds on non-approved functions. As a result, the

³This example draws on Bradford and Oates (1971).

ISD moves from the black budget constraint to the blue budget constraint when it receives additional grant funding for special education. Then, the ISD reallocates spending to spend more on special education, and it increases spending by exactly the size of the grant to spend \$2,000 on special education indicated by the green indifference curve and bundle B .

While strong oversight ensures that the ISD spends grant funding for approved purposes, the ISD would like to spend the increase in the same way that it would spend any other increase in its budget constraint. Without oversight, this is entirely feasible, this is illustrated in panel (a) of Figure 1. In this example, the ISD would use the additional grant funding to spend slightly more on special education and substantially more on non-special education purposes. This is illustrated by the red indifference curve and the bundle at point C in which the ISD reallocates to a bundle that shouldn't be attainable under the conditions of the grant. If the ISD treats conditional grant funding as unconditional, theory predicts that non-matching categorical grant funds could “leak” to other purposes aside from their original purpose (Addonizio, 1997). Further, residents of the ISD may also decrease local tax effort in response to the grant increase expenditures on completely different goods outside of education.

Without strong oversight, panel (b) of Figure 1 predicts that additional grant funding could supplant an existing budget. Fisher and Papke (2000) identify several cases in education in which funds are supplanted in this way, and both Addonizio (1997) and Cascio et al. (2013) find direct evidence of this supplanting of funds. While non-matching categorical funds are technically restricted, weak oversight enables ISDs and local school districts to spend additional funds in any manner they choose.

In contrast to the weak oversight example in panel (b), panel (a) of Figure 1 illustrates that strong oversight can induce ISDs and other local entities to spend in alignment with grant funding priorities. Notably, these examples ignore the possibility that such oversight could have additional costs, and this oversight could also cause inefficiencies if governments already have sufficient resources to invest in special education. Nevertheless, if grant funders perceive that special education services are underprovided by local governments, then this oversight could ensure that ISDs and local school districts provide these services appropriately.

3 Michigan Context and Data

3.1 Michigan Special Education Funding

Michigan school districts are mandated to provide special education services to students with disabilities under IDEA (Individuals with Disabilities Education Act, 2019). This policy requires that school districts provide services to ensure that students have access to a “free and appropriate public education,” and school districts are responsible for organizing and financing additional services. Substantial research demonstrates that special education programs are more expensive to provide than general education services, and school districts may underprovide special education services in the presence of resource constraints (Ballis & Heath, 2021; Chambers et al., 2005; Cullen, 2003; Guzman, 2026). Across the U.S., school districts spend an average of \$13,047 more for the average student with a disability relative to a general education student, and these additional expenditures vary dramatically by disability (Chambers et al., 2005).

To support special education, the Michigan’s 538 traditional public school districts and 287 charter school districts are organized into 56 Intermediate School Districts (ISDs). These administrative groups of geographically neighboring districts share resources for special education services. This structure enables collaboration and returns to scale as ISDs typically provide support for the highest need disabilities directly as well as coordinate special education services for all students in their constituent districts (Arsen et al., 2019).⁴

ISDs receive funding to support special education through local, state, and federal sources, and average ISD per pupil revenues for special education are illustrated in Figure 2. Local revenues for special education are generated by special education-specific property taxes subject to an ISD-wide vote. Unlike other states, Michigan ISDs levy dedicated property taxes for special education, and these property taxes describe special education in the text of the ballot. Proceeds from these property taxes may not be used for any purpose other than special education, and ISDs submit to state audits to ensure that funds are spent appropriately (The Revised School Code, 2004).

While state statute requires that proceeds from special education property taxes be spent on special education functions, ISDs’ own outreach indicates that they are aware that this funding is fungible. For example, public reporting related to a new special education property tax in 2015 described that “districts are spending more of their general fund on special ed. That means less money for regular education students,” (Mack, 2015). The article goes on to say that “the real beneficiaries will be regular-education students who have

⁴One example ISD is presented in Figure A1. This illustrates that local school districts are nested with the 56 ISDs across the state.

borne the brunt of school budget cuts,” (Mack, [2015](#)). This demonstrates that while revenues from this tax are restricted, ISDs are aware of the possibilities for fiscal fungibility under this policy.

Considering state funding, ISDs receive funding from the state of Michigan from several categorical state aid programs (Burns & Guzman, [2025](#)). In 2025, 93% of this funding was provided via a matching grant, and ISDs are reimbursed for 28.6% of their total approved special education expenditures each year.⁵ Funding provided by this grant is not subject to restrictions on how funds may be spent, although ISDs must submit total expenditures for approved special education functions to receive reimbursement.⁶

Federal funding for ISDs to support special education is provided primarily through IDEA. This funding covers about 15% special education spending in the U.S. (Kolbe, [2019](#); Kolbe et al., [2022](#)), and funding provided under this policy is subject to strict oversight. Like other federal grants for education, expenditures for special education from IDEA must be thoroughly documented to ensure that they are spent for approved purposes. In addition, funds provided via IDEA incorporate a “maintenance of effort” requirement which mandates that school districts spend the same a baseline amount of non-federal dollars on special education each year. Failure to meet this requirement or failure to spend revenues within 27 months of receipt could result in a claw back of federal funds (Dragoo, [2026](#); for IDEA Fiscal Reporting, [2024](#)).

3.2 Identification of Funding Effects

Local property taxes for special education must be approved by voters, and these taxes are typically adopted for between 5 and 20 years. Taxes must be reauthorized by voters when they expire, and ISDs may choose any property tax level to place on the ballot subject to a state maximum. This structure can create sudden, sharp increases in local funding for special education when ISDs adopt new, larger property taxes to support special education. In addition, funds generated by these property taxes are subject to a state mandate to spend funds for special education, and ISDs are subject to audits from the State to ensure that funds are only spent for special education purposes (The Revised School Code, [2004](#)).

ISDs place new property taxes for multiple reasons, although the most common reason is that old property taxes for special education expire. In the year prior to one millage expiring, an ISD will submit a new property tax to voters in a general ISD-wide referendum.

⁵See Michigan State School Aid Section 51 for more details on this matching grant.

⁶This matching grant program was established via a series of court cases that culminated in 1998, and this court case dramatically increased the level of state funding for special education (Cleary & Summers-Coty, [1999](#)).

Property taxes for special education tend to receive strong support from voters, and additional millages for special education rarely fail. This is illustrated in Appendix Figure A2. This figure presents the voting margins for 62 elections for which voting data are available. The majority of special education property taxes pass by a wide margin. Among ISDs where voters fail special education property tax initiatives, ISDs often run large-scale campaigns to promote the property tax and place the tax on the ballot again in the next election cycle. This leads to most property taxes eventually being approved for ISDs (Autism Alliance of Michigan & Public Sector Consulting, 2025).

Notably, an ISD may also increase property taxes for special education due to growing needs of students with disabilities or more severe resource constraints overall. This is less common, although this type of adoption creates concerns that ISDs could adopt new property taxes strategically. To address this concern, I match pre-trends between ISDs that adopt and do not adopt a property tax for special education on the outcome and covariates in robustness analyses, and I find similar results to my main findings. As a result, I argue that there is limited evidence that strategic behavior by ISDs drives my findings.

Federal funding for special education is provided through IDEA grant funding, and this funding is distributed to states using a base amount set in 1999 as well as additional allocations based on total enrollment and the proportion of economically disadvantaged students in each state (Dragoo, 2026). Similarly, the Michigan Department of Education uses these same criteria to distribute revenues to ISDs. Critically, this funding is not related to the proportion of students with disabilities in the ISD, and the amount of funding is related to broader population trends and federal funding levels.

Total funding under IDEA increased by \$12.2 billion between 2010 and 2011 through the American Recovery and Reinvestment Act of 2009 (ARRA), and this resulted in a short-term increase in average federal funding for ISDs in those years. Additional dollars were distributed to states and ISDs in the same manner as other IDEA revenues, and these revenues were subject to the same oversight and reporting requirements as other IDEA revenues (*Funding for education in the American Recovery and Reinvestment Act of 2009 (P.L. 111-5)*, 2009).

Examples of revenue changes under the local property tax policy (grant funding without strong oversight) and revenues changes under ARRA (grant funding with strong oversight) are provided in Figure 3. The top panel of Figure 3 illustrates a sharp increase in per pupil local revenues for special education in 2015 in Montcalm Area ISD. Additional funds in this ISD were provided via a new property tax for special education, and this resulted in a nearly \$400 per pupil increase in local special education revenues.⁷ Notably, this property tax only

⁷Note that this ISD observed a smaller increase in local special education revenues in 2012 as well. This

impacted this ISD, and other ISDs were unaffected in this year. The lower panel of Figure 3 depicts the policy change in Branch ISD following the increase in federal funding for special education under ARRA. In 2010 and 2011, this ISD observed a sharp, short-term increase in federal funding for special education. This policy similarly resulted in an approximately \$200 per pupil increase in federal special education revenues for the ISD, and all ISDs were affected by similar funding changes in that year.

While the examples in Figure 3 suggest that funding increases under these policies are large in many ISDs, effects are not uniform. Figure 4 presents kernel density plots of year-over-year changes in revenues under each policy change in Figure 3. The top panel of Figure 4 illustrates that increases in special education funding from local property taxes have large and varied impacts on school district revenues. At the highest level, ISDs may increase local per pupil revenues for special education by almost \$500 through these property taxes, although many ISDs observe small or even negative revenue changes if they adopt a small millage increase or if property values decline concurrently with the property tax change. In addition, the average revenue increase under the local tax increase is approximately \$200.

The second panel of Figure 4 presents year-over-year federal revenue changes for special education resulting from the influx of ARRA funds. Funding changes under this policy were less varied than the local changes, and no ISDs lost federal revenues under this change. The average ISD received approximately \$200 in increased revenue per pupil under this policy, although some ISDs received as little as \$100 and some received almost \$400 in additional revenue per pupil.

In this paper, I explore differences between the effects of local funding with a mandate and federal funding with a requirement to use revenues for special education purposes. These grants operate similarly in that both are distributed to ISDs, and ISDs may choose to either spend the funds themselves or transfer them to local school districts. In the case that these funds are transferred, the relevant oversight provisions follow the dollars to the local level.⁸ Notably, local school districts may not levy property taxes for special education or receive federal funding for special education directly. Rather, they may only receive revenues from these sources via transfers from their ISD. The ISD has full discretion to distribute revenues for special education, and ISD administrators may also keep the funding for the ISD and support special education directly.

Notably, I do not consider the effects of these policy changes on local tax effort. In

was due to an increase in revenues from fees-for-service in the ISD in that year.

⁸Appendix Figure A3 presents average ISD-level per pupil expenditures for special education between 2003-04 and 2024-25 separated by expenditure function. This demonstrates that ISDs spend a substantial proportion of revenues on transfers to local school districts to support special education programs at that level of the educational system.

contrast to other research on grant aid, the local policy change under consideration is generated by a local property tax itself. As a result, local tax effort mechanically increases with the change. Regarding the federal policy change, this grant policy was short-lived, and local school districts could not have reasonably decreased property taxes before the additional funds expired.

3.3 Data

To determine the effect of strong oversight on special education grant effects, I use public and private datasets provided by the Michigan Department of Education (MDE) between the 2003-04 and 2024-25 academic years. First, I leverage school district-level and ISD-level financial data from the Michigan Education Research Institute (MERI). Revenues are separated by their source (local, state, or federal) and their intended function if the revenues are restricted, and I use these to isolate local revenues for special education from a property tax and federal revenues under IDEA or ARRA. In addition, expenditures are separated by their educational function, and special education comprises a subset of total expenditures related to special education teacher and specialist salaries, benefits, supplies, purchased services, and transfers to local school districts for special education programming.

In addition to financial data, I also leverage school district and ISD-level student demographic data from MERI between the 2003-04 and 2024-25 academic years. These data contain each student’s school district and ISD as well as their gender, economically disadvantaged status, race or ethnicity, and their special education status. Using these data, I calculate the total full-time equivalency enrollment in ISD in each academic year to convert revenues and expenditures to per pupil terms as well.⁹

Notably, changes in local special education funding are staggered and persistent while changes in federal funding were concurrent and temporary. To estimate the effects of these policies, I construct separate analytic samples for each policy change. First, I construct a sample to explore the effects of local changes without strong oversight on ISD spending (the “local” sample). This sample comprises all ISDs in Michigan between the 2003-04 and 2024-25 academic years. Notably, I observe re-treatment of ISDs during my sample period as old special education property taxes may expire prompting ISDs to adopt new millages. This

⁹In Michigan, a student FTE is defined as a fractional value between 0 and 1 indicating the proportion of 1,098 minimum total instructional hours a student is scheduled to receive. This value is also separated for the amount of time spent in general education and special education services. For example, if a student were scheduled to receive special education programming for 1 hour per week and general education instruction for the rest of the week, this would equate to a 0.03 FTE in special education and 0.97 FTE in general education. This approach avoids double counting students if they appear in both a general education and special education program in the same school district.

leads to re-adoption of special education property taxes for some ISDs during my sample period. To account for this, I drop ISD-year observations in any time period after a secondary treatment in this sample.¹⁰ In addition, I drop ISDs treated in before the 2005-06 academic year as these ISDs do not have sufficient pre-period data.

In the local sample, I define the continuous treatment as the year-over-year dollar change in local funding for special education in the year that the property tax rate increased. This is illustrated in panel A of Figure 4. This implies that treatment is defined as an increase in property tax rates induced by a special education property tax election, and not only a property tax election itself.

Averages for ISD-level revenues from each local, state, and federal revenues and student demographics using the local property tax treatment sample are presented in Table 1. Considering the local treatment, ISDs observe an average of \$134 increases in per pupil local revenues for special education following the adoption of a special education property tax change on average. Note that this is smaller than the average in Figure 4 as pre- and post-periods in Table 1 include all available sample years before and after the property tax change. In addition, ISDs in the local sample also observe average increases in state revenues for special education of approximately \$134 between pre- and post-periods. This increase in state funding is mechanically driven by additional expenditures for special education as well as increases in the total state aid for special education during my sample period. ISDs spent approximately \$160 more per pupil on special education in the post period as well. Demographic differences between pre- and post-periods are small except for economically disadvantaged students who increase in the state during my sample period (Burns & Guzman, 2025).¹¹

Next, I construct a second analytic sample to explore the effects of increasing federal revenues with strong oversight for special education on ISD spending (the “federal” sample). Unlike in the local sample, no ISD-year observations need to be dropped in this sample due to retreatment, and this panel is balanced. Because this treatment was very brief, I use all ISDs between the 2003-04 and 2009-10 in this sample. As in the local sample, I define the continuous treatment to be the year-over-year dollar change in federal funding for special education in the 2009-10 academic year.

Table 2 provides averages for per pupil local, state, and federal revenues for special education, special education expenditures, and student demographics for the pre- and post-

¹⁰In addition, I drop all observations for one ISD that is fully operated by the State of Michigan and one ISD that has a large online enrollment program. These ISDs are funded have different administrative structures relative to other ISDs.

¹¹The proportion of economically disadvantaged students also increases mechanically during my sample period due to changes in the state definition of this student population (Thiel, 2025).

periods in the federal sample. Federal revenues for special education increased sharply during the post-treatment period by approximately \$187 per pupil on average, and this drives the majority of a total revenue increase of approximately \$307 in the 2009-10 academic year. Further, special education spending increased by \$278 per pupil on average in the post treatment period. As in the local sample, student demographic differences are small the proportion of economically disadvantaged students.

4 Methods

To understand the effects of each of these grants on special education spending, I estimate two-way fixed effect (TWFE) models with continuous treatments for each sample of Michigan ISDs. Following Wooldridge (2025), my main estimating equation takes the following form:¹²

$$y_{it} = \beta_0 + \sum_g \gamma_g Cohort_g \times f(RevIncrease_{it}) + \mathbf{\Omega X} + \alpha_i + \delta_t + \varepsilon_{it} \quad (1)$$

For each ISD i in each year t , y represents the total real per pupil expenditure for special education, $Cohort$ represents an indicator for the first year in which an ISD becomes treated, $RevIncrease$ represents a time-varying treatment variable equal to 0 in years before treatment and equal to dollar change in special education revenues from a source that takes effect when the ISD becomes treated, $\mathbf{X}_{it}$ represents a vector of time-varying, ISD-level covariates, α_i represents an ISD-level fixed effect, δ_t represents a year fixed effect, and ε_{it} represents a normally distributed error term.

For each model, $f(RevIncrease_{it})$ represents a linear or quadratic functional form of a continuous treatment indicator in a standard difference-in-differences framework. For example, considering the effect of increases in local spending following the adoption of a new property tax for special education in 2008, $RevIncrease$ would represent the change in per pupil local revenues for special education an ISD observed between 2007 and 2008. In this case, never treated units and not-yet treated units provide control groups for treated units.

Callaway et al. (2024) discuss issues associated with OLS estimation of Equation (1). First, selection bias could enter the estimation of each γ_g coefficient, and this can cause bias except in the presence of strong parallel trends between treated and control units. Second, the functional form of $f(\cdot)$ is not known, and limited guidance exists for researchers to choose a functional form. Finally, each γ_g coefficient represents a weighted average of the effects of the dosage in each cohort. While the weights in this average are all positive and sum to 1,

¹²This is similar to Equation 5.6 in Wooldridge (2025), although I restrict treatment heterogeneity by not including interaction terms with time dummies or with covariates.

these weights may not return a weighting scheme that follows the distribution of doses in the treated group.

To address selection bias, I invoke the strong parallel trends assumption from Callaway et al. (2024) to give the γ_g an average causal response interpretation.¹³ Further, I test parallel trends in both samples directly using event study models, and I find no evidence of violations of parallel trends.¹⁴ To address the functional form of *RevIncrease*, I test models with linear and quadratic forms of $f(\cdot)$. Given the sample sizes for both the local and federal samples, testing higher order functional forms is infeasible, although I find similar estimates between linear and quadratic estimates.¹⁵

For the local property tax sample, treatment is staggered over time, and Equation (1) will provide estimates of treatment for each cohort. Following Wooldridge (2025), I aggregate these estimates taking the average of treatment estimates weighting by the size of each cohort using the following equation to calculate the average causal response (ACR):

$$ACR = \sum_{g=1}^G \frac{N_g \gamma_g}{N} \quad (2)$$

All standard errors are clustered at the ISD-level and computed unconditional on covariates.

In contrast to changes in local funding, changes to federal funding occurred for all ISDs concurrently. This implies that the cohort interactions in Equation 1 collapse to a single treatment cohort, there are no untreated units, and binary treatment difference-in-differences designs are infeasible. Nevertheless, Figure 4 illustrates that treatment intensity of additional federal funding varies across ISDs. As a result, estimates of the coefficient on $f(RevIncrease_{it})$ will represent the dollar change in spending associated with one additional dollar of grant funding. As in the local sample, *RevIncrease* variable is calculated using the change in federal revenues for special education between 2009 and 2010.¹⁶

As local and federal samples comprise subsets of the same population of ISDs, I compare estimates from Equation (1) in each sample using seemingly unrelated regression (SUR). This approach combines the covariance matrices of estimates and allows me to directly compare

¹³See Assumption 5-MP in Callaway et al. (2024).

¹⁴See Equation (3) for the event study model.

¹⁵In addition, given that my question relates to whether increased funding has dollar-for-dollar impacts on spending, this hypothesis is most suited to a linear functional form. As a result, I prefer linear functional forms in my main estimates, and this functional form is also invariant to weighting over the distribution of the dose.

¹⁶Callaway et al. (2024) also discuss identification in the context with no treated units. Maintaining my strong parallel trends assumption, treatment is identified and I estimate the average causal response γ_g resulting from an additional dollar of per pupil federal revenue for special education.

the treatment effects of additional grant funding with weak oversight with additional grant funding with strong oversight. SUR estimates cluster all standard errors at the ISD-level.

In addition to aggregate effects, I also estimate event study models of the effect of each grant funding change for special education as well. Due to my sample size, I again restrict treatment heterogeneity, and I do not interact event study indicators with treatment cohorts. This model takes the form of Equation (3):

$$y_{it} = \beta_0 + \sum_e \gamma_e Event_e \times f(RevIncrease_{it}) + \mathbf{\Omega X}_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (3)$$

All variables are defined as in Equation (1), and I interact the treatment indicator with event time dummies $Event_e$ which correspond to the number of years until treatment. In addition, I cluster all standard errors at the ISD-level, and I compute unconditional standard errors for all estimates as well.

5 Results

5.1 Comparison of Grant Effects

Table 3 presents estimates of the average causal response from Equations (1) and (2) for both the local and federal samples using a linear functional form of treatment. Column (1) of Table 3 provides the estimate of the effect of the federal increase in funding for special education, and this indicates that increased ARRA funds with strong oversight increased special education spending by \$0.94 per dollar of grant funding. Given the size of the standard error, I interpret this as evidence of one-to-one spending increases. This follows the prediction under strong oversight given in panel (a) of Figure 1. Here, the ACR in column (1) represents a direct OLS estimate of γ_g in Equation (1) given that all units in the federal sample were treated concurrently.

Column (2) of Table 3 presents the estimate of the effect of local grant funding on spending in Equations (1) and (2) from the local sample using a linear functional form. This indicates that following an increase in special education property tax revenues, special education spending increases by \$0.67 per additional dollar of special education funding. Michigan state law requires that this funding be used for special education, although this does not prohibit ISDs from supplanting current expenditures for special education with these revenues. This suggests that some “leakage” occurs under this mechanism, and this is illustrated in panel (b) of Figure 1.

Column (3) of Table 3 uses SUR methods to compute the difference between the effect of grant funding with a claw back provision and grant funding with weaker oversight. This

indicates that the claw back provision increases the efficacy of grant dollars to increase special education spending by \$0.27 per dollar of grant funding. This difference is not significant, although this suggests that strong oversight could have strong effects on ISD-level spending.

Figure 5 presents event studies of the effects of each of these policy changes on per pupil special education spending using estimates from Equation (3). Here, all local property tax changes are aligned in time with the federal revenue change in 2009. Considering the local sample in the first panel, special education spending has smooth or slightly declining pre-trends prior to the local property tax change, and ISD-level special education spending immediately increases following the millage adoption. Increases in spending following the change are persistent, although these are consistently less than \$1 per dollar of grant funding.

The second panel in Figure 5 presents an event study of special education spending following the federal change in special education revenues under ARRA. This influx of funding was brief, and ISDs only increased spending in a measurable way for one year. Note that estimates of spending changes in Tables 2 and Table 3 only incorporate the first year that this policy was enacted due to its temporary nature. This policy change produced immediate and large spending increases for special education greater than \$1 per dollar of grant funding provided, although this spending faded out almost immediately.

While the estimates in Table 3 and Figure 5 present the total effect of each policy change on spending, Table 4 separates the outcome variable by educational function. Panel A of Table 4 presents the effects of each policy change on each of salaries, benefits, purchased services, supplies, other expenditures, and transfers of special education dollars. These results suggest that ISDs used additional dollars to increase salaries by \$0.28, benefits by \$0.19, and transfers to local school districts by \$0.25 per dollar of federal grant aid received, although none of these estimates are individually significant. Panel (b) of Table 4 separately estimates the effects of the local policy change on each of these categories, and in contrast to federal dollars, local spending changes are almost entirely driven by increasing transfers to local school districts. As the mandate to spend revenues on special education follows the dollars, this transfer to a lower level of government still constitutes a legitimate expenditure for special education. That said, the ISD does not directly use grant funding with weak oversight to increase special education expenditures.

While transfers of special education revenues support local school districts more directly, it is not immediately clear that transferred dollars are still spent on special education. To explore the effects of transferred dollars, Appendix Table A1 re-estimates the models from Table 4 using local school district-level data. In this table, treatment is defined for each school district as the year-over-year change in the amount of per pupil funding transferred from the federal or local grant. All models are defined as in Equations (1) and (2), although

ISD-level fixed effects are replaced with school district-level fixed effects in these models.

Appendix Table A1 indicates that local school districts also increase special education expenditures in response to increases in transfers from local and federal grant funding, although this analysis suggests different trends relative to the ISD-level effects. Considering panel (a) of Appendix Table A1, local school districts increase special education spending by \$0.21 per dollar of federal grant funding with strong oversight, and this funding is primarily comprised of salaries, purchased services, and supplies for special education. In contrast, local funds for special education increase expenditures for special education salaries and benefits and decrease expenditures for special education services.

These differences suggest that ISDs do treat additional revenues from these grants differently. Federal revenues are primarily spent directly by the ISD, and local revenues are primarily transferred to local districts. Given that the local revenues comprise a new, permanent stream of income, ISDs and school districts may be able to use these dollars to fund permanent positions or other long-term investments.

5.2 Robustness Checks

Appendix Tables A2 and A3 present robustness checks of these models. In Appendix Table A2, I present robustness of treatment effects in the federal sample, and I find broad consistency across estimates. I find a range of estimates of the effects of federal grants on special education spending between \$0.66 and \$1.21 per dollar of additional funding, and these estimates are almost all above \$0.94. In Appendix Table A3, I similarly present robustness of treatment effects in the local sample. Given that I have more data, never treated units, and staggered adoption in this sample, I estimate more robustness checks in this table than in Appendix Table A2. Similarly to robustness in the federal sample I find broad consistency across estimates, and I estimate a range of the effects of local funding on special education spending between \$0.29 and \$0.81 per dollar of additional grant funding.

While I ascribe the differences in the effects of treatment between the two types of grants to the claw back provisions in Table 3, this estimate may suffer from bias due to the timing of treatment. Additional federal funding was provided to ISDs during the 2009-10 academic year, and effects of the Great Recession could impact spending as well. In addition, given that ISDs receive local grant funds for the entire duration of the property tax, ISDs may exhibit different spending patterns with this funding. To address differences in timing between the samples, column (8) of Appendix Table A3 re-estimates Equation 1 and the aggregation in Equation 2 using the intersection of the federal sample and the local sample. Only the 2008 cohort of ISDs has sufficient data in this sample to estimate treatment

effects. Using the intersection of these samples suggests that local treatment effects have a larger stimulatory effect on special education spending during the federal sample time period, although these estimates remain smaller than the federal sample estimates.

To explore non-linearities in the effects of treatment from these grants on spending, I re-estimate the models in Table 3 using a quadratic functional form in Appendix Table A4. Notably, given the additional covariates in these models, I use the restricted form of Equation (1) without cohort indicators in column (2) of Appendix Table A4. Estimates using quadratic functional forms of treatments are extremely similar to the effects of grant funding with linear functional forms. Using a quadratic functional form, Appendix Table A4 indicates that ISDs increase spending by \$0.94 per dollar of grant funding with a claw back provision relative to \$0.64 per dollar of grant with weaker oversight. The difference in the effects of these grants is \$0.31 per dollar of grant funding in column (3) of Appendix Table A4.

One additional threat to identification could be strategic behavior by ISDs to adopt property taxes for special education. While it is more common for ISDs to adopt new property taxes as old taxes expire, ISDs do have latitude regarding the timing and reasons for why they propose a new millage. To explore this, Appendix Table A5 estimates the effects of adopting a new property tax for special education on local special education revenues and special education expenditures (Clarke et al., 2024). These synthetic models include all demographic covariates as well as special education expenditures in the case of revenues and local revenues in the case of expenditures. Including revenues and expenditures as well matches treatment and control units on these variables as well ensuring that ISDs that observe declining revenue or increasing expenditures will be appropriately matched.

Appendix Table A5 indicates that ISDs observe approximately \$187.70 increases in local per pupil funding for special education following the adoption of a new property tax for special education, and column (2) of this table indicates that they only increase spending by \$111.85. Taking the ratio of these effects yields 0.60 suggesting that ISDs increase spending for special education by \$0.60 per dollar of additional revenue following a property tax change. Notably, dollar estimates require bootstrapped standard errors and can't be combined using SUR, although this estimate is closely aligned with other robustness estimates of the effects of local grant funding on spending.

5.3 Heterogeneity of Strong Grant Oversight

In addition to differences in the effects grants, I also explore heterogeneity of the differences in grant effects in Table 5. Column (1) of Table 5 presents the overall difference in the effect

of grants with strong oversight versus grants with weak oversight from column (3) of Table 3. Note that again, due to a smaller sample size in heterogeneity analyses, local sample models do not use cohort indicators in these analyses, although estimates are very similar to results in Table 3. Column (2) of this table re-estimates this difference using the subset of low-income ISDs. In this table, low-income ISDs are defined as those with above median economic disadvantage in their student populations over the entire sample period.

Column (2) of Table 5 indicates that the effects of strong grant oversight are the most salient for low-income ISDs. Grants with strong oversight increase special education expenditures by \$0.79 more than grants without strong oversight in these ISDs. This may be because these ISDs have populations with greater needs or because they have fewer avenues to increase revenues generally. Alternatively, these ISDs may be more likely to lose revenue from other sources concurrently with receiving additional grant funding. In any case, these ISDs may be more resource constrained and may therefore have a greater incentive to use additional funds for different purposes. Strong grant oversight may therefore be more effective to ensure that these ISDs spend funds in alignment with grant goals.

Column (3) of Table 5 replicates the result in column (2) with high-income ISDs, and this indicates that strong grant oversight is associated with a negative and insignificant difference in spending for special education. As these ISDs serve populations with lower average needs, this insignificant difference may reflect the fact that these ISDs already spend local grant funding in alignment with grant goals. If these ISDs have fewer demands for resources, then they may have fewer incentives to increase spending in other areas. Alternatively, this negative estimate could also reflect the inefficiency caused by increased reporting requirements and oversight when the ISD would otherwise spend funding with weak oversight on special education.

Column (4) and (5) of Table 5 present similar decomposition estimates for small ISDs and large ISDs. As with low-income ISDs, these are defined by ISDs that have below (above) median enrollment over the entire sample period. Differences in these columns are less dramatic than in column (2) and (3), although these indicate that effects are largely driven by smaller ISDs. As these ISDs are more likely to be rural as well, this may similarly reflect the fact that smaller ISDs are more resource constrained and may have greater demands on their funding relative to larger ISDs.

6 Discussion and Conclusion

This research has two primary implications for research. First, this corroborates theoretical predictions from simple models of local government responses to grant funding with over-

sight. Prior research finds that restricted education grants increase spending for the target function, but by less than the full amount of the grant (Addonizio, 1997; Fisher & Papke, 2000). Similarly, I find that conditional grants without strong oversight in the form of local tax funding increases special education spending by \$0.67 per dollar of additional revenue. Further, I find stronger stimulatory effects from federal funding with strong oversight. Increased grant funding with strong oversight increases special education spending by \$0.94 per dollar of additional revenue, and ISDs are more likely to keep additional funding rather than transfer this funding to a lower level of government.

Using seemingly unrelated regression, I find that grant funding for special education with strong oversight increases expenditures for special education by \$0.27 more than grant funding without strong oversight. Importantly, there are several aspects of strong oversight including the maintenance of effort requirement, federal versus local enforcement, claw back provisions, and the timing of spending requirements. My analysis does not enable me to determine which of these features are the most salient for inducing spending effects, and future research should explore the effects of these grant mechanisms further. Nevertheless, my analysis demonstrates that strong oversight is highly effective for stimulating spending in desired areas.

Heterogeneity of the effects of strong oversight comprises the second key contribution of this paper to research. I find that strong oversight is more effective for increasing spending in low-income relative to high-income ISDs. This corroborates theoretical predictions as well. ISDs that are more resource constrained and those that face greater demands on their resources are more likely to spend funds on other purposes without the presence of strong oversight.

Regarding policy implications, policymakers working to increase expenditures for special education or another public function should be cognizant of these effects when designing grant funding policies. Lump sum categorical grant funding without strong oversight is less effective to stimulate spending in desired areas than the same funding with strong oversight. In Michigan, much of the data to enforce strong oversight already exists and could be used by state or ISD-level policymakers to increase oversight, although this could increase administrative burden in some cases. Notably, a key consideration for policymakers is whether funds are intended to supplement or supplant current expenditures. If funds are intended to supplant current expenditures and reduce local financial obligations, then leakage may be entirely acceptable with weak oversight. In this case however, there may be limited value in adopting categorical grants for special education or a dedicated function at all, and policymakers could consider increasing unrestricted grant funding rather than categorical funding.

In addition to these considerations, policymakers should also consider the costs of additional oversight as well. Federal programs that include strong oversight require significant and granular reporting structures, and these provisions must be enforced to ensure that grants are effective. This structure also places a substantial administrative burden on local governments to track and report expenditures. Alternative grant programs such as matching grants may have strong stimulatory effects on spending in some cases, and future research should compare the efficacy of these grants to lump sum categorical grants to induce spending in specific areas.

References

- Addonizio, M. F. (1997). The efficiency of state categorical funding for children educationally at risk. *Planning and Changing*, 28(1 & 2), 26–56.
- Arsen, D., Delpier, T., & Nagel, J. (2019, January). *Michigan School Finance at the Crossroads: A Quarter Century of State Control* (tech. rep.). Michigan State University. East Lansing, MI. <https://education.msu.edu/ed-policy-phd/pdf/Michigan-School-Finance-at-the-Crossroads-A-Quarter-Center-of-State-Control.pdf>
- Autism Alliance of Michigan & Public Sector Consulting. (2025, October). *MI Special Education Finance Reform Blueprint: Legislative Report* (tech. rep.). Michigan. <https://autismallianceofmichigan.org/education-initiatives/mi-blueprint/>
- Ballis, B., & Heath, K. (2021). The Long-Run Impacts of Special Education. *American Economic Journal: Economic Policy*, 13(4), 72–111. <https://doi.org/10.1257/pol.20190603>
- Bartlett, C., Cimpian, J. R., & Mavrogordato, M. (2026). Leveling the playing field: Default policy and its effects on English learner reclassification rates. *Educational Evaluation and Policy Analysis*. <https://doi.org/10.3102/01623737251400379>
- Bradford, D. F., & Oates, W. E. (1971). Towards a predictive theory of intergovernmental grants. *The American Economic Review: Papers and Proceedings*, 61(2), 440–448. <https://www.jstor.org/stable/1817026>
- Burns, J., & Guzman, M. (2025, September). *Funding Michigan’s future: Three decades of school finance and the policy questions ahead* (tech. rep.). Education Policy Innovation Collaborative at Michigan State. <https://epicedpolicy.org/funding-michigans-future-k-12-finance-report/>
- Callaway, B., Goodman-Bacon, A., & Sant’Anna, P. H. (2024). Difference-in-Differences with a Continuous Treatment. *arXiv:2107.02637*. <https://doi.org/10.48550/arXiv.2107.02637>

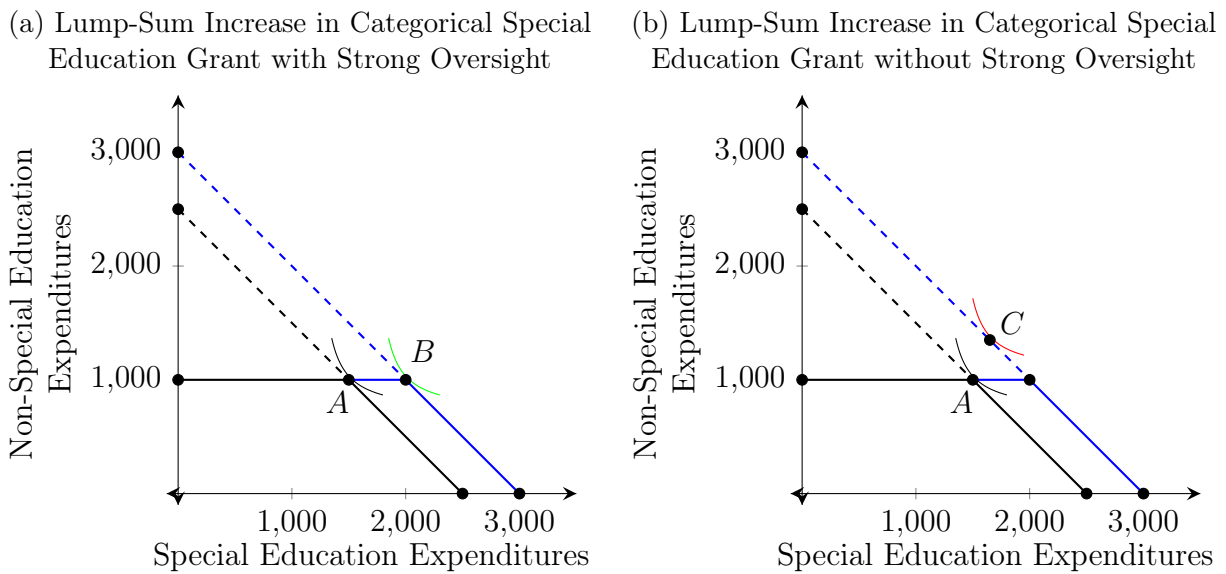
- Cascio, E. U., Gordon, N., & Reber, S. (2013). Local response to federal grants: Evidence from the introduction of Title I in the South. *American Economic Journal: Economic Policy*, 5(3), 126–159. <https://doi.org/10.1257/pol.5.3.126>
- Chambers, J. G., Pérez, M., Harr, J. J., & Shkolnik, J. (2005). Special Education Spending Estimates from 1969-2000. *Journal of Special Education Leadership*, 18(1), 5–13.
- Clarke, D., PailaÑir, D., Athey, S., & Imbens, G. (2024). On synthetic difference-in-differences and related estimation methods in Stata. *The Stata Journal*, 24(4), 557–598. <https://doi.org/10.1177/1536867X241297914>
- Cleary, M. A., & Summers-Coty, K. (1999). Durant: What Happened and Implications for the Future. *Fiscal Forum*, 5(2).
- Craig, S. G., & Inman, R. P. (1982). Federal aid and public education: An empirical look at the new fiscal federalism. *The Review of Economics and Statistics*, 64(4), 541–552. <https://doi.org/10.2307/1923938>
- Cullen, J. B. (2003). The impact of fiscal incentives on student disability rates. *Journal of Public Economics*, 87, 1557–1589. [https://doi.org/10.1016/S0047-2727\(01\)00203-1](https://doi.org/10.1016/S0047-2727(01)00203-1)
- Dee, T. S., & Levine, J. (2004). The fate of new funding: Evidence from Massachusetts’ Education Finance Reforms. *Educational Evaluation and Policy Analysis*, 26(3), 199–215. <https://doi.org/10.3102/01623737026003199>
- Dragoo, K. E. (2026, February). *The Individuals with Disabilities Education Act (IDEA) funding: A primer* (tech. rep. No. R44624). <https://www.congress.gov/crs-product/R44624>
- Duncombe, W., & Yinger, J. (1998). School finance reform: Aid formulas and equity objectives. *National Tax Journal*, 51(2). <https://doi.org/10.1086/NTJ41789325>
- Duncombe, W., & Yinger, J. (2005). How much more does a disadvantaged student cost? *Economics of Education Review*, 24(5), 513–532. <https://doi.org/10.1016/j.econedu.2004.07.015>
- Evans, W. N., Murray, S. E., & Schwab, R. M. (1997). Toward increased centralization in public school finance. In R. C. Fisher (Ed.), *Intergovernmental Fiscal Relations*. Kluwer Academic Publishers.
- Fischer, A., & Duncombe, C. (2024, March). 50-State Comparison: K-12 Funding. <https://www.ecs.org/50-state-comparison-k-12-funding-2024/>
- Fisher, R. C., & Papke, L. E. (2000). Local government responses to education grants. *National Tax Journal*, 53(1), 153–168. <https://doi.org/10.17310/ntj.2000.1.09>
- for IDEA Fiscal Reporting, C. (2024, November). *Understanding the IDEA Part B state grant funding cycle and different fiscal years* (tech. rep.). <https://cifw.wested.org/resource/understanding-the-idea-grant-funding-cycle-and-different-fiscal-years/>

- Funding for education in the American Recovery and Reinvestment Act of 2009 (P.L. 111-5)* (tech. rep. No. R40151). (2009, April). Congressional Research Service. <https://www.everycrsreport.com/reports/R40151.html>
- Goertz, M. E., & Natriello, G. (1999). Court-mandated school finance reform: What do the new dollars buy? In *Equity and adequacy in education finance: Issues and perspectives* (pp. 99–135). National Academies Press.
- Gordon, N. (2004). Do federal grants boost school spending? Evidence from Title I. *Journal of Public Economics*, 88, 1771–1792. <https://doi.org/10.1016/j.jpubeco.2003.09.002>
- Gramlich, E. M. (1977). Intergovernmental Grants: A Review of the Empirical Literature. In W. E. Oates (Ed.), *The Political Economy of Fiscal Federalism*.
- Grossman, P. J. (1990). The impact of federal and state grants on local government spending: A test of the fiscal illusion hypothesis. *Public Finance Review*, 18(3), 313–327. https://doi.org/10.1177/109114219001800304open_in_new
- Guzman, M. (2026, September). Estimating the expenditures associated with special education: Evidence from Michigan. <https://doi.org/10.26300/e372-gz08>
- Hines, J. R., & Thaler, R. H. (1995). The Flypaper Effect. *Journal of Economic Perspectives*, 9(4), 217–226. <https://doi.org/10.1257/jep.9.4.217>
- Hoxby, C. M. (2001). All School Finance Equalizations Are Not Created Equal. *The Quarterly Journal of Economics*, 116(4), 1189–1231. <https://doi.org/10.1162/003355301753265552>
- Individuals with Disabilities Education Act (2019). <https://sites.ed.gov/idea/statuteregulations/>
- Kolbe, T. (2019, June). *Funding Special Education: Charting a Path That Confronts Complexity and Crafts Coherence* (tech. rep.). National Education Policy Center. Boulder, CO. <http://nepc.colorado.edu/publication/special-ed>
- Kolbe, T., Dhuey, E., & Doutre, S. M. (2022, October). More Money is not enough: The case for reconsidering federal special education funding formulas. <https://www.brookings.edu/articles/more-money-is-not-enough-the-case-for-reconsidering-federal-special-education-funding-formulas/>
- Levaggi, R., & Zanola, R. (2003). Flypaper effect and sluggishness: Evidence from regional health expenditure in Italy. *International Tax and Public Finance*, 10, 535–547. <https://doi.org/10.1023/A:1026118222901>
- Levin, A. G. (2025, June). *Federal grants to state and local governments: Trends and issues* (tech. rep. No. R40638). Congressional Research Service. Washington, D.C. <https://www.congress.gov/crs-product/R40638>

- Mack, J. (2015). KRESA tax hike approved, thanks to strong 'yes' vote in Kalamazoo schools. *MLive*. https://www.mlive.com/news/kalamazoo/2015/05/voters_kresa_special-ed_millag.html
- Musgrave, R. A. (1959). *Theory of Public Finance: A Study in Public Economy*. McGraw Hill Book Company.
- Oates, W. E. (1968). The theory of public finance in a federal system. *The Canadian Journal of Economics*, 1(1), 37–54. <https://www.jstor.org/stable/133460>
- The Revised School Code (2004, November). <https://www.legislature.mi.gov/Laws/MCL?objectName=mcl-380-1724a>
- Rich, M. (2006). Categorical Grants. <https://federalism.org/encyclopedia/fiscal-federalism/categoricalgrants/>
- Thiel, C. (2025, March). *Major drop in economically disadvantaged student counts will create "at-risk" funding cliff for schools next year* (tech. rep.). Citizens Research Council of Michigan. <https://cremich.org/major-drop-in-economically-disadvantaged-student-counts-present-several-schools-with-at-risk-funding-cliff-next-year>
- Tsang, M., & Levin, H. M. (1983). The impact of intergovernmental grants on educational expenditure. *Review of Educational Research*, 53(3), 329–367. <https://doi.org/10.3102/00346543053003329>
- Wooldridge, J. (2025). Two-way fixed effects, the two-way Mundlak regression, and difference-in-difference estimators. *Empirical Economics*, 69, 2587. <https://doi.org/10.1007/s00181-025-02807-z>

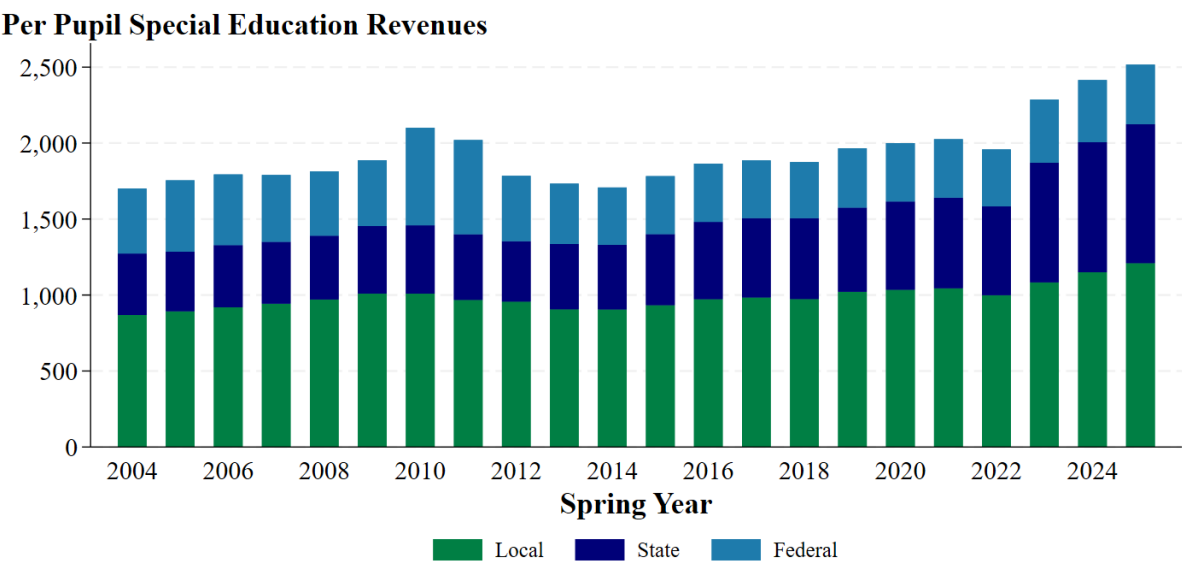
7 Tables and Figures

Figure 1: Theoretical Background for Effects of Lump Sum Categorical Grant Funding with Weak Versus Strong Oversight



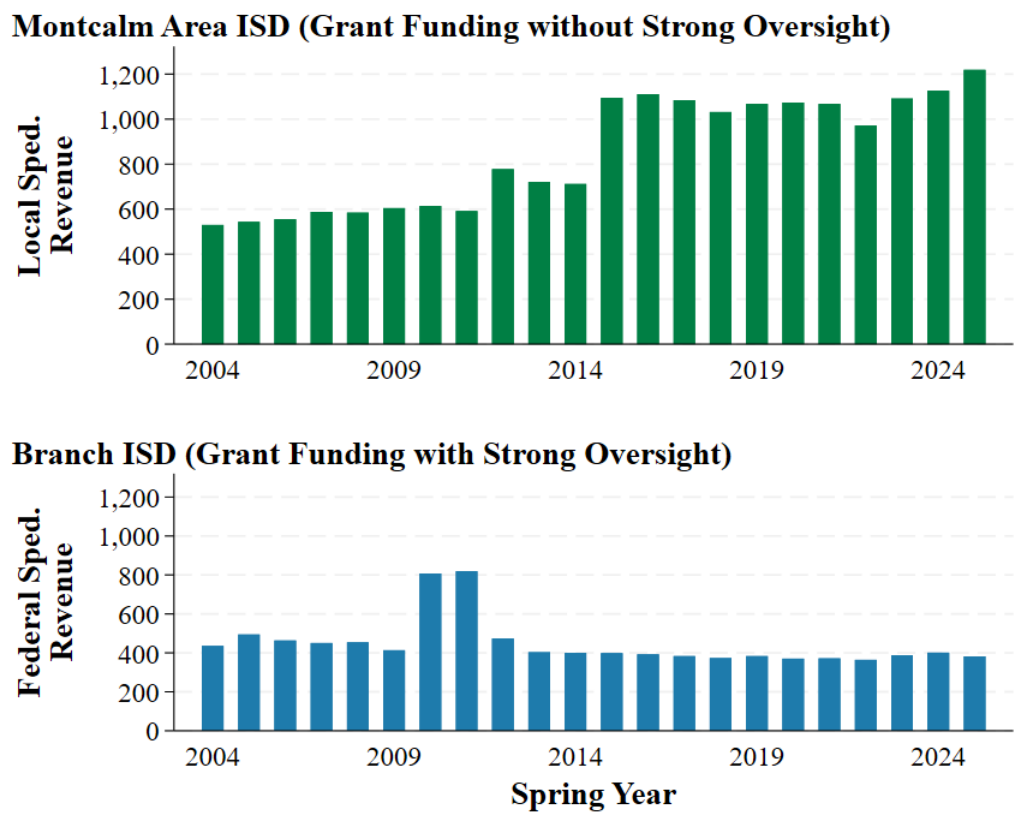
Notes: Figure illustrates the theoretical predications of increasing grant funding with weak versus strong oversight. Panel (a) illustrates the predicted effect of a grant on spending in the presence of strong oversight. In this case, the ISD moves from the black indifference curve to the green indifference curve increasing special education spending by the size of the grant. In contrast, panel (b) presents the effects of an increase in lump-sum categorical grant funding with weak oversight. In this scenario, an ISD could increase spending for non-special education purposes following an increase in categorical grant funding, and it could shift its allocation from the black indifference curve to the red indifference curve.

Figure 2: Average ISD Revenues for Special Education by Revenue Source, 2003-04 through 2024-25



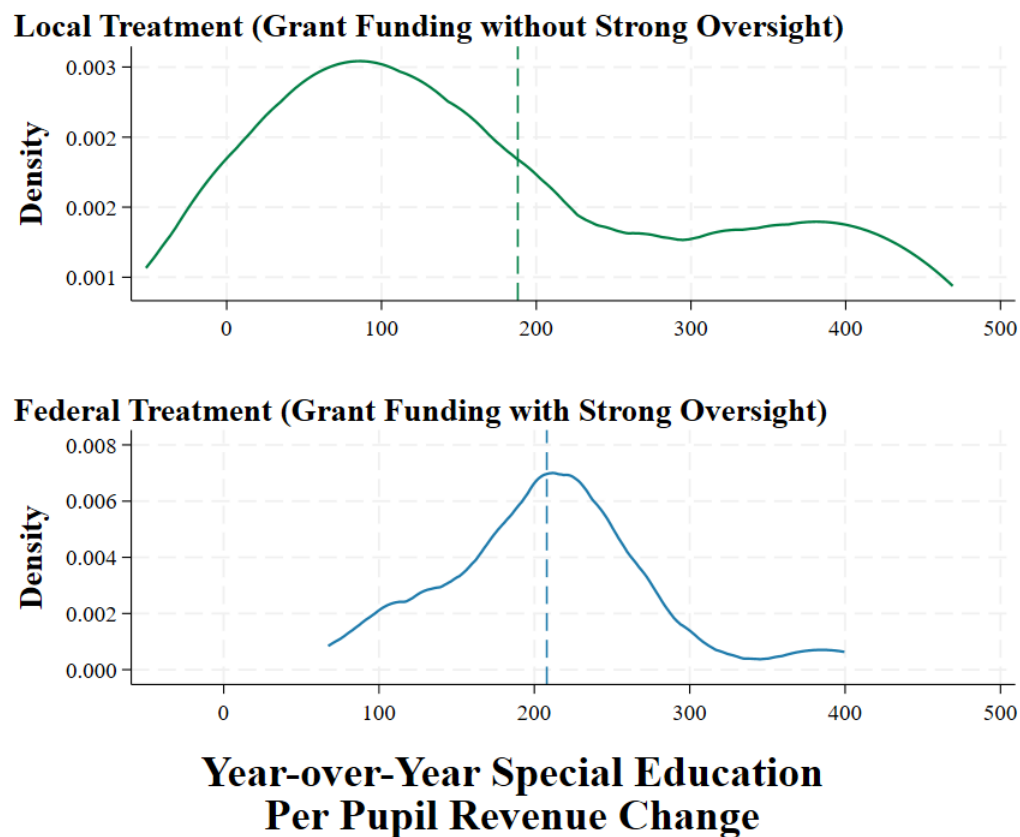
Notes: Average per pupil revenues for special education in Michigan ISDs, 2003-04 through 2024-25 school years. Revenue data collected from Michigan Financial Information Database and Form B. District-level enrollment collected from Michigan State Aid Financial Status Reports. Local revenues for special education comprise revenues generated by a dedicated special education property tax. State revenues for special education comprise all state categorical grants for special education, although the majority of these is the state reimbursement program. Federal revenues for special education comprise all revenues provided via IDEA for the provision of special education services. All dollar values adjusted to 2025 dollars using the GDP S&L price deflator.

Figure 3: ISD-Level Examples of Revenue Changes Under Local and Federal Grant Policies 2003-04 through 2024-25 Academic Years



Notes: Revenues for special education per pupil by source for Montcalm Area ISD and Branch ISD between 2003-04 and 2024-25. Montcalm Area ISD adopted a new property tax for special education in 2014, and the revenue from this tax increase was observed during the 2014-15 academic year. In this year, local revenues for special education increased sharply and remained elevated until the end of the sample period. Branch ISD received a large influx of federal funding for special education under ARRA in 2010 and 2011. All dollar values adjusted to 2025 dollars using the GDP S&L price deflator.

Figure 4: Kernel Density Plots of Year-over-Year Changes in Special Education Revenues by Treatment



Notes: Year-over-year revenue change under each grant funding change. The first panel presents the density of year-over-year local special education revenue changes under property tax change (multiple years), and the second panel presents the density of year-over-year federal special education revenue changes (2009-2010). All dollar values adjusted to 2025 dollars using the GDP S&L price deflator.

Table 1: Summary of Local Sample ISD Revenues, Expenditures, and Student Demographics

	Control Units	Treated Units		
	Never Treated	Pre-Treatment	Post-Treatment	Change
Total Special Education Rev. Per Pupil	\$1,815.92	\$1,776.42	\$1,968.31	191.89
Local Special Education Rev. Per Pupil	\$750.96	\$791.30	\$924.92	133.62
State Special Education Rev. Per Pupil	\$535.07	\$430.62	\$565.01	134.40
Federal Special Education Rev. Per Pupil	\$422.65	\$449.18	\$411.08	-38.10
Other Special Education Rev. Per Pupil	\$107.24	\$105.32	\$67.29	-38.03
Special Education Exp. Per Pupil	\$1,660.14	\$1,684.06	\$1,843.20	159.14
Female	0.48	0.48	0.48	0.00
Black	0.05	0.06	0.03	-0.03
Hispanic/Latino 0.06	0.06	0.05	-0.01	
Asian	0.01	0.01	0.01	0.00
Other Race/Ethnicity	0.04	0.05	0.08	0.03
Economically Disadvantaged	0.51	0.45	0.55	0.09
English Learner	0.01	0.01	0.02	0.01
Special Education	0.17	0.16	0.18	0.01
Total Students with Disabilities	929,821	639,519	304,430	
Total Students	5,557,961	3,968,359	1,809,226	
Total Observations	317	223	150	

Notes: ISD-level averages of special education revenues, expenditures, and demographics from each by treatment status in the local sample. Local sample averages comprise pre- and post-treatment averages for ISDs before and after special education property tax changes between the 2003-04 and 2024-25 academic years. In the case that an ISD adopts a second property tax for special education during the sample period, data for years following the second adoption are removed from the local sample. The “change” column represents the difference in the post-treatment and pre-treatment variables, and significance stars represent the significance of t-tests between the samples. All dollar values adjusted to 2025 dollars using the GDP S&L price deflator. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Summary of Federal Sample ISD Revenues, Expenditures, and Student Demographics

	Treated Units		
	Pre-Treatment	Post-Treatment	Change
Total Special Education Rev. Per Pupil	\$1,855.93	\$2,174.07	318.14
Local Special Education Rev. Per Pupil	\$934.26	\$1,009.01	74.75
State Special Education Rev. Per Pupil	\$412.56	\$449.96	37.40
Federal Special Education Rev. Per Pupil	\$443.30	\$641.67	198.37
Other Special Education Rev. Per Pupil	\$65.81	\$73.43	7.63
Special Education Exp. Per-Pupil	\$1,729.98	\$2,022.26	292.28
Female	0.48	0.48	0.00
Black	0.06	0.06	0.00
Hispanic/Latino	0.05	0.06	0.01
Asian	0.01	0.01	0.00
Other Race/Ethnicity	0.03	0.04	0.01
Economically Disadvantaged	0.39	0.49	0.10
English Learner	0.00	0.00	0.00
Special Education	0.16	0.16	0.00
Total Students with Disabilities	1,657,118	266,285	
Total Students	10,780,269	1,710,343	
Total Observations	342	57	

Notes: ISD-level averages of special education revenues, expenditures, and demographics from each by treatment status in the federal sample. Federal sample averages comprise pre- and post-treatment averages for ISDs before and after special education property tax changes between the 2003-04 and 2009-10 academic years. The “change” column represents the difference in the post-treatment and pre-treatment variables, and significance stars represent the significance of t-tests between the samples. All dollar values adjusted to 2025 dollars using the GDP S&L price deflator. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Average Causal Response of ISD-Level Special Education Spending following Increases in Conditional Grant Funding

	(1) Federal Treatment: Grant Increase with Strong Oversight	(2) Local Treatment: Grant Increase without Strong Oversight	(3) Effect of Strong Oversight
ACR of Total Special Education Expenditures	0.941*** (0.266)	0.673*** (0.202)	0.268 (0.336)
Observations	399	690	

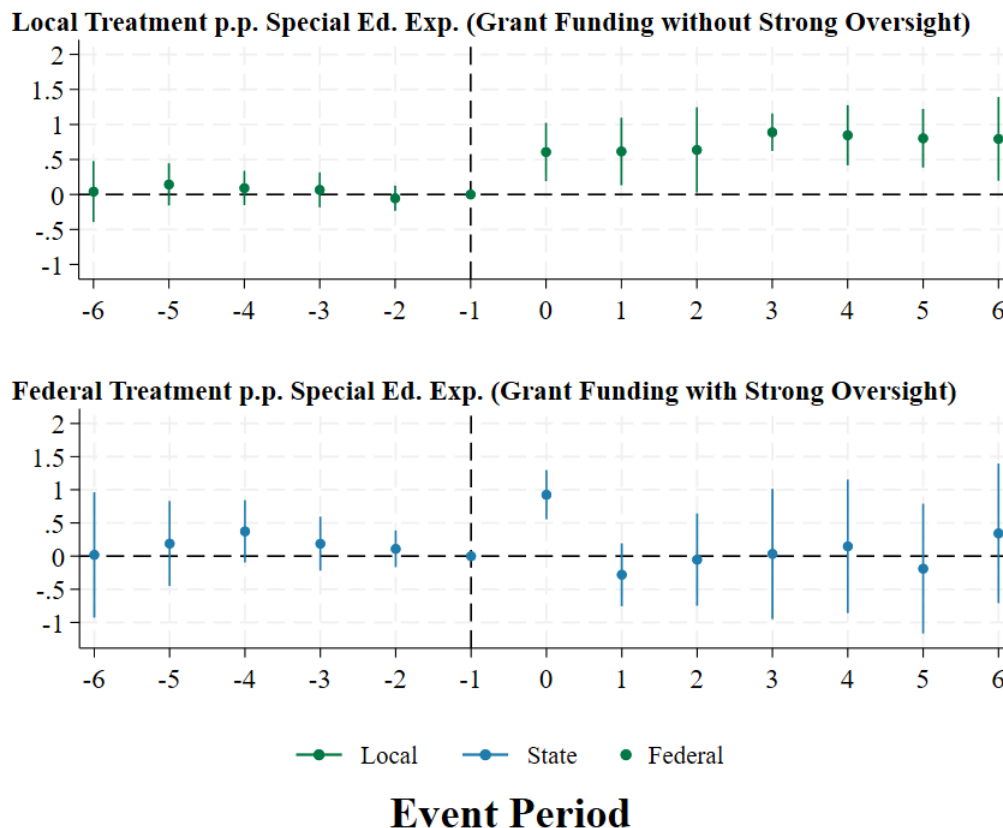
Notes: Average causal response (ACR) of special education spending from a \$1 increase in special education. ACR estimates represent marginal effects of γ_g from Equation (1) using a linear functional form for the federal sample and the ACR from Equation (2) for the local sample. Dosage represents a continuous measure of the year-over-year the year-over-year increase in federal funding for special education induced by ARRA in column (1) and the year-over-year increase in local funding for special education induced by a property tax change in column (2). All models include the proportion of female students, the proportion of non-White students, the proportion of economically disadvantaged students, the proportion of students with disabilities, and the log of student enrollment in the ISD, ISD dummies, and year dummies. All standard errors clustered at the ISD-level and unconditional on covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Average Causal Response of ISD-Level Special Education Spending following Increases in Conditional Grant Funding, by Spending Type

<i>Panel A: Federal Sample Conditional Grant Increase with Strong Oversight</i>							
	(1) Overall	(2) Salaries	(3) Benefits	(4) Services	(5) Supplies	(6) Other	(7) Transfers
ACR	0.941*** (0.266)	0.276 (0.234)	0.188 (0.147)	0.201 (0.153)	0.036** (0.017)	-0.010 (0.014)	0.250 (0.292)
<i>Panel B: Local Sample Conditional Grant Increase without Strong Oversight</i>							
	Overall	Salaries	Benefits	Services	Supplies	Other	Transfers
ACR	0.673*** (0.202)	0.040 (0.095)	0.052 (0.108)	0.081 (0.091)	-0.017 (0.011)	0.011 (0.012)	0.506*** (0.117)

Notes: Average causal response (ACR) of special education spending from a \$1 increase in special education. ACR estimates represent marginal effects of γ_g from Equation (1) using a linear functional form for the federal sample and the ACR from Equation (2) for the local sample. Dosage represents a continuous measure of the year-over-year the year-over-year increase in federal funding for special education induced by ARRA in column (1) and the year-over-year increase in local funding for special education induced by a property tax change in column (2). All models include the proportion of female students, the proportion of non-White students, the proportion of economically disadvantaged students, the proportion of students with disabilities, and the log of student enrollment in the ISD, ISD dummies, and year dummies. All standard errors clustered at the ISD-level and unconditional on covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: Event Study of ISD-Level Per Pupil Expenditures for Special Education following Increases in Conditional Grant Funding



Notes: Average causal response (ACR) event study estimates and 95% confidence intervals of the effects of local property tax increases and federal funding increases on ISD-level special education spending from Equation (3). Dosage represents a continuous measure of the year-over-year increase in federal funding for special education induced by ARRA and the year-over-year increase in local funding for special education induced by a property tax change. All models include the proportion of female students, the proportion of non-White students, the proportion of economically disadvantaged students, the proportion of students with disabilities, and the log of student enrollment in the ISD, ISD dummies, and year dummies. All standard errors clustered at the ISD-level and unconditional on covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Heterogeneity of Strong Oversight Effects

	(1) Overall	(2) Low-Income ISDs	(3) High-Income ISDs	(4) Small ISDs	(5) Large ISDs
Effect of Strong Oversight On Sped. Spending	0.290 (0.309)	0.785** (0.347)	-0.408 (0.508)	0.488 (0.452)	0.059 (0.445)

Notes: Average causal response (ACR) of special education spending from a \$1 increase in special education. ACR estimates represent marginal effects of γ_g from Equation (1) using a linear functional form for the federal sample and the ACR from Equation (2) for the local sample. Dosage represents a continuous measure of the year-over-year the year-over-year increase in federal funding for special education induced by ARRA in column (1) and the year-over-year increase in local funding for special education induced by a property tax change in column (2). All models include the proportion of female students, the proportion of non-White students, the proportion of economically disadvantaged students, the proportion of students with disabilities, and the log of student enrollment in the ISD, ISD dummies, and year dummies. All standard errors clustered at the ISD-level and unconditional on covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

8 Appendix Tables and Figures

Table A1: Average Causal Response of District-Level Special Education Spending following Conditional Grant Funding, by Expenditure Type

<i>Panel A: Federal Sample Conditional Grant Increase with Strong Oversight</i>						
	(1) Overall	(2) Salaries	(3) Benefits	(4) Services	(5) Supplies	(6) Other
ACR	0.207*** (0.063)	0.118** (0.048)	0.021 (0.021)	0.059* (0.031)	0.008* (0.004)	0.001 (0.001)
<i>Panel B: Local Sample Conditional Grant Increase without Strong Oversight</i>						
	Overall	Salaries	Benefits	Services	Supplies	Other
ACR	0.414*** (0.071)	0.393*** (0.063)	0.259*** (0.042)	−0.245*** (0.043)	0.008** (0.003)	−0.001 (0.000)

Notes: Average causal response (ACR) of special education spending from a \$1 increase in special education. ACR estimates represent marginal effects of γ_g from Equation (1) using a linear functional form for the federal sample and the ACR from Equation (2) for the local sample. Dosage represents a continuous measure of the year-over-year the year-over-year increase in federal funding for special education induced by ARRA in column (1) and the year-over-year increase in local funding for special education induced by a property tax change in column (2). All models include the proportion of female students, the proportion of non-White students, the proportion of economically disadvantaged students, the proportion of students with disabilities, and the log of student enrollment in the district, district dummies, and year dummies. All standard errors clustered at the ISD-level and unconditional on covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Robustness of Average Causal Response of ISD-Level Per-Pupil Special Education Expenditures following Increases in ARRA Special Education Funding

	Base Model	Lag of Per Pupil Spending	Poisson Regression	Interact with Demeaned Covariates	Local Sample Observations
ACR	0.941*** (0.266)	0.948*** (0.217)	1.031*** (0.236)	0.657** (0.264)	1.207*** (0.307)
Observations	399	342	399	399	239

Notes: Robustness checks of average causal response estimates from Equation (1) Dosage represents a continuous measure of the year-over-year increase in federal funding for special education induced by ARRA. All models include the log of student enrollment, proportion of non-White students, the proportion of female students in the ISD, ISD dummies, and year dummies. All standard errors clustered at the ISD-level and unconditional on covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Robustness of Average Causal Response of ISD-Level Per-Pupil Special Education Expenditures following Local Property Tax Increases

	(1) Base Model	(2) No Cohort Interac- tions	(3) Lag of Per Pupil Spending	(4) Poisson Regression	(5) Interact with Demeaned Covariates	(6) Balanced Panel	(7) CH WAS Estimator	(8) Federal Sample Observa- tions	(9) One Year Post Period
ACR	0.673*** (0.245)	0.651*** (0.224)	0.287*** (0.087)	0.389 (0.258)	0.692** (0.303)	0.835** (0.340)	0.576*** (0.214)	0.811*** (0.172)	0.466* (0.234)
Observations	690	690	655	690	690	550	274	239	571

Notes: Robustness checks of average causal response estimates from Equation (1). Dosage represents a continuous measure of the year-over-year increase in local funding for special education induced by a special education property tax change. All models include the log of student enrollment, proportion of non-White students, the proportion of female students in the ISD, ISD dummies, and year dummies. All standard errors clustered at the ISD-level and unconditional on covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Average Causal Response of ISD-Level Special Education Spending following Changes in Earmarked Revenues, by Source, Quadratic Functional Form

	(1) Federal Treatment: Grant Increase with Strong Oversight	(2) Local Treatment: Grant Increase without Strong Oversight	(3) Effect of Strong Oversight
ACR of Total Special Education Expenditures	0.942*** (0.272)	0.636*** (0.233)	0.306 (0.308)
Observations	399	690	

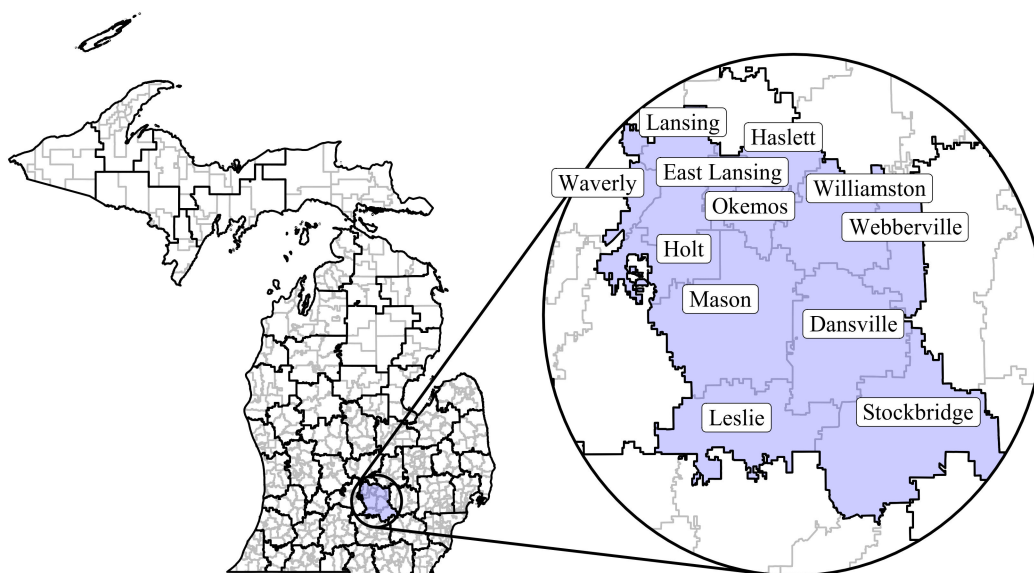
Notes: Average causal response (ACR) of special education spending from a \$1 increase in special education. ACR estimates represent marginal effects of γ_g from Equation (1) using a quadratic functional form for the federal sample and the ACR from Equation (2) for the local sample. Dosage represents a continuous measure of the year-over-year increase in federal funding for special education induced by ARRA in column (1) and the year-over-year increase in local funding for special education induced by a property tax change in column (2). All models include the proportion of female students, the proportion of non-White students, the proportion of economically disadvantaged students, the proportion of students with disabilities, and the log of student enrollment in the ISD, ISD dummies, and year dummies. All standard errors clustered at the ISD-level and unconditional on covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Synthetic DiD Estimates of Changes in Special Education Revenues and Expenditures following Local Grant Funding Changes

	(1) Local Special Education Revenues	(2) Special Education Expenditures	(3) Ratio of Effects
Binary Treatment Effect	187.702*** (53.172)	111.853 (85.723)	0.596
Observations	550	550	

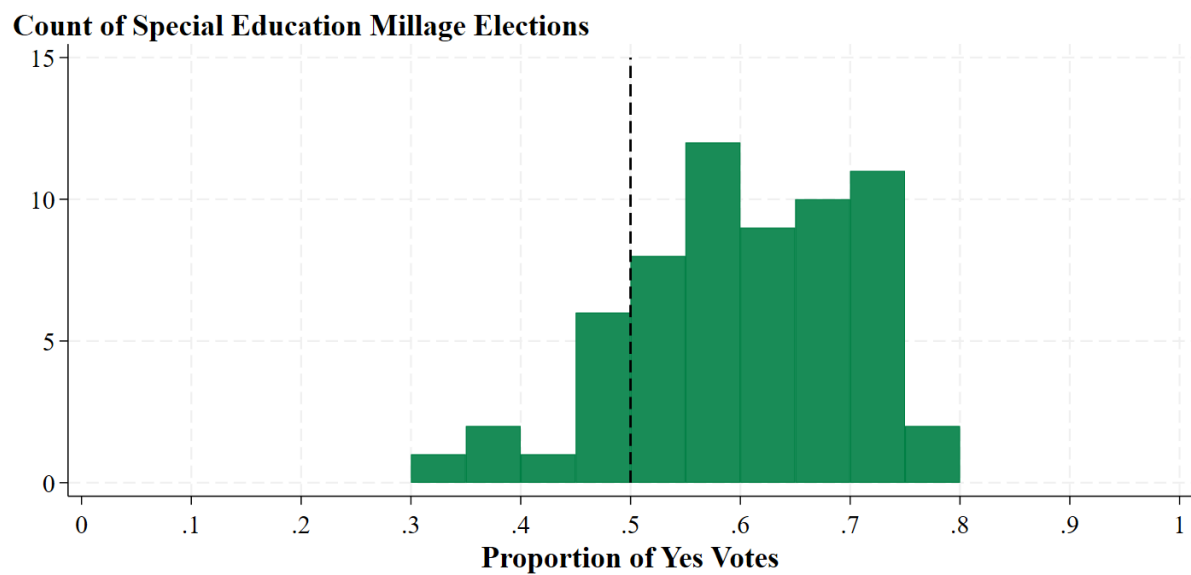
Notes: Synthetic difference-in-differences models of the effect of local property tax adoption of local special education revenues and special education expenditures. All models include the proportion of female students, the proportion of non-White students, the proportion of economically disadvantaged students, the proportion of students with disabilities, and the log of student enrollment in the ISD, ISD dummies, and year dummies. All standard errors clustered at the ISD-level and unconditional on covariates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: Map of Ingham ISD and Constituent School Districts



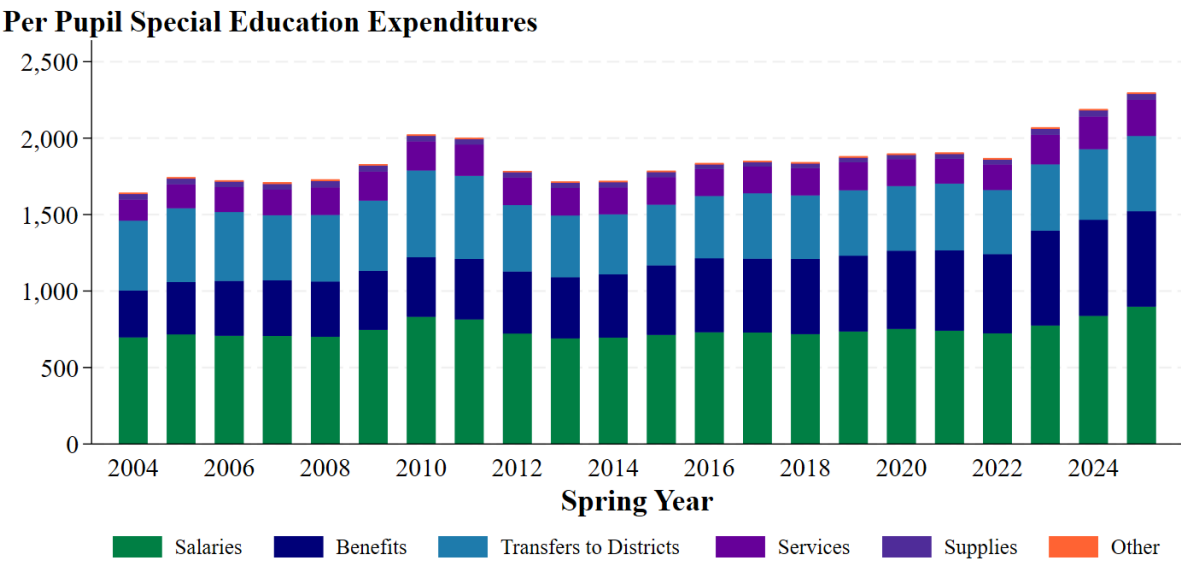
Notes: Map of Michigan school districts and Intermediate School Districts (ISDs). The left panel presents all school districts in Michigan in grey lines, and black lines identify ISDs. The inset presents Ingham ISD and the 12 constituent school districts. Ingham ISD levies an earmarked property tax for special education and coordinates special education services across the local school districts.

Figure A2: Voting Margins for Available Special Education Property Tax Elections



Notes: Histogram of available special education property tax elections by proportions of yes votes. Special education property taxes require simple majorities to pass, and most elections pass by a wide margin. Of the 62 elections for which vote shares were able to be identified, 10 property tax elections failed.

Figure A3: Average ISD-Level Expenditures for Special Education by Expenditure Type, 2003-04 through 2024-25



Notes: Average per pupil expenditures for special education in Michigan ISDs, 2003-04 through 2024-25 school years. Expenditure data collected from Michigan Financial Information Database and Form B. District-level enrollment collected from Michigan State Aid Financial Status Reports. Special education salaries and benefits include those for all special education teachers and special education specialists including school psychologists, speech pathologists, special education administration, and other functions. Transfers to districts comprise any transfer of grant funding to a lower level of government. Purchased services may include contracting services to provide special education programming. All dollar values adjusted to 2025 dollars using the GDP S&L price deflator.