Getting Down to FACTS

The Impact of Intervention: LCAP, Differentiated Assistance, and Resource Effectiveness in California School Districts

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Abstract

This study examines the effects of Differentiated Assistance (DA)—California's triggered support mechanism for local education agencies (LEAs) that fall short on key student outcome benchmarks—on both resource use and student achievement in the post-pandemic period. DA is a central component of California's System of Support, launched in 2017 to build local capacity for continuous improvement and to reduce disparities in student opportunities and outcomes. Prior research suggests that DA identification can improve subsequent student achievement, but existing evidence is limited to pre-pandemic years and offers little insight into *how* DA may shift LEA resource configurations and intervention strategies.

We use a mixed-methods design that links quasi-experimental estimates of DA's impact on achievement (via a regression-discontinuity framework) with detailed LEA resource profiles and a systematic, action-level analysis of Local Control and Accountability Plans (LCAPs) that bridges the autonomy, finance and accountability literatures.

Because DA-identified LEAs must document strategies for focal student groups in their LCAPs, the LCAP analysis provides a direct window into the district's theory of action, planned interventions, and the extent to which resources are targeted toward identified needs. Together, these approaches illuminate whether—and through what mechanisms—DA is associated with changes in spending patterns, planned supports, and student outcomes. In doing so, it advances understanding of how equity-weighted funding and performance-triggered assistance interact within real-world planning sysstems–and whether that interaction produces resource shifts.

A. Introduction

A.1 The Problem

Differentiated Assistance (DA) is a central intervention mechanism in California's Statewide System of Support. Under current rules, local educational agencies (LEAs) become eligible for DA when student-group performance meets State Board of Education criteria in at least two Local Control Funding Formula (LCFF) priority areas, with charter LEAs subject to the same criteria but across two Dashboard years rather than one. DA is defined by the California Department of Education (CDE) as targeted technical assistance intended to help LEAs address the underlying causes of low outcomes while strengthening their capacity to evaluate, adapt, and sustain improvement over time (California Department of Education [CDE], 2026a, 2026b).

That intervention matters because California's 2013 LCFF overhaul changed more than the way funds flow to schools. It also changed how districts are expected to explain what they plan to do with those funds and for whom. The Local Control and Accountability Plan (LCAP) is the central planning document through which a district translates low performance into a theory of action: which student groups it names, which indicators it prioritizes, which actions it proposes, and how much funding it says it will devote to those actions (CDE, 2026c, 2026d).

The problem this paper addresses is therefore straightforward but important. The literature on LCFF, county support, and accountability redesign has established a good deal about California's new governance architecture, yet much less is known about the mechanism through which DA may alter district behavior. Stated differently, if DA matters, what does it appear to change in district planning and resource decisions? This study treats the LCAP as the most direct statewide record of that planned response and asks whether DA changes what districts say they intend to do, for whom, and with what kinds of resources. In doing so, the paper also introduces a more detailed taxonomy for describing school-system actions than is typically available in standard school-finance accounting (Hahnel & Humphrey, 2021; Warren, 2016).

A.2 California's Accountability and Support Framework

California's accountability and support framework is best understood as part of a broader national shift away from the narrow, test-centered accountability model associated with No Child Left Behind and toward state systems built around multiple measures, local context, and improvement-oriented support. Researchers examining ESSA-era accountability have emphasized that states were given greater latitude to design systems that combine academic outcomes with broader indicators of school quality, opportunity, and support rather than relying exclusively on single-score sanction regimes (Bae & Stosich, 2018; Cook-Harvey & Stosich, 2016; Portz & Beauchamp, 2022). California took that shift further than many states by pairing a multiple-measure dashboard with a local planning instrument and a statewide support infrastructure.

At the center of California's model are three interlocking components: the California School Dashboard, the LCAP, and the Statewide System of Support. The Dashboard provides the public performance signals that identify strengths and needs across student groups and indicators. The LCAP is the annual planning instrument through which those signals are translated into reflection on results, goals, actions, and planned expenditures. The Statewide System of Support is the delivery infrastructure that provides graduated assistance when those needs become serious enough to trigger additional help. In practice, that infrastructure includes county offices of education, the California Collaborative for Educational Excellence (CCEE), CDE, charter authorizers, and other lead agencies that help connect LEAs to expertise, tools, and continuous-improvement supports (CCEE, 2026; CDE, 2026a, 2026b).

Figure 1. Three levels of California's Statewide System of Support. Adapted from CDE and CCEE descriptions of universal support, differentiated assistance, and intensive intervention.

A.3 California School Dashboard and the Statewide System of Support

Within that framework, the California School Dashboard is the main public-facing performance system. The Dashboard reports districts, schools, and student groups on a defined set of state measures and local indicators. State indicators currently include academic performance in English language arts and mathematics, chronic absenteeism, graduation rate, suspension rate, English Learner Progress, college and career readiness, and science. In most years, state-indicator performance is determined by combining current-year Status and year-over-year Change in a five-by-five table that yields one of five colors—blue, green, yellow, orange, or red—with blue representing the highest performance level and red the lowest (CDE, 2026e, 2026f, 2026g).

Local indicators serve a different function. They are used for LCFF priorities for which statewide administrative data are not collected in a comparable way and therefore rely on locally gathered evidence and self-reporting. As of the current Dashboard structure, those local indicators include Basic Services and Conditions, Implementation of State Academic Standards, Parent and Family Engagement, School Climate, Access to a Broad Course of Study, and, for county offices of education only, coordination of services for expelled pupils and foster youth. In other words, the Dashboard is not a purely test-based tool. It is a multiple-measure system that combines statewide metrics with locally reported indicators anchored in California's statutory priorities (CDE, 2024, 2026f).

Within the Statewide System of Support, DA occupies the targeted middle tier between universal assistance available to all LEAs and more intensive intervention for the most persistent or complex cases. CDE's current descriptions emphasize that DA is not a separate corrective-status plan so much as a support process rooted in continuous improvement. LEAs identified for DA continue to complete their LCAPs, but they do so with added support in reviewing data, diagnosing root causes, engaging educational partners, and selecting or adjusting strategies. County superintendents, CDE, charter authorizers, and CCEE all play roles in this targeted assistance, depending on LEA type and the nature of the need (CDE, 2026a, 2026b; CCEE, 2026).

The timing of that process has also changed in ways that matter for district planning. Pursuant to Senate Bill 114, the Dashboard release schedule has been moved earlier in the school year: the 2025 Dashboard was scheduled for November 15, 2025, the 2026 Dashboard for October 15, 2026, and the

Dashboard is then scheduled to be released by October 15 annually thereafter. These timing changes are paired with earlier CALPADS certification deadlines so that DA-identification signals arrive earlier in the planning cycle and can, in principle, feed more directly into the next LCAP revision. The accountability system is also still evolving substantively. For example, the Science Indicator is reported with status, change, and colors beginning with the 2025 Dashboard for informational purposes, and the State Board has indicated that full state-indicator status for science will be considered beginning with the 2026 Dashboard, which would make the indicator eligible for use in support determinations. Similarly, the State Board approved the removal of testing-participation grace periods for ELA, mathematics, and science beginning with the 2026 Dashboard (CDE, 2025a, 2026a, 2026h).

A.4 LCAPs in California: Origins and Statutory Framework

The LCAP is the principal planning and accountability document for California's K–12 public education system. Established under the LCFF, the LCAP requires each LEA—school districts, county offices of education, and charter schools—to adopt a three-year plan, updated annually, that describes how the LEA intends to meet annual goals for all students and for numerically significant student groups across the state priorities. Those priorities span conditions of learning, engagement, and outcomes, and the LCAP is designed to link goals, actions, services, and expenditures in a single public document (CDE, 2026c, 2026d; Legislative Analyst's Office, 2023).

The LCAP also sits directly inside the weighted-funding logic of the LCFF. Under the formula, districts receive a base grant plus supplemental and concentration funding tied to the enrollment of low-income students, English learners, and foster youth. The concentration grant adds a larger amount once a district's unduplicated pupil percentage rises above 55 percent. The LCAP is the connective tissue between that funding model and the state's accountability expectations because districts must explain how they are using increased and improved services to address the needs of high-need students in proportion to the additional funding they receive (Lafortune, Herrera, & Gao, 2023; Legislative Analyst's Office, 2023).

A.5 Strengths of the LCAP Framework

Several features of the LCAP represent genuine advances over California's prior accountability architecture. First, the LCAP institutionalizes community engagement by requiring districts to consult with parents, students, staff, and community members as part of the annual planning cycle. However imperfectly implemented, this requirement creates a formal mechanism for community voice in local priority-setting and resource allocation. Second, the LCAP asks districts to articulate a theory of action that links identified needs to proposed actions and expenditures, creating a level of strategic transparency that was largely absent from the state's older categorical-funding system. Third, the LCAP generates an unusually large corpus of local planning data, giving community a window into how districts describe goals, beneficiaries, and intended interventions (CDE, 2025b, 2026c; Warren, 2016).

That last point is especially important for this study. Traditional accounting files such as SACS organize expenditures by fund, function, object, and related accounting dimensions, but they do not explain how districts narrate the relationship among student groups, indicators, and intended actions. The LCAP does. It records district-declared actions in a way that links spending claims to equity-oriented goals and named beneficiaries, even if imperfectly. That makes the LCAP analytically valuable as both a policy instrument and a planning dataset (Hibel & Beberman, forthcoming; Lafortune et al., 2023).

A.6 Limitations and Critiques

A decade of implementation has also made the LCAP's limitations hard to ignore. Multiple studies have concluded that the LCAP often functions more as a compliance exercise than as a concise strategic-planning tool. Many plans extend well beyond one hundred pages, repeat boilerplate language, or describe actions so broadly that it becomes difficult to distinguish real budget priorities from administrative packaging. PPIC's statewide work on targeted funding reached a related conclusion: planned LCAP spending often does not map cleanly onto the supplemental and concentration dollars districts receive, and the LCAP itself is difficult to use as a consistent statewide reporting instrument (Hahnel & Humphrey, 2021; Lafortune et al., 2023).

A foundational clarification therefore needs to be stated plainly. LCAPs are planning documents, not audited expenditure ledgers. What they reveal is declared intent, not verified execution. That distinction matters because it shapes what this study can and cannot claim. The paper is a study of districts' planning responses to DA identification, not a direct audit of resource deployment per se. That is still a meaningful contribution, but it requires careful interpretation throughout the analysis (Howle, 2019; Lafortune et al., 2023).

These interpretive limits are compounded by data-quality and comparability challenges. The LCAP template has been revised repeatedly since 2014, districts vary substantially in how specific they are about action-level expenditures, and California still lacks a centralized machine-readable LCAP database. Any large-scale analysis therefore depends on substantial extraction and cleaning work applied to individual PDFs. Recent statewide parsing work by Hibel and Beberman reinforces both the promise and the unevenness of the corpus: in their 2024–25 sample, 36.8 percent of district and charter goals were exact or near-exact duplicates, and only 7.9 percent of goals included an explicit numeric target. Those findings do not make the LCAP unusable, but they do make clear that analysts are working with an uneven planning instrument whose quality and specificity vary across LEAs (Hibel & Beberman, forthcoming).

A.7 The LCAP as a Data Resource, Policy Instrument, and Engagement Tool

The present study therefore treats the LCAP as three things at once: a community-engagement tool, a policy instrument, and a data resource. Its engagement function matters because the statute assumes districts will use the LCAP process to gather local input and surface local priorities. That dimension is important to any full evaluation of LCFF, even if it is not the central object of analysis here. What matters more directly for this paper is that the LCAP makes districts' planning logic visible in a standardized public form (CDE, 2025b, 2026c).

As a policy instrument, the LCAP is the document through which districts translate accountability signals into a local theory of action. When a district is identified for DA, the LCAP becomes the public record in which the district names the affected student groups, identifies the problems it intends to address, and describes the actions and expenditures it believes will improve outcomes. In that sense, the LCAP is not merely a disclosure device. It is the document through which the district organizes, justifies, and communicates its intended response to accountability pressure (CDE, 2026b, 2026c).

As a data resource, the LCAP offers something California's accounting files do not: action-level linkages among student groups, indicators, and proposed expenditures. That is why mechanism matters in this study. Prior work on California's accountability and finance reforms suggests that additional resources and support can matter, but the pathway by which a district converts identification into a stated response remains much less clear. One plausible mechanism is that DA prompts districts to redirect staff, programs, and dollars toward the groups and indicators that triggered concern. Recent advances in generative AI and large language model-based parsing now make it possible to extract those declared actions and expenditures from LCAP PDFs at scale. In that sense, this study complements Hibel and Beberman's statewide parsing work: their study demonstrates that generative AI can recover goal and action text from the corpus, while the present study uses that same planning record to ask how DA appears to reshape districts' stated resource response (Hibel & Beberman, forthcoming).

B. Background and Literature Review

B.1 Conduct a Post-Pandemic Impact Study

Accountability-based intervention systems rest on the premise that identification and external support can alter district behavior—strategy selection, implementation supports, and resource allocation—in ways that improve student outcomes. A substantial body of work has used regression discontinuity and related quasi-experimental designs to estimate the causal effects of threshold-based policies and labels. The core logic is that units close to an eligibility cutoff are comparable in expectation, allowing analysts to estimate the effect of treatment at the margin (Imbens & Lemieux, 2008). Classic threshold-based work, such as Angrist and Lavy's (1999) study of class size, also underscores why rule-driven cutoffs can generate credible causal inference. California's Differentiated Assistance (DA) system, which is triggered by defined Dashboard performance thresholds, is therefore well-suited to this design logic.

Pre-pandemic analyses of DA suggested modest positive effects on selected student outcomes, especially for the focal student groups that triggered identification (Krausen, Tanner, et al., 2022). Yet the post-pandemic environment is materially different from the one in which those earlier estimates were produced. California suspended Dashboard color assignments in 2019–20 and 2020–21; federal relief funding temporarily altered district resource constraints, staffing instability increased; and multiple indicators—especially chronic absenteeism—shifted sharply. These changes complicate simple extrapolation from pre-pandemic findings and necessitate a renewed impact study.

Just as importantly, the accountability literature has emphasized outcome effects more than organizational mechanisms. We still know comparatively little about how districts modify planning documents, budgeting priorities, staffing choices, or intervention portfolios in response to identification. That omission is especially consequential in California, where the Local Control and Accountability Plan (LCAP) is the formal instrument through which local educational agencies (LEAs) translate performance signals into a stated theory of action. Without understanding how DA reshapes that planning process, it is difficult to interpret either subsequent outcome gains or the absence of such gains.

The present study addresses that gap by pairing a regression discontinuity design with systematic extraction of LCAP action and expenditure data. In doing so, it extends the DA literature beyond treatment-effect estimation toward mechanism identification. The study asks not only whether DA matters after the pandemic, but also whether it changes what districts say they intend to do, for which student groups, and with what kinds of resources.

B.2 Equality, equity, and adequacy debates ("money first, then how to spend it")

Debates over school finance have long turned on the relationship between resources and outcomes. Earlier legal and policy disputes focused on equality, understood as equalizing per-pupil expenditures across districts. Later reforms shifted toward equity, meaning more resources for students with greater needs. Over time, those debates increasingly blended into adequacy arguments about whether states provide sufficient resources for schools to help students meet established standards. California's Local Control Funding Formula (LCFF) is firmly situated in this latter equity-oriented tradition: it provides supplemental and concentration funding to districts serving larger shares of low-income students, English learners, and foster youth.

The empirical question beneath these normative debates is whether additional spending produces measurable improvements in student outcomes. Contemporary causal evidence has made the answer harder to dismiss. Most notably, Jackson, Johnson, and Persico (2016) show that court-mandated school finance reforms generated long-run gains in educational attainment, adult earnings, and poverty reduction, with especially large benefits for low-income students. That study is important for the present paper because it strengthens the proposition that resources can matter substantially when they are sustained, targeted, and embedded in school systems long enough to influence student trajectories.

At the same time, the finance literature does not suggest that money operates mechanically. Resources matter through the uses to which they are put. California evidence likewise underscores the importance of local trade-offs in converting dollars into educational opportunities. Rose and colleagues (2004), for example, highlight how school and district budgeting choices reflect constrained decisions about staffing, programs, and priorities rather than straightforward one-to-one translations from revenue to results. In other words, weighted funding is necessary but not sufficient; the strategic conversion of funds into effective services remains the central challenge.

That point makes DA especially important to study. LCFF provides districts with flexibility and additional funding for higher-need students, while DA supplies accountability pressure and support when outcomes remain weak. By combining regression discontinuity estimates of DA's impact with large-scale extraction of LCAP action and expenditure data, this study bridges the autonomy, finance, and accountability literatures. It treats the LCAP not only as a compliance requirement but also as a data source that captures the district's theory of action. In doing so, it advances understanding of how equity-weighted funding and performance-triggered assistance interact within real-world planning systems—and whether that interaction produces resource shifts consistent with evidence-based improvement strategies.

B.3 The Education Production Function and Evidence on High-Impact Interventions

The education production function literature provides a framework for moving from the broad claim that money matters to the more precise question of which uses of money matter most. Spending is not itself the operative educational input; rather, it purchases specific inputs such as smaller classes, more effective teachers, tutoring, leadership capacity, or additional learning time. Those inputs vary in quality and in expected effect size. Research on class size offers a well-known example. Krueger's (1999) analysis of Project STAR provides experimental evidence that smaller classes in the early grades improve achievement, while Angrist and Lavy (1999) reach similar conclusions using a quasi-experimental threshold rule. Together, those studies show that some resource-intensive interventions can produce meaningful academic returns.

Evidence on teacher effects further sharpens the point. Rivkin, Hanushek, and Kain (2005) document substantial variation in teacher effectiveness, and Kane and Staiger (2008) strengthen confidence that measured differences in teacher impact are not merely statistical noise. Chetty, Friedman, and Rockoff (2014) push the implications even further by showing that teacher value-added predicts adult outcomes, including later earnings. From a resource-use perspective, this means that staffing decisions are not simply administrative choices: hiring, assignment, support, and retention policies can alter long-run student trajectories. Related work on compensation suggests that labor-market conditions matter as well. Loeb and Page (2000) show that teacher wages are linked to student outcomes through recruitment and labor-market channels, while Hendricks (2014) finds that higher teacher pay can reduce turnover and improve achievement. For districts, resource shifts affecting salary structures or workforce stability may be consequential, even when they do not appear to be direct instructional interventions.

Recent evidence on targeted supports is especially relevant in the post-pandemic context. Nickow, Oreopoulos, and Quan (2020) synthesize experimental and quasi-experimental evidence showing that tutoring—especially high-dosage tutoring—produces some of the largest and most consistent gains in PreK–12 learning. Nickow (2024) extends that case, arguing that tutoring remains among the most promising scalable interventions for academic recovery. Professional development also matters, but not all forms of professional development are alike. Kraft, Blazar, and Hogan (2018) show that teacher coaching can improve instruction and student achievement, suggesting that sustained job-embedded support operates more like an intervention than a traditional workshop. Leadership similarly matters: Branch, Hanushek, and Rivkin (2012) find meaningful differences in principal effectiveness, and Grissom, Loeb, and Master (2013) show that the content of leaders' time use matters more than a simplistic assumption that more nominally "instructional" time is always better.

Taken together, this literature suggests that districts' action portfolios should not be evaluated as though all categories of spending were equally productive. If DA leads districts to expand tutoring, improve staffing stability, strengthen instructional coaching, refine principal supports, or invest in other high-leverage interventions, subsequent improvement is plausible. If DA instead primarily intensifies compliance activity or diffuses resources across lower-leverage strategies, effects may be muted. This production-function literature, therefore, provides an interpretive framework for the present study's LCAP coding: it helps distinguish between action types that are more plausibly aligned with causal evidence on effectiveness and those that may be less likely to move outcomes.

B.4. Planning and spending decisions by leaders

Even when funding is adequate and the evidence base is relatively clear, outcomes still depend on how organizational actors interpret and implement policy. Research on autonomy is useful here. Steinberg (2014) finds that greater school autonomy can improve performance under certain conditions, and Jackson (2023) argues more broadly that autonomy is most productive when it is paired with organizational capacity, goal clarity, and accountability. These insights map closely onto California's policy architecture: LCFF grants districts substantial fiscal discretion, while DA applies pressure and support when performance problems persist. The practical question is whether districts possess the planning capacity to translate that flexibility into coherent action.

District finance scholars have framed this translation problem directly. Roza and Knight (2022) describe districts as "conversion machines" that turn revenue into school experiences, emphasizing the importance of internal allocation rules, priorities, and implementation routines. Earlier work by Roza and Swartz (2007) on school spending profiles likewise argues for greater transparency in linking dollars to strategy. That framing is especially relevant here because the LCAP can be read as a public statement of how districts propose to make that conversion. In this sense, the present study's large-scale extraction of LCAP actions and planned expenditures functions as a modern extension of the transparency agenda: it makes strategy-linked spending more visible and more comparable across LEAs.

At the same time, California's own implementation literature suggests reasons for caution. Koppich (2018) argues that the LCFF/LCAP system has often produced planning documents that function more as compliance artifacts than as concise strategic tools. Marsh and colleagues (2020) similarly find that civic engagement within LCFF can become procedural rather than genuinely deliberative. Rose and colleagues (2004) add a complementary budgeting insight: even when leaders intend to make strategic choices, they do so under real fiscal and organizational constraints. Together, these studies suggest that planning infrastructure, stakeholder engagement, and budget transparency are not peripheral matters; they mediate whether weighted funding and accountability signals are translated into classroom-level change.

Despite these insights, relatively little empirical work links accountability identification, district planning documents, and action-level expenditure choices within a single design. We know too little about whether districts revise their LCAP goals and spending patterns in response to DA, whether those revisions center the student groups and indicators that triggered intervention, and whether repeated identification is associated with different resource portfolios than one-time identification. By combining a causal design for DA eligibility with action-level analysis of LCAP resource plans, this study helps bridge the autonomy, finance, and planning literatures and clarifies how accountability pressure may—or may not—change district theories of action.

B.5 Conceptual Framework and Expectations

The paper's conceptual framework is straightforward. DA is the treatment, and the LCAP is the district's public theory of action. If DA changes district behavior, that change should first become visible in what districts write and budget: which student groups they name, which indicators they prioritize, whether they emphasize limited or broader responses, and whether their portfolios move toward higher-leverage interventions suggested by the finance and production-function literatures. Only after those shifts occur would one expect any later change in student outcomes.

That logic yields four working expectations. First, DA should increase the salience of the student groups and indicators that triggered identification in the district's LCAP. Second, those shifts are likely to be more incremental than transformative because districts operate within established planning routines, staffing constraints, template requirements, and compliance pressures. Third, districts whose

LCAP portfolios shift more clearly toward evidence-aligned interventions—such as tutoring, targeted academic support, staffing stability, instructional coaching, or well-designed attendance and engagement systems—should be more likely, on average, to show later improvement for focal student groups. Fourth, those relationships should vary by problem type and by local capacity: chronic absenteeism, academic performance, graduation, and support for students with disabilities are unlikely to respond to identical strategies, and autonomy is unlikely to generate improvement where implementation capacity is weak. These expectations guide the empirical analysis that follows.

C. Research Questions and Methods

C.1 Research Questions

1. What impact does identification for Differentiated Assistance have on subsequent student outcomes for marginally eligible districts?

2. How do the planned actions and expenditures recorded in districts' LCAPs differ by DA status, DA history, and the student groups and indicators that triggered identification?

3. To what extent does DA appear to alter districts stated theory of action—that is, the portfolios, scopes, and subgroup targeting districts declare in the LCAP?

4. Are some planned resource configurations more strongly associated with later subgroup improvement than others?

C.2 Impact Analysis

We employed a regression discontinuity design (RDD) to estimate the causal effect of DA eligibility on districts' subsequent student outcomes. The RDD is a quasi-experimental research method that can be used when a cutoff clearly defines access to a treatment; in this case, the performance thresholds used to determine DA eligibility. The RDD model relies on the assumption that the relationship between the eligibility score and the outcome do not differ meaningfully except for access to DA. Comparing these relationships on either side of the eligibility cutoff mimics a randomized controlled trial at the eligibility threshold, with DA eligibility serving as the treatment variable.

The eligibility formula for the 2022 DA assignment year considers performance levels across numerous indicators and student groups, requiring our model to be substantially more complex than a textbook RDD with a single eligibility score and threshold that is common to all units (in this case, school districts). We use a variation of the "binding score" method that allows each district to have a distinct eligibility variable and cutoff, depending on which performance indicators for which student groups are close to the DA-triggering performance level. For each district, there is always a binding score that will either assign LEAs to DA status or not. This binding score is always associated with a specific student group and an indicator (e.g., chronic absenteeism among students with disabilities). As we describe below, we identify the binding score for each LEA in the 2022 assignment year and match the DA assignments to resource allocation and student achievement in the 2022-23, 2023-24, and 2024-25 school years, allowing us to track the impact of DA as it unfolds across school years. For the LCAP portion of the study, the relevant outcome is not audited expenditure alone, but the district's stated planning response: which student groups, indicators, action types, and planned expenditures it chooses to name in the LCAP after DA identification.

C.2.1 DA Eligibility Rules in California

Assignment to DA in California is based on how student groups perform across multiple indicators: ELA, Math, English Learner Progress, Graduation Rate, Chronic Absenteeism, and Suspension Rate. Each indicator is a continuous, district-level aggregation of individual student performance within a specific student group. The continuous indicators are broken up into five status levels: very high, high, medium, low, very low. The 2022 DA assignment year uses very low status to assign DA for ELA, Math, English Learning Progress, and Graduation Rate and very high status to assign DA for Suspension and Chronic Absenteeism Rates. Table 1 lists the relevant cutoffs for the very low and very high status levels for these indicators.

Table 1. DA Assignment Cutoffs by Indicator and Grade Span

Indicator	Status for DA	Cutoff
ELA	Very Low	Grades 3 – 8: -70.1 points or lower Grade 11: -45.1 points or lower
Math	Very Low	Grades 3 – 8: -95.1 points or lower Grade 11: -115.1 points or lower
English Learner Progress	Very Low	34.9% or less making progress towards EL Proficiency
Graduation Rate	Very Low	67.9% or less
Suspension Rate	Very High	Elementary: 6.1% or greater High: 9.1% or greater Unified: 8.1% or greater
Chronic Absent Rate	Very High	20.1% or greater

These indicators are clustered into "priority areas," which serve as the basis for DA identification. Of the state's multiple priority areas, only three meaningfully determine DA status. If a student group has poor enough performance in two priority areas, their district is assigned to DA status. Table 2 provides the eligibility criteria for each priority area.

Table 2. DA Eligibility by Priority Area

LCFF State Priority Area	Differentiated Assistance Criteria
Pupil Achievement (Priority 4)	• **Very Low** Status on both the ELA and Mathematics Academic Performance; • **Very Low** Status on the English Learner Progress Indicator.
Pupil Engagement (Priority 5)	• **Very Low** Status on the Graduation Rate Indicator; or • **Very High** Status on the Chronic Absenteeism Indicator.
School Climate (Priority 6)	• **Very High** Status on the Suspension Rate Indicator.

C.2.2 Determining the "Focal" (Binding) Score: Focal Groups and Focal Indicators

In these analyses, the student group that led to DA eligibility (or the group that brought the district closest to DA eligibility) is the "focal" group. The focal group is the one whose second-lowest indicator score determines DA eligibility. The second-lowest indicator score, rather than the lowest, determines eligibility because if the second-lowest indicator score were to improve enough, then the district would only have one low-performance area, and two areas are needed for DA eligibility. This indicator, which determines DA eligibility, is referred to as the "focal" indicator. We refer to the focal indicator for the focal group as the "focal score." It is akin to the binding score in the RDD literature. Every district has a focal score, whether that district is assigned to DA or not.

The focal score in each LEA is determined in a multi-step process: center and standardize each indicator for each student group, rank indicators within priority areas by LEA and student group, rank priority areas by student group within LEAs. We summarize each step below.

1. **Center and standardize each indicator:** We center each student group's indicator at the relevant threshold (see Table 1 above), then divide by the statewide standard deviation of that indicator. For suspension and chronic absenteeism, where higher levels indicate

normatively worse performance, we multiply the centered, standardized indicator by negative one.

2. **Rank indicators within priority areas**: Within each priority area, only one indicator needs to be very low (or very high) for the priority area to count toward DA assignment for each student group. Priority area 6 contains only the suspension indicator, so we use the suspension indicator as the priority 6 indicator. For priority area 5, we use the worse (within student group within LEA) of either graduation rate or chronic absenteeism rate as the priority 5 indicator. Priority area 4 is slightly more complicated. For non-English learners, the priority area 4 indicator is their *better* of either Math or ELA because both need to be very low to count toward DA. For English learners, the priority area 4 indicator is worse of either their English learner progress indicator or their higher math or ELA indicator. By way of example, if Math were to be the indicator that counts in priority 4, English learners in a district would have to have a centered, standardized math score that is higher than their ELA score and lower than their English progress score.

3. **Rank priority areas by student group within LEAs**: At this step, each student group within each LEA has three indicators – the one that counts for each priority area. To determine the focal group, indicator, and score for each LEA, we first rank the indicators within student group and LEAs to find each group's lowest and second lowest indicator, then compare across groups within LEAs to find the student group who has the lowest second-lowest indicator. Within each LEA, the student group with the lowest second-lowest indicator is the "focal group" and their second-lowest indicator is the "focal score" (i.e. the binding score) for that district. At the district level, the indicator associated with the focal score is the "focal indicator."

This coding scheme allows us to ask several questions about the impact of DA on aggregate LEA performance. Most importantly, the focal score unlocks the ability to run an RDD and determine the impact of DA on district performance. Additionally, the definitions of focal group and focal indicator allow us to understand the impact of DA on focal group and focal indicator performance in general, rather than dividing the analysis into student group by indicator segments that would lack the statistical power to yield meaningful insights (e.g. the impact of DA on Black students who were eligible due to suspension rate, the impact of DA on English learners who were eligible due to Math, etc.).

C.2.3 Limitations of the RDD

While an RDD is able to yield causal inference about the impact of DA, the approach comes with limitations, the most important of which is that the impact of DA can only be calculated for "marginally" eligible districts. The analysis relies on the subset of districts with a single student group whose indicator status level in the 2022 assignment year is low enough that their indicator change level will determine whether the entire district is eligible for DA. The effect of DA cannot be calculated for districts with multiple student groups whose performance across multiple indicators makes them eligible for DA, nor for high-performing districts whose scores are far above the DA eligibility threshold.

RDD's are also subject to greater statistical uncertainty than randomized control trials. As with any statistical procedure, the effect sizes reported here are subject to inherent uncertainty; they could be somewhat larger or smaller. Compounding this limitation is that, although the number of students in the state is in the millions, the relevant "sample size" for assessing the impact of DA is merely the number of marginally eligible districts (only a few hundred).

C.4 LCAP Data Extraction and Analysis

C.4.1 Data Sources, Analytic Sample, Cleaning, and De-duplication

To document patterns of LEAs proposed actions and examine whether Differentiated Assistance alters patterns of resource use, we assembled an AI-assisted action-level file from the 2023–24 and 2024–25 LCAP master files. The extraction pipeline combines document retrieval from COE and LEA websites, PDF processing, and structured prompting of large language models to recover quantitative and categorical information from narrative plan text.

The merged analytic file includes 953 LEAs, 1,689 LEA-years, and 32,492 de-duplicated action line items with usable coding fields. Across those rows, LEAs report $51.94 billion in planned action expenditures. We merge the action file to administrative LEA metadata (district type, enrollment, unduplicated pupil percentage, and DA history) and to SACS financial totals using the California-District-School (CDS) code. This merged structure allows us to compare planned action portfolios across DA and non-DA district-years while scaling action-level spending against the broader LEA financial context.

The two-yearly action files contribute 18,107 actions in 2023–24 and 14,385 actions in 2024–25. In dollar terms, the action tables sum to $35.40 billion in 2023–24 and $16.54 billion in 2024–25. Because the statewide files include both identified and non-identified LEAs, DA enters the statistical models as a current or historical treatment characteristic rather than as a sample restriction.

Three auxiliary data sources support linkage and interpretation: the statewide DA assistance-status extracts, which attach CDS codes and DA year; SACS expenditure totals, which allow us to express planned action funds as a share of total LEA spending; and the California School Accounting Manual (CSAM), helps interpret the goal, function, and object codes embedded in California's finance system.

LCAP action rows were standardized to a common schema and cleaned before analysis. Financial columns (Total Funds and funding source amounts) were converted from formatted strings to numeric values, and categorical fields were standardized (e.g., Contributing designation normalized to binary; scope standardized to LEA-wide / Schoolwide / Limited). To reduce inflation of counts from repeated reporting, actions were de-duplicated to a "unique action" unit (one record per distinct action line item within an LEA), while retaining links to student group and indicator tags for cross-tab analyses.

LEAs were matched to CDS codes via exact and fuzzy matching on LEA names. The design is sharp for administrative eligibility, but fuzzy for realized support intensity. That is, crossing the binding threshold deterministically changes eligibility status for DA. In that sense, the assignment rule is sharp. But the amount of assistance actually received, the quality of county support, and the local degree of LCAP revision are all downstream and variable. So, the causal design is sharp at assignment, but substantively fuzzy in treatment dosage.

Using the current dataset, the year-specific LEA match rate is extremely high. For 2023–24, 709 of 713 LEAs matched to year-specific DA master records (99.4%). For 2024–25, 970 of 974 LEAs matched (99.6%). Using CDS-only matching regardless of whether the year-specific assistance field is populated, the rates rise to 712 of 713 and 973 of 974, respectively. The remaining misses are concentrated in a tiny set of very small or charter-like cases, not a broad failure of linkage. CDS codes enable merging to SACS totals and DA metadata (district type, UPP%, DA year/run length). All spending ratios and LEA-level comparisons use matched CDS codes.

C.4.2 Sample and DA Identification Cycles

The study population comprises all LEAs in California that were eligible for DA identification across the following Dashboard release cycles post-COVID: 2022, 2023, and 2024, and had accessible LCAPs. DA identification occurs in the winter of each calendar year, i.e., between November and February, based on the availability of California School Dashboard results. The corresponding LCAP treatment windows are structured as follows: the first treatment year begins in the school year approximately 6 months after identification (e.g., a December 2022 identification corresponds to a 2022–23 SY first-treatment LCAP), and the lagging treatment year extends to 18 months post-identification. A district identified for DA in December of year *t* first has an opportunity to revise its next LCAP in the spring and summer of year *t+1*. We therefore treat the LCAP adopted in June of year *t+1* as the first-treatment planning response. The LCAP adopted in June of year *t+2* is treated as the lagged-treatment response, because it reflects a second planning cycle under the shadow of the prior identification. For example, a district identified in December 2022 first responds in the June 2023 LCAP for 2023–24, and then June 2024 LCAP, 2024–25.

Our analytic design categorizes LEAs into three groups based on their DA history: (a) never identified for DA during the study period, (b) identified for DA in a single year only, and (c) identified for DA in two or more consecutive years. This categorization addresses a key measurement concern: districts with persistent DA identification may exhibit different resource allocation behaviors than those with a single identification episode, and pooling them may obscure treatment effects.

C.4.3 LCAP Document Retrieval, Processing, and Auditing Sample

LCAP documents were retrieved from individual COE and LEA websites as PDFs. Because California does not maintain a centralized, machine-readable repository of LCAP data, retrieval required targeted web searches and direct navigation of county and district websites. Documents were collected for the LCAP plan years corresponding to each DA identification cycle in which the file was available and accessible. Not all LCAPs were accessible in each of the school years.

Once retrieved, each LCAP PDF was processed through a structured extraction protocol using a large language model. The prompt architecture was designed to elicit the same small set of outputs from each plan: the actions explicitly dedicated to or clearly referencing the student groups that triggered DA, the budgeted expenditures associated with those individual actions, the student-group and indicator tags attached to each action, cross-tabulations of spending by group and indicator when the plan allowed it, and the total LCAP-reported expenditures for the LEA. In the case of LEAs that were in the category of never DA, the same outputs were generated from the LCAP except actions were extracted on the basis of the lowest performing student group for that LEA. This structured prompting approach addresses a basic challenge in LCAP analysis: the documents are narrative-heavy, inconsistently formatted across LEAs, and often exceed 100 pages. Manual coding would be prohibitively expensive at the scale required here. The LLM pipeline makes statewide extraction feasible while preserving the ability to audit individual cases against the underlying PDF.

We employed a sampling technique to manually check the quality of the LLM's extraction of the LCAP PDFs. Specifically, we randomly selected a 10% sample of the total LCAPs available in LEA-years (n=96 LEAs). We then compared the LLM’s extracted output data to the actual data in the LCAP. Across the review, we compared 1,298 action lines. Of those lines, there were 51 that contained errors, but none that obscured the intended action by the LEA. Examples of errors include word misspellings, cutting off the end of a sentence by a few sentences, and mis-categorizing an action description as the action title.

C.4.4 Thematic Coding of LCAP Actions

Because LCAP action descriptions are not standardized across LEAs, we developed a thematic action taxonomy to enable comparable analysis across districts. Each action line item, defined by its title and description, was assigned to one of 39 intervention categories representing recurrent LCAP action types, such as English Learner Development, Professional Development, Attendance, Tutoring, Counseling, Mental Health/Social-Emotional Learning, and Special Education. Coding was implemented using a rule-based text classification procedure that employed regular expressions, keyword patterns, and iterative review of action text. Rules were refined over multiple passes to refine existing codes and reduce the size of the residual classified category by reassigning vague “support” language into more substantively meaningful categories when the text permitted. Residual “other” actions reflect blank or near-blank descriptions, boilerplate language without discernible intervention content, or descriptions too generic to classify reliably. See Appendix 1 for the codebook.

C.4.5 Primary and Secondary Coding

A single thematic code was often insufficient to characterize complex LCAP actions. We therefore added a second coding layer, using the same underlying taxonomy, in which each action received both a primary and a secondary category. The primary code captures the dominant intervention logic of the action, while the secondary code captures the most important adjacent feature, co-occurring support, or implementation mechanism. We hand-coded ~4,000 action lines to create a calibration set and then used the same LLM-assisted extension procedures to code the remaining actions.

Following the LLM-assisted extension procedures to code all actions with a secondary category we conducted various tests for fit and coverage. The text-fit-IDF cosine similarity showed a mean improvement (combined - original) of +0.0212 (combined=0.0772, original=0.0560) and a significant, positive improvement ($p < 0.001$). The codebook-term coverage metric measures the share of unique action unigrams plus bigrams that appear in the union of selected codebook terms. The mean improvement (combined - original) for this measure was +0.0504 (combined=0.1001, original=0.0497) and showed a significant, positive improvement ($p < 0.001$).

This dual-category approach is analytically important because it captures intervention bundles that a single-code system would obscure. In the current file, for example, recurring combinations such as English Learner Development | Professional Development and Mental Health/SEL | Counseling/Social Work reveal that districts frequently budget actions as composite strategies rather than as single-purpose interventions.

C.4.6 Student Group and Indicator Tagging

Actions were linked to student groups and DA indicators using two sources of information. First, when actions were marked as Contributing, we used structured LCAP fields such as student group, scope, and location. Second, we used text-based tagging from action descriptions when explicit references appeared to student groups or indicators, such as English learners, students experiencing homelessness, students with disabilities, chronic absenteeism, ELA, mathematics, graduation, or suspension. This combined approach was necessary because the formal LCAP fields do not capture all subgroup- or indicator-relevant information, and because some actions clearly address a focal group or problem in narrative text without naming it in the structured fields.

Table 3. Descriptive Statistics on LCAP Actions and Planned Spending

Descriptor		Action Description (#)	Actions (%) of Total	Planned Spending ($)	Planned Spending (%) of Total
Year					
	2023-24	19,229	57%	$38.909B	69%
	2024-25	14,744	43%	$17.259B	31%
Contributing					
	Yes	22,158	65%	$30.926B	55%
	No	11,815	35%	$25.240B	45%
Contributing	**(Yes)**				
	English Learners	18,243	54%	$26.491B	47%
	Low-Income	16,348	48%	$21.742B	39%
	Foster Youth	17,053	50%	$28.339B	51%
Scope					
	Limited	2,440	7%	$1.269B	2%
	LEA-wide	17,171	51%	$22.225B	40%
	School-wide	3,352	10%	$4.913B	9%
Goal					

Descriptor		Action Description (#)	Actions (%) of Total	Planned Spending ($)	Planned Spending (%) of Total
	Goal 1	12,745	38%	$31.426B	56%
	Goal 2	9,507	28%	$10.785B	19%
	Goal 3	6,632	20%	$7.052B	13%
	Goal 4	2,899	9%	$3.921B	7%
Planned Spending					
	LCFF	24,902	73%	$40.406	72%
	Federal	4,273	13%	$2.016B	4%
	Other State	5,548	16%	$4.927B	9%
	Local	1,350	4%	$1.119B	2%

Notes: Rows under 'Contributing (=Yes)' and 'Planned Spending' are not mutually exclusive: a single action may name multiple UPC groups and may draw from multiple funding sources.

C.4.7 Financial Linkage and CSAM Alignment

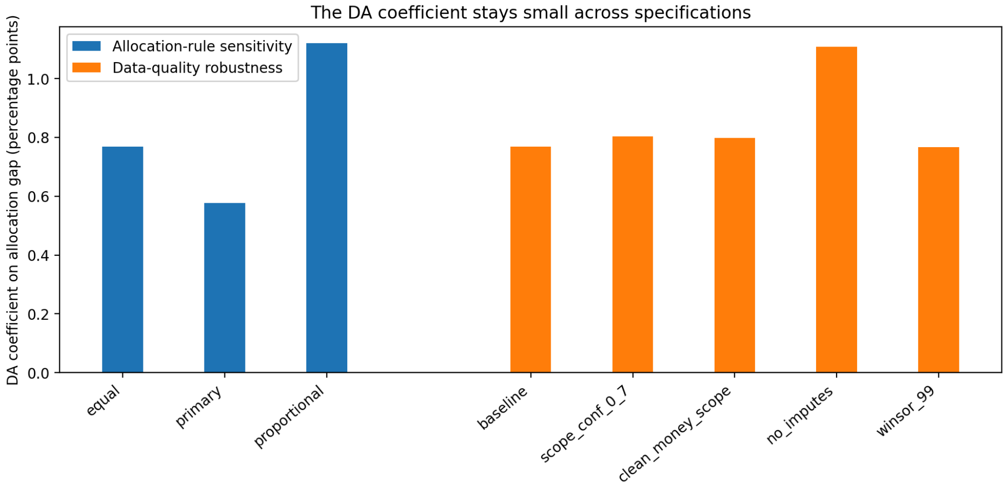
To contextualize action-level spending, we merged LEA-level SACS totals to compute LCAP action funds as a share of total LEA expenditures. This ratio is interpreted as the share of an LEA's overall spending that is explicitly itemized in the DA-relevant action set, recognizing that LCAPs are planning documents and do not provide a full accounting of all district expenditures. We also used CSAM definitions to interpret the accounting structure of California education finance. Goal codes identify the instructional or service purpose, function codes identify the activity, and object codes identify the expenditure type. For each thematic action category, the codebook records the typical CSAM goal-function-object pattern expected for that intervention type. This allows the analysis to connect district planning language to the state's accounting architecture while recognizing that CSAM categories are much broader than the intervention bundles revealed by the dual-category taxonomy.

To anchor the LCAP analysis in audited district spending, we merged the statewide DA file to LEA-year SACS operating expenditure records and constructed five broad expenditure cuts: direct instruction, pupil services, special education, administration plus plant, and purchased services. This linkage allows us to ask whether districts identified for Differentiated Assistance differ from other districts not only in what they say in the LCAP, but also in the structure of their realized spending.

C.4.8 Measurement-Error and Allocation-Rule Robustness Checks

Because the action file is derived from narrative PDFs and includes imputed fields, we did not assume perfect extraction. Instead, we subjected the subgroup-gap models to a series of measurement-error robustness checks.

Figure 2. The DA coefficient stays small across most allocation rules and robustness checks.



Specifically, we re-estimated the models under progressively stricter screens: a baseline specification, a high-confidence-scope subset, a clean-money-plus-scope subset, a no-imputes subset, and a winsorized specification. Across these specifications, the DA coefficient remained small, ranging from 0.77 to 1.11 percentage points, and statistically weak, while model fit remained stable (R^2 = 0.556 to 0.571). This pattern indicates that the main descriptive conclusions are not being driven by a small number of obviously noisy rows.

Table 4. Specification for measurement error and results

Specification	DA coefficient (pp)	p-value	R-squared
baseline	0.77	0.245	0.556
scope_conf_0_7	0.80	0.226	0.558
clean_money_scope	0.80	0.231	0.561
no_imputes	1.11	0.099	0.571
winsor_99	0.77	0.245	0.557

A second, conceptually distinct, robustness problem concerns multi-group allocation rules. Many LCAP actions name more than one student group, but the document does not reveal the within-row apportionment of funds across those groups. We therefore estimated the student group-gap models under three alternative allocation rules:

- Equally, i.e., the associated action has two student groups, and the budgeted expenditure is $100, therefore each student group is assigned $50 for that action.
- Primary, i.e., the associated action has two student groups, and the budgeted expenditure is $100; therefore, the dominant student group is assigned $100, and the secondary student group is assigned $0.
- Proportional to group enrollment, i.e., the association action has two student groups, the budgeted expenditures are $100, and the primary student group's proportion of total enrollment is 75%, and the secondary student group's proportion of total enrollment is 25%; therefore, the primary student group is assigned $75, and the secondary student group is assigned $25.

The table below shows the DA coefficient and the 2024-25 year coefficients.

Table 5. Recurring district portfolios and how targeted they look

Allocation rule	DA coefficient (pp)
equal	0.8
primary	0.6
proportional	1.1

The DA coefficient itself remains small across all three rules: 0.8 percentage points under equal split, 0.6 under primary-group-only-allocation, and 1.1 under proportional allocation, none of which are statistically significant at conventional levels.

A related source of uncertainty lies upstream of the LCAP allocation problem itself. California's accountability system counts students independently within each qualifying student group, even when the same student carries multiple demographic or program flags. To assess whether overlapping student-group architecture introduces additional measurement error beyond the allocation-rule problem, we construct an LEA-year overlap proxy using the observed set of DA-triggering student groups in each LEA-year and pairwise overlap priors drawn from the companion trigger analysis memo.

The average pairwise overlap score (APO) summarizes the expected degree of overlap across the triggered groups in a given LEA-year. We then translate the nominal number of triggered groups into an effective distinct group count (EDG), which discounts the raw trigger count in proportion to estimated overlap, and define duplication share as one minus the ratio of EDG to the nominal trigger count. Because exact student-level intersections are not observed in the present dataset, these measures are used as memo-based sensitivity corrections and bounded proxies for duplication rather than as exact student-level overlap estimates. Unless otherwise noted, results reported below use the central overlap specification, with conservative and upper specifications used as bounds.

C.4.10 Statistical Analyses

Analyses proceed in two stages. First, we describe the distribution of action types and spending using frequencies, totals, and cross-tabulations by district type, student group, DA indicator, contributing status, and scope. We visualize these relationships using bar charts and heatmaps, and we replicate the core figures used for internal reporting (Appendix Figures A1–A8).

Second, we implement a set of complementary multivariate and unsupervised regression analyses to characterize predictability and structure in district LCAP text. These include a multiclass classification model that tests how far observable LEA characteristics predict action-code choice; correspondence analysis to map associations between student groups and action codes; concentration measures such as the Herfindahl–Hirschman Index and Shannon entropy to summarize how narrowly or diffusely districts distribute action spending; Tobit and ordered logistic models to examine evidence strength and strong-evidence spending shares; and a co-occurrence network that identifies recurring bundles of actions within LEA portfolios as well as co-targeting network analysis was used. Supplemental models then extend this framework to event-study, outcome-linkage, evidence-alignment, thematic, funding-decomposition, co-targeting, and subgroup-heterogeneity questions.

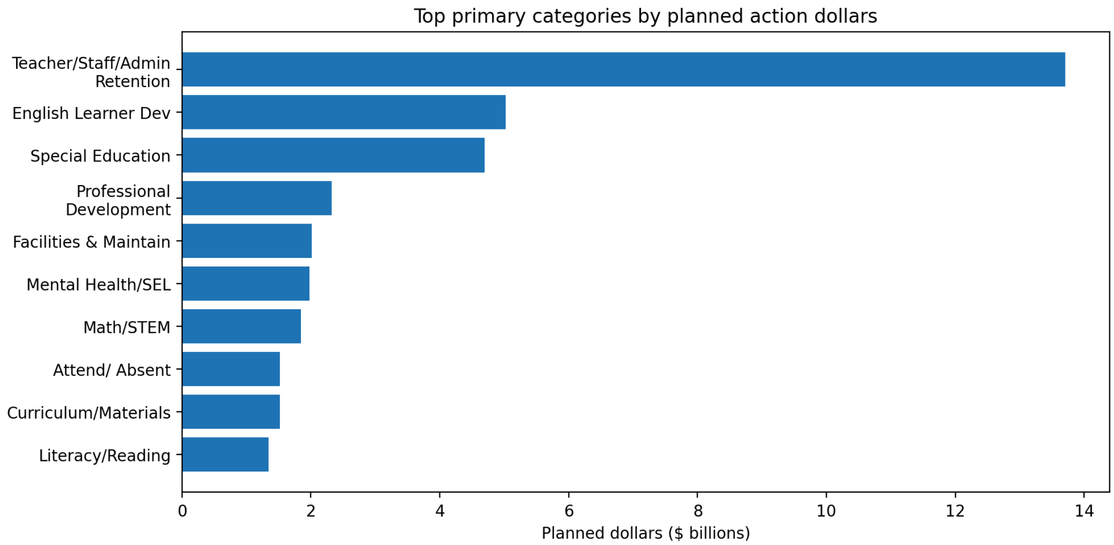
D. Findings

Because the LCAP analysis is best understood as evidence of districts' stated planning responses rather than audited expenditures, the findings below shift from a broad descriptive structure to narrower mechanism tests. We first examine what LCAP plans, for DA and non-DA districts, look like in the aggregate; we then ask how those plans vary by evidence strength, contributing status, scope, subgroup visibility, and district context; and finally, we use the supplemental models to test whether some planning responses appear more tightly connected to later improvement than others.

D.1 LEA's planned actions are organized around a small set of recurring categories, more than one student group is often targeted, and dollars are highly concentrated.

Across the merged 2023–24 and 2024–25 action files, the study observes 32,492 de-duplicated actions across 953 LEAs and 1,689 LEA-years, totaling $51.94 billion in planned action expenditures. The distribution is highly concentrated. By planned dollars, the largest categories are Teacher/Staff/Admin Retention, English Learner Development, and Special Education, with Professional Development, Facilities & Maintenance, Mental Health/SEL, Math/STEM, Attend/Absent, Curriculum/Materials, and Literacy/Reading forming a second tier (Figure 3). That ranking matters because it shows that the action file is not dominated only by narrowly targeted programs; some of the largest planned dollars sit in staffing and system-support categories. At the same time, districts repeatedly pair targeted categories with broader infrastructure.

Figure 3. Top primary categories by planned action dollars



We also look at actual spending in the year following DA identification to understand any relationship of planned investments. In FY 2024-25, multi-year DA districts devoted smaller shares of operating expenditure to administration, plant, and purchased services, and materially larger shares to pupil services and special education than never-DA districts. The strongest adjusted associations are for special education and pupil services. Relative to non-DA districts, current DA status is associated with a 1.88-percentage-point higher special-education share and a 0.71-percentage-point higher pupil-services share. Restricting the treatment to districts whose DA trigger included students with disabilities produces an even larger special-education coefficient of 2.09 points. By contrast, the direct-instruction, administration-plus-plant, and purchased-services coefficients are small and statistically weak.

Plans also rely primarily on broad scope and LCFF financing. Figure 4 shows that LEA-wide actions dominate in both years, with smaller schoolwide and limited shares, and Figure 5 shows LCFF as the largest funding stream across both fiscal years. Figure 6 then shows that LCFF carries most named support for English Learners, Foster Youth, Homeless students, and Low Income students, whereas Students with Disabilities depend much more heavily on other state/local funds. Together, the figures indicate that the LCAP file is concentrated not only by category, but also by scope and funding source.

Figure 4. Scope of actions by fiscal year.

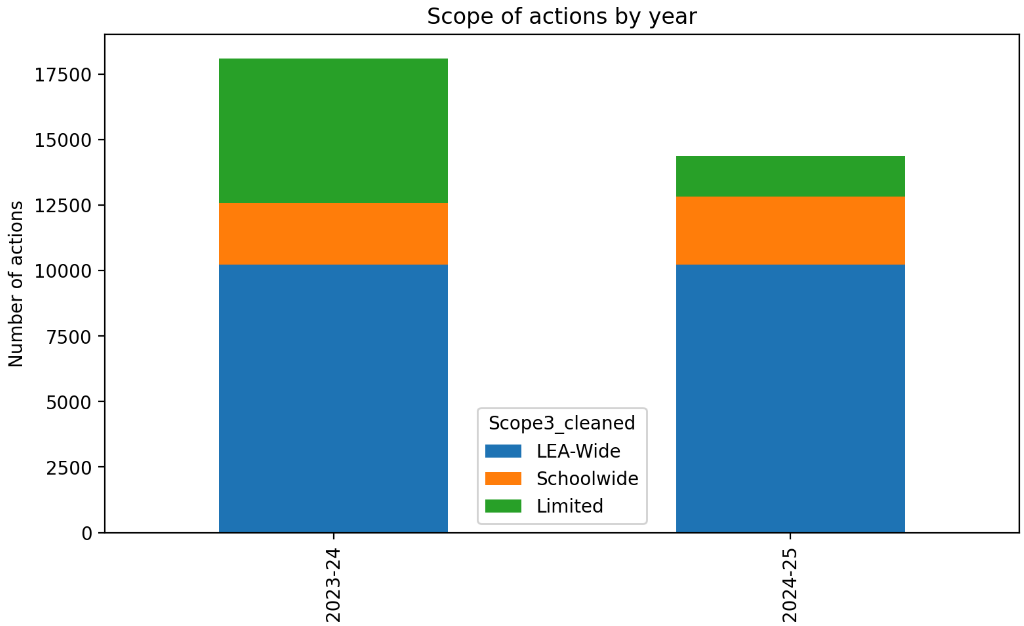
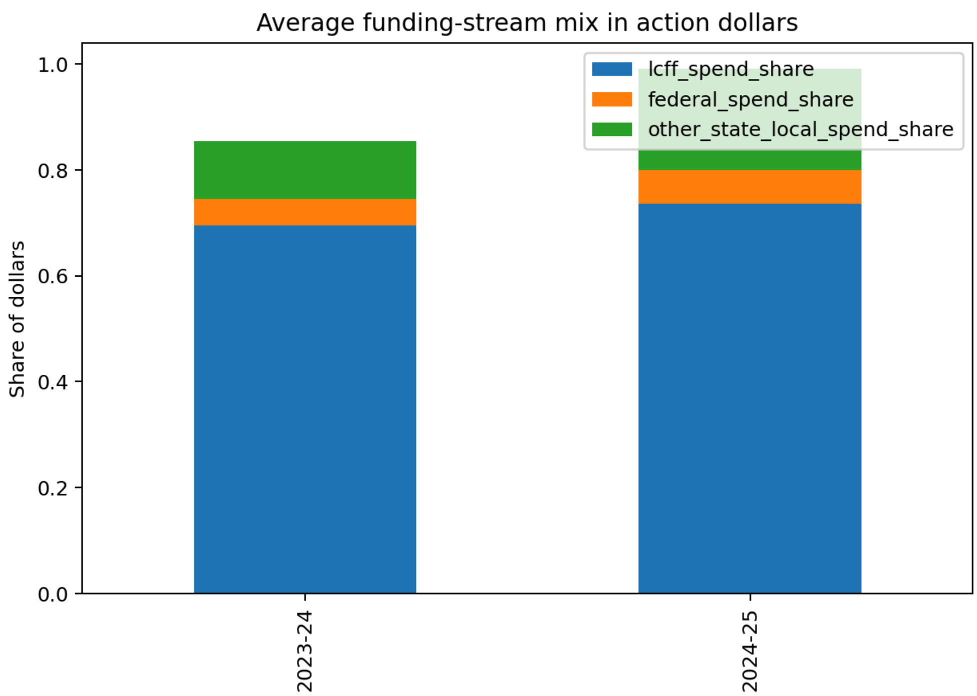
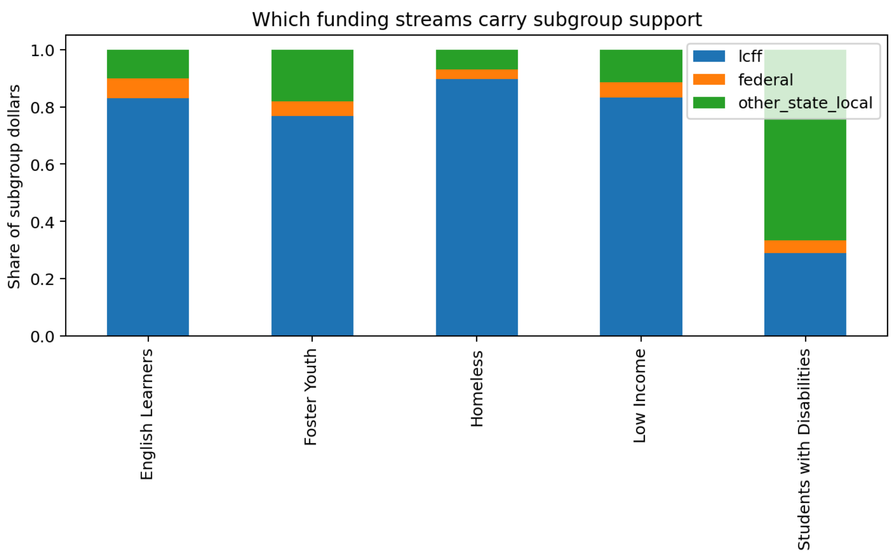


Figure 5. Funding-source composition of action dollars



Looking at funding decomposition by student groups tells a slightly different story. Funding decomposition shows that most student group support is carried by LCFF, but federal and other state/local funds still matter. Across the unduplicated student groups and homeless students, they show a substantial LCFF investment, in excess of 75%, as compared to students with disabilities, in which other state and local share makes up over 60% of the budgeted spending. This may reflect spending rules in which a large portion of unrestricted general fund dollars are transferred to the special education program to make support available to students as agreed upon in their individual education plans (IEPs).

Figure 6. Funding stream composition by student group



D.2 LEA action portfolios for the lowest performing student groups sort into recurring multi-dimensional support clusters, and portfolio make-up matters more than DA status alone.

Districts do not write wholly idiosyncratic plans. The cluster analysis sorts LEA-years into four recurring portfolio types: English Learner Development + Mental Health/SEL (1,122 LEA-years), Teacher/Staff/Admin Retention + Facilities (279), Foster Youth/Homeless + English Learner Development (174), and Special Education + Counseling/Social Work (114) (Table 6). The Foster Youth/Homeless plus English Learner Development cluster is the most explicitly targeted, with 84.7 percent of planned dollars attached to targeted actions, while the English Learner Development plus Mental Health/SEL cluster is similarly targeted at 74.2 percent. By contrast, the Teacher/Staff/Admin Retention plus Facilities cluster devotes 47.6 percent of dollars to targeted actions, and the Special Education plus Counseling/Social Work cluster only 36.0 percent. The corresponding limited-scope shares are much smaller, which underscores that districts often encode support through broad or blended portfolios rather than through narrowly bounded action sets (Figure 7).

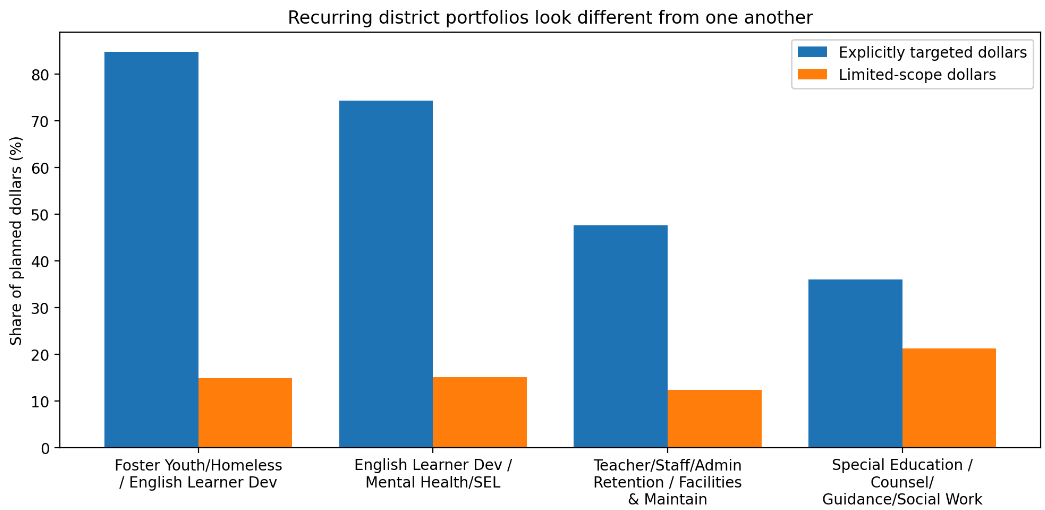
Table 6. Most common portfolio types across LEAs, targeted dollars, limited-scope dollars, average mismatch

Portfolio type	LEA-years	Targeted dollars (%)	Limited-scope dollars (%)	Average mismatch (%)
English Learner Dev + Mental Health/SEL	1122	74.2	15.0	27.9
Teacher/Staff/Admin Retention + Facilities	279	47.6	12.3	26.6
Foster Youth/Homeless + English Learner Dev	174	84.7	14.9	26.5
Special Education + Counselor/Social Worker	114	36.0	21.2	31.3

A separate multiclass prediction model – essentially, do LEA characteristics predict action categories -- reinforces the point that districts are not easily sorted by observable structure alone. Predicting action code from LEA characteristics yields only 17.1 percent accuracy (weighted F1=0.082). The story is therefore not one of district uniqueness, but of recurring multi-dimensional support portfolios.

The regression models tell the same story. Relative to the English Learner Development plus Mental Health/SEL multi-dimensional support cluster, the Foster Youth/Homeless plus English Learner Development cluster devotes 6.7 percentage points more of its dollars to targeted actions (coef = 0.0667, p = 0.002). The Teacher/Staff/Admin Retention plus Facilities cluster devotes 25.0 points less (coef = -0.2497, p < 0.001), and the Special Education plus Counseling/Social Work cluster 37.2 points less (coef = -0.3723, p < 0.001). In the limited-scope model, the Special Education plus Counseling/Social Work cluster is 7.4 points more likely than the reference cluster to place dollars in limited actions (coef = 0.0739, p = 0.003), while the staffing/facilities cluster is 5.6 points less likely to do so (coef = -0.0561, p < 0.001). Figure 8 illustrates the differences between explicitly targeted dollars and limited-scope dollars.

Figure 7. Recurring district portfolios and how targeted they look



The takeaway is that the way an LEA builds its plan matters a great deal. Some portfolios are much more likely to spell out who the money is for, while others bury support inside broader system investments.

This result aligns with Hibel and Beberman's statewide parsing study, which found extensive duplication in LCAP goal language and a relatively small set of recurrent action types across California LEAs. In their statewide 2024–25 corpus, 36.8 percent of district and charter goals were exact or near-exact duplicates, and only 7.9 percent of goals included an explicit numeric target. Our contribution is to show that once the focus is narrowed to DA, the same regularity carries over into how districts describe and fund their intended response. The relevant question is not whether DA districts write wholly different plans, but which recurring portfolios they emphasize, for whom, and with what scope.

D.2.1 Once portfolio structure is considered, DA status by itself is small and often statistically weak.

Once portfolio structure is held constant, DA status by itself is modest. In the persistence model, the one-year DA coefficient is 0.0476 ($p = 0.113$) and the multi-year coefficient is 0.0400 ($p = 0.223$), while the 2024–25 year effect is larger and statistically significant (Table 7). The practical implication is that the more important planning difference is not DA history alone, but the kind of portfolio a district builds and the way that portfolio encodes scope, subgroup visibility, and targeting.

Table 7. Targeted-share persistence results by DA history, including limited share and average mismatch

Year	DA history	Targeted share (%)	Limited share (%)	Average mismatch (%)
2023-24	multi-year	69.1	25.5	26.9
2023-24	never	49.6	22.1	27.2
2023-24	one-year	66.1	27.0	30.1
2024-25	multi-year	76.6	7.1	26.8
2024-25	never	62.1	7.6	30.6
2024-25	one-year	70.3	9.4	28.0

The one-year DA coefficient is 0.0476 ($p = 0.113$) and the multi-year coefficient is 0.0400 ($p = 0.223$), while the 2024–25 year effect is larger and statistically significant (0.0437, $p = 0.006$). In the limited-scope model, persistence again contributes little independently, whereas the 2024–25 year effect is large and negative (-0.1415, $p < 0.001$). The implication is not that DA is irrelevant. It is the planning signal associated with DA that is mediated by portfolio design, scope choice, and subgroup visibility, rather than appearing as a large, stand-alone DA coefficient.

D.3. Student group-specific tailoring and resource targeting are weaker than the policy design might suggest

Student-group-specific tailoring is real, but it is much less precise than the policy design might suggest. Under the updated single-group-plus-hybrid allocation backbone, three findings are clearest. First, English Learners remain above their student share under every rule tested in 2024–25. Second, students experiencing homelessness remain below their student share under every rule. Third, Low Income students are the most rule-sensitive case: their apparent gap changes direction depending on how multi-group actions are apportioned. Taken together, the results suggest that subgroup targeting is visible in the LCAPs, but a large share of that targeting remains embedded in bundled actions that blur the ultimate beneficiary.

This is the core reason the current paper should not describe Low Income students as stably under-targeted. The more defensible statement is that English Learners are the strongest robust positive descriptive result, homelessness is the strongest robust negative result, and Low Income remains substantively ambiguous because so many actions bundle that group with others.

If DA operated as a tightly targeted improvement mechanism, we would expect triggered indicators and student groups to map onto comparatively distinct intervention sets. That is not what the action-level evidence shows. English Learner Development is the leading category for every major indicator, including chronic absenteeism, ELA, mathematics, graduation, suspension, EL progress, college and career readiness, and local indicators. Correspondence analysis points in the same direction: the first two dimensions explain 30% and 26% of the inertia, but most student groups and action codes still cluster near the origin, consistent with weak specialization. Districts name focal groups and problems, but they often respond through a common repertoire of cross-cutting strategies rather than sharply differentiated indicator-specific interventions.

Here, the connection to Hibel and Beberman is especially useful. Their statewide analysis shows substantial goal duplication, weak measurability, and repeated action structures across LEAs, including duplication that clusters within counties. Those findings help explain why indicator-specific tailoring may be muted in the DA subset. The LCAP is asked to do many things at once—planning, communication, and accountability—and the form itself encourages districts to translate varied problems into a relatively stable set of program categories.

A second reason subgroup-specific tailoring appears weaker than the policy design might suggest is that many LCAP actions name more than one student group, while the plans do not reveal how dollars are divided within those bundled actions. Following the logic used in prior LCFF targeting work, we therefore treat subgroup attribution as an allocation problem rather than as an observed fact. In the main paper, we rely on a cleaner backbone that combines single-group actions, where the beneficiary is directly observed, with a hybrid rule for bundled actions that assigns 50 percent of the action to the listed primary student group and allocates the remaining 50 percent across all listed groups using year-specific district enrollment shares. We then compare those estimates to appendix bounds that use equal split, primary-only, and proportional allocation rules. This approach is preferable to any single deterministic split because it anchors the main text in the most defensible observed cases while still showing how much the subgroup results move when bundled actions are treated differently.

D.3.1 Student group visibility and resource gaps are uneven

The clearest reason subgroup targeting appears uneven is that the formal LCAP beneficiary fields capture far fewer student groups than districts actually mention in their action narratives. The strongest examples are Students with Disabilities and Homeless students. Students with Disabilities appear in action text in 61.3 percent of district-year observations but in the formal field in only 8.7 percent, producing a masked rate of 53.6 percent. Homeless students show the same pattern: 36.1 percent narrative visibility versus 2.6 percent formal visibility, for a 34.0 percent masked rate. In other words, some of the groups that districts appear to be discussing are materially under-recorded in the structured fields.

The regression results reinforce that interpretation. A DA trigger is associated with about 12.8 percentage points more narrative visibility but only 2.3 points more formal-field visibility; conditional on being named, a DA trigger is associated with about 2.4 points more LCAP dollar share. Accountability pressure, then, appears to increase what districts say in the action narrative much more than what they encode in the structured beneficiary field.

The practical implication is that subgroup visibility in the LCAP is partly a planning issue and partly a reporting issue. English Learners and Low Income students are comparatively legible because the template is organized around unduplicated-pupil logic. By contrast, Students with Disabilities, Homeless students, and some racial or ethnic student groups are more likely to be visible in narrative text than in the structured fields. Those groups should therefore be treated as partially masked rather than simply absent.

Table 8. Masking rates for various student groups

Case	Narrative visibility (%)	Formal-field visibility (%)	Masked rate (%)	Interpretation
Students with Disabilities	61.3	8.7	53.6	Strongest example of formal under-recording.
Homeless students	36.1	2.6	34.0	Second clearest masking case; visibility problem begins before dollars.
DA trigger effect	≈12.8 points	≈2.3 points	—	DA increases narrative visibility much more than formal visibility.
Condition being named	—	—	—	DA trigger is associated with ≈2.4 points more LCAP dollar share.

D.4 Action categories, action portfolio concentration, and Contributing designation choices explain LEA's intention for targeted versus diffuse approaches

D.4.1 Some action types are more likely than others to be written as limited or contributing

The interaction models show that DA does not shift all action types in the same direction. Instead, it changes how some categories are encoded in the plan. In the limited-scope model, English Learner Development carries a strong positive baseline association with limited scope (coef = 0.3423, $p < 0.001$), but the DA × English Learner Development interaction is negative and statistically strong (-0.1255, $p < 0.001$). By contrast, the DA × Special Education interaction is positive (0.1130, $p = 0.002$), and the DA × Facilities interaction is negative (-0.0602, $p = 0.037$). In the contributing-action model, DA is associated with lower contributing probabilities for English Learner Development (-0.1133, $p < 0.001$), Foster Youth/Homeless (-0.0966, $p = 0.043$), Professional Development (-0.0891, $p = 0.007$), and Counseling/Social Work (-0.0802, $p = 0.043$).

Table 9. Action type and results of the interaction models test

Action type	What the model says
English Learner Development	Much more likely to be written as limited and contributing.
Foster Youth / Homeless	More likely to be written as limited and contributing.
Counseling / social work	More likely to be written as contributing; slightly more likely to be limited.
Facilities / maintenance	Much less likely to be written as limited or contributing.
Mental health / SEL	More likely to be written as contributing, but not strongly more limited.
Curriculum / materials	Less likely to be written as limited.

The practical implication is that some categories are naturally used to target student groups, while others are naturally used to support the system around them. English Learner development, foster and homeless supports, and counseling-related categories are the clearest examples of targeted categories. Facilities are the clearest example of a system-support category. DA therefore changes the encoding of strategy more than it uniformly increases targeting across every action type.

D.4.2 The Contributing designation captures one part of targeting, but not the whole LEA response.

The Contributing designation reveals the LCAP's dual role as a planning document and a compliance instrument. Nearly three-quarters of actions are marked Contributing, yet they account for less than half of all planned action dollars. At the LEA level, the median district marks 83.3 percent of actions and 96.9 percent of reported LCAP dollars as Contributing, though coding varies sharply by action type. The highest Contributing rates occur in class-size reduction (92.8 percent of actions), coaching (89.5 percent), English Learner Development (89.0 percent), and Foster Youth/Homeless supports (83.7 percent). The lowest occurs in Special Education (38.2 percent) and Facilities (43.3 percent).

This pattern should not be read as proof that non-contributing actions are unrelated to high-need students. Instead, it shows that districts use the Contributing designation to satisfy the statutory logic of unduplicated-pupil proportionality while still housing large, planned expenditures in broader, cross-cutting categories. Pointedly, limited actions are concentrated within contributing actions and may undercount support for non-unduplicated groups, such as students with disabilities or

African American students. This may be explained by the LCAP instructions that define, “a limited action as one that serves only unduplicated groups.” (CDE, 2016)

D.4.3 Action scope and portfolio concentration shape whether plans look targeted or diffuse

The LCAP’s own reporting fields help determine how targeting appears on the page. Broad goals carry lower contributing rates than focus goals and much larger mean dollars per action, suggesting that broad goals serve as containers for large base-program investments. Scope operates similarly. Among contributing actions with reported scope, schoolwide actions carry the highest mean dollars per action, followed by LEA-wide actions, while limited actions are much smaller. Concentration models deepen this point. In the pooled LEA-year model, the Herfindahl–Hirschman concentration index is positively associated with larger subgroup allocation gaps (coef = 0.1176, $p = 0.011$) and with greater limited-scope concentration (coef = 0.2284, $p < 0.001$). Shannon entropy moves in the same direction, indicating that narrower portfolios are associated with less even subgroup distributions. The implication is that how districts package the response—through broad goals, scope choices, and concentrated portfolios—matters as much as, and in some models more than, the DA label itself.

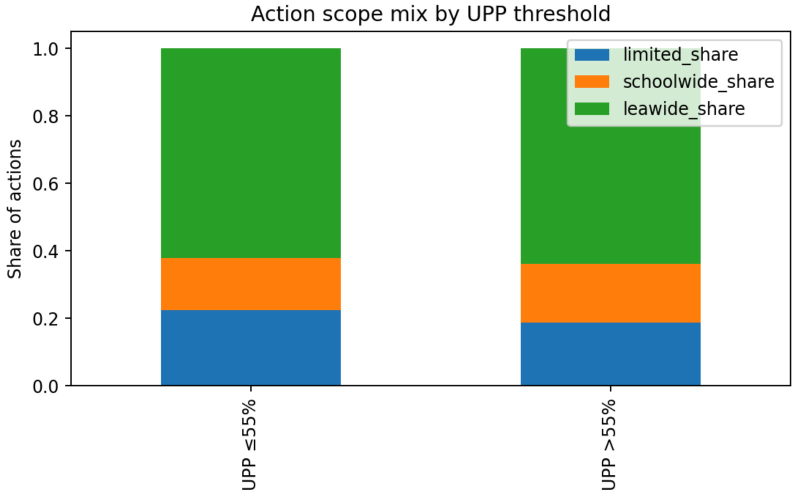
Descriptively, overlap severity in the DA LCAP sample is associated with less LEA-wide scope—high-overlap LEA-years show lower LEA-wide action shares (0.409 versus 0.484) and lower LEA-wide funding shares (0.459 versus 0.538)—although the core targeting results remain directionally similar once this sensitivity layer is introduced.

D.4.4 Unduplicated pupil percentage threshold of 55 percent pushes more LEA-wide actions.

Districts above the 55 percent threshold are less likely to document support through limited actions and more likely to document it through LEA-wide actions. The descriptive scope mix points displays this point. In 2023–24, districts below the threshold wrote 31.2 percent of actions as limited, compared with 28.0 percent above the threshold; their LEA-wide shares were 54.4 and 56.0 percent, respectively. In 2024–25, the limited-action gap widened to 13.5 percent below the threshold versus

9.6 percent above it, while the LEA-wide shares were 71.8 and 70.5 percent. The figure below shows the action scope mix for districts above and below the threshold.

Figure 8. Action scope mix by UPP threshold



In the limited-action regression model, the coefficient on being above the 55 percent UPP threshold is -0.046 (SE = 0.006, $p < .001$). In the LEA-wide model, the coefficient is 0.024 (SE = 0.007, $p = 0.001$). Put plainly, districts above the 55 percent threshold are less likely to write actions as limited and more likely to write them as LEA-wide, even after accounting for plan year, LEA size, urbanicity, district type, and lagged DA status.

This is a planning and reporting effect rather than proof that high-UPP districts are less targeted in any simple sense. Districts above the threshold operate inside a funding and justification environment that makes schoolwide and LEA-wide direct-service staffing easier to document than highly bounded limited actions. Accordingly, the threshold appears to push districts toward broader implementation language and broader action scope, not away from support for high-need student groups. See Appendix 3 for additional statistical results.

D.5 DA changes LEA planning at the margin rather than reordering district strategy

The supplemental and next-round models point in the same direction: DA changes planning at the margin, but it does not reorder district strategy. In the district fixed-effects event study around first

DA identification, the limited-scope share averages 20.5 percent before first identification, 19.5 percent in the first post-identification year, and 12.0 percent in the second year, while the attendance-related share rises from 83.3 to 90.4 percent. The coefficient estimates are noisy: in the event model, the pre-period limited-share coefficient is 0.1918 ($p = 0.194$) and the second-year coefficient is -0.2385 ($p = 0.053$). The mean-evidence event model is no meaningful pre- or post-shift.

Outcome-linkage and evidence-alignment models tell a similar story. In the next-year persistence model, subgroup allocation share is not statistically distinguishable from zero (coef = -0.0226, $p = 0.332$), but the mean evidence score is negative and statistically significant (coef = -0.0229, $p < 0.001$), implying that stronger-evidence subgroup portfolios are associated with a lower probability that the same subgroup remains flagged the following year. The DA coefficient in the evidence-alignment model is small and statistically weak (-0.0455, $p = 0.143$), and the thematic models show similarly small DA coefficients for attendance language (-0.0096, $p = 0.390$), trauma language (-0.0009, $p = 0.946$), inclusion/disability language (-0.0411, $p = 0.072$), and acceleration language (-0.0216, $p = 0.160$). In other words, districts often change the language of their plans faster than they change the mix of dollars.

The next-round models further suggest that the relationship varies by problem type. Indicator-specific response models show that about 66 percent of ELA- and math-triggered cases are no longer triggered in the following year, roughly 73 percent of chronic-absenteeism and graduation cases are no longer triggered, and 81.5 percent of suspension cases are no longer triggered. Yet only the ELA indicator model yields a stable coefficient on limited-action share (0.222, $p = 0.030$), and the pooled dose-response model implies that a larger limited-action share is associated with a lower probability of remaining flagged overall (coef = -0.156, $p = 0.045$). Taken together, these results suggest real but modest planning movement: districts seem to become somewhat more explicit, targeted, and attentive to the focal problem, but they do not fully reorganize their planning logic around DA.

D.6 Different high-priority indicators and student groups result in different action approaches

D.6.1 Chronic absenteeism-focused actions are typically broader and more system-oriented.

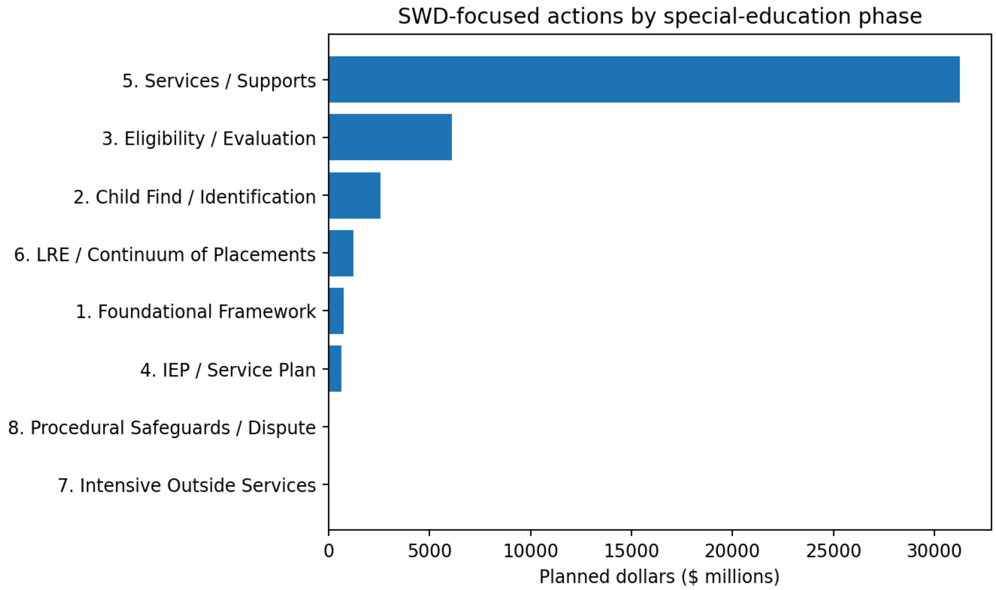
Attendance-focused actions account for an average of 11.4 percent of planned action dollars. The DA district-years average 14.1 percent, compared with 11.3 percent in non-DA district-years. In the district-year model, however, the coefficient on DA status is modest and statistically weak (0.0120, $p = 0.565$). That pattern means the biggest difference is whether a district has attendance-focused actions at all; once it does, DA status by itself adds only a modest amount.

Districts usually respond to absenteeism with broad systems such as attendance teams, outreach, counseling, climate support, and family contact rather than with highly individualized spending. The implication is that they see absenteeism as a problem in school and district operations, not simply a student-compliance problem. That broad approach may be appropriate, but it can also make it harder to track which resources are most directly reaching students at the highest risk of low attendance.

D.6.2 Students with disabilities' actions combine targeted supports with larger systemwide structures.

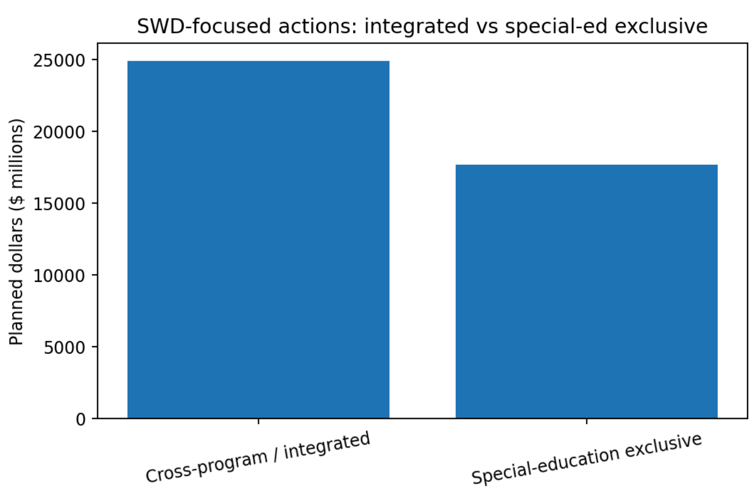
Students with disabilities work combines specialized targeted supports with larger systemwide structures. Using an action-based definition of students with disabilities work based upon the structure of the federal Individuals with Disabilities Education Act (IDEA), focused actions account for an average of 9.5 percent of all planned action dollars. DA district-years average 8.9 percent, compared with 9.6 percent in non-DA district-years. In the district-year model, the DA coefficient is -0.0642 ($p < 0.001$), while the action-level limited-scope model does not yield a strong DA effect. Within SWD-focused actions, the mean scope mix is 27.7% limited, 14.8% schoolwide, and 57.5% LEA-wide. The deeper coding exercise shows why these actions can look simultaneously targeted and diffuse. Most SWD-related dollars are concentrated in Services/Supports and Eligibility/Evaluation, and the dominant change types are increases and maintenance rather than decreases.

Figure 9. Students with disabilities-focused actions by special education phase



At the same time, many SWD actions are coded as cross-program or integrated rather than special-education-exclusive, linking special education to MTSS, counseling, behavior, attendance, and general-education access. That hybrid structure is substantively important because it indicates that districts are responding to students with disabilities not only through specialized services, but also through the broader systems that determine whether those services can operate effectively. At the district-year level, the SWD spending-share model estimates the DA-status coefficient at 0.039 (p = 0.385). Taken together, these results suggest that a narrow reading of special education spending will miss part of the actual planning response.

Figure 10. Students with disabilities-focused actions by integrated versus special education exclusive



D.7 Causal inference of DA on budgeted expenditures and student outcomes

D.7.1 Which Indicators Were Most Frequently the Focal Indicator

Table 10 shows the number of districts for which each indicator is the focal indicator based on 2022 Dashboard data, again separated by the two categories of districts: those eligible for DA and those not eligible for DA. The data indicate that suspension rate was most likely to be the focal indicator (287 of 853 districts), followed by ELA (237 districts), chronic absenteeism (156 districts), and math (152 districts). Graduation rate was the focal indicator for only 21 districts and ELPI was not the focal indicator for any district. Because the focal indicator is the second lowest score for the focal group, these figures are not representative of which indicators are generally lowest across the state. To illustrate that point, we present the focal group's lowest indicator in the following table.

Table 11 shows the number of districts for which each indicator is the lowest for the focal group, based on the 2022 Dashboard data, separated by DA status. As can be seen, chronic absenteeism is by far the most common lowest indicator for the focal group (596 of 853 districts), followed by suspension (148 districts), with ELA, graduation rate, and math all far less common.

Table 10. Numbers of Districts in Which a Given Indicator Was the Focal Indicator in DA Non-DA LEAs, Based on 2022 Dashboard Data

Indicator	Not Eligible for DA	DA-Eligible	Total
Chronic Absenteeism	20	136	156
ELA	61	176	237
Graduation	8	13	21
Math	47	105	152
Suspension	112	175	287
Total	**248**	**605**	**853**

Table 11. Numbers of Districts in Which a Given Indicator Was the Lowest Indicator for the Focal Group, Based on 2022 Dashboard Data

Indicator	Not Eligible for DA	DA-Eligible	Total
Chronic Absenteeism	184	412	596
ELA	14	30	44
Graduation	15	6	21
Math	13	31	44
Suspension	22	126	148
Total	**248**	**605**	**853**

D.7.2 Which Student Groups Were Most Frequently the Focal Group

Table 12 presents data on which student groups were most frequently the focal group on the 2022 Dashboard, separately for DA and non-DA districts. Students with disabilities are the most common focal group, being so in 376 of 853 districts. To restate what that means, in the plurality of districts, the performance of students with disabilities will determine DA status. Further to the duplicated count of students of the 605 total districts: 491 of those are students with disabilities, foster or homeless.

Table 12. Numbers of Districts in Which a Given Group Was the Focal Group, Based on 2022 Dashboard Data

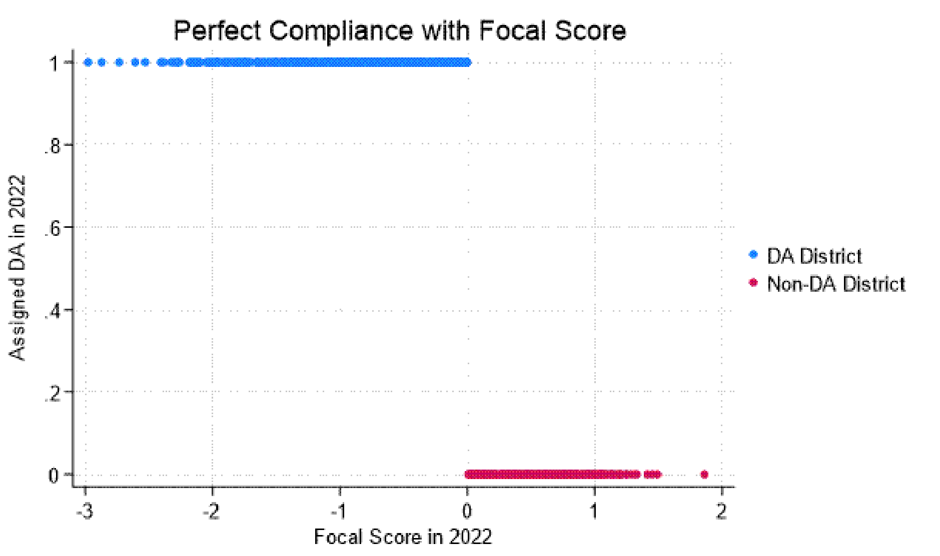
Indicator	Not Eligible for DA	DA-Eligible	Total
AA	5	38	43
AI	0	16	16
AS	1	0	1
EL	19	17	36
FOS	2	134	136
HI	17	7	24
HOM	17	63	80
MR	3	3	6
PI	1	2	3
SED	72	21	93
SWD	82	294	376

WH	29	10	39
Total	**248**	**605**	**853**

D.7.3 Credibility of the RDD

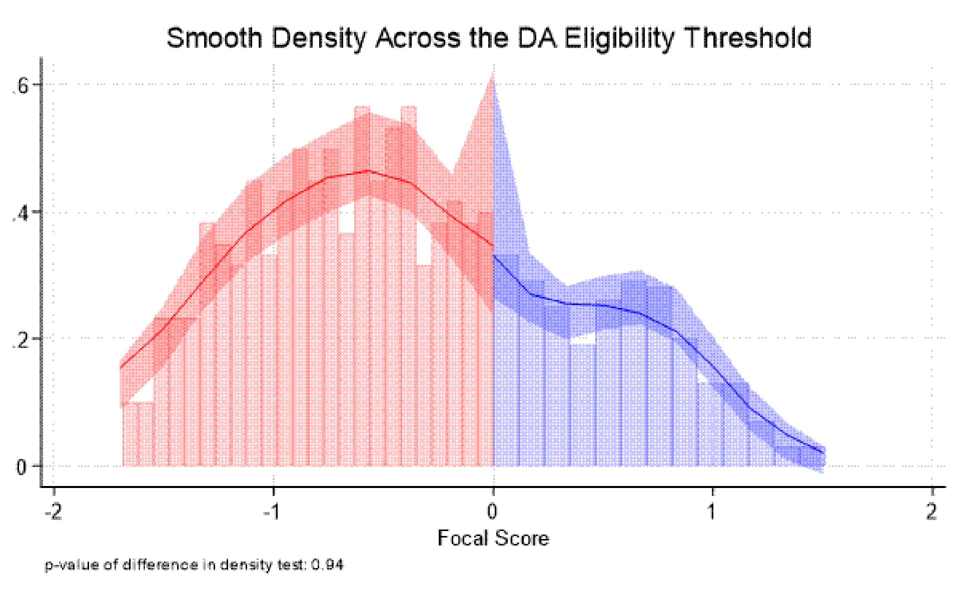
In this section, we provide evidence that the RDD is a credible analytic model for determining the impact of DA. First, we provide evidence that we have correctly identified the focal score (i.e. binding score) for each district. Figure 11 presents a scatterplot of the focal score on the x-axis and the probability of DA assignment on the y-axis for the 2022 assignment year. The data is not binned; each dot is its own district. As can be seen, the focal score perfectly predicts DA assignment – every district with a score below zero is assigned DA, whereas every district with a score above zero is not.

Figure 11. Focal score for DA and non-DA districts



Next, we present evidence that districts do not manipulate their position with respect to the eligibility criteria. Figure 12 presents the density of the focal score on either side of the cutoff. A discontinuity in the density of this variable would suggest manipulation or some other aspect of the score that renders it not credible for causal inference in an RDD. As can be seen, the density is smooth around the cutoff. A statistical test for the difference in density yields a p-value of .94, indicating that the null hypothesis of continuity of density can not be rejected (i.e. there is not evidence of manipulation).

Figure 12. Density of districts on either side of the DA eligibility threshold



We assume a linear relationship between the focal score and the outcome, which can be different on either side of the cutoff, and use a data-driven procedure (cite) to select bandwidths. In the table below, we present evidence that there is no discontinuity in the outcome-focal score relationship at values of the focal score other than the cutoff. For the outcome, we use DA identification in the next year (2023 assignment year). As can be seen, there is not a statistically significant "impact" of DA on subsequent assignment to DA, suggesting that the outcome-focal score relationship is continuous other than at the genuine DA eligibility threshold (which is zero because of centering).

Table 12. Continuity Tests at False Cutoffs

False Cutoff (in standardized units)	*Impact Estimate*	*Standard Error*	*P-value*	*Bandwidth*
0.9	0.14	0.22	0.53	0.22
0.7	0.19	0.19	0.30	0.40
0.6	0.22	0.13	0.09	0.26
0.5	-0.19	0.16	0.22	0.43
-0.5	-0.06	0.10	0.55	0.69
-0.6	0.09	0.09	0.33	0.58
-0.7	-0.19	0.12	0.11	0.50
-0.9	-0.16	0.13	0.23	0.42

D.7.4 Impact of DA on District Performance

As a summary measure of district performance, we assess the impact of DA on a district's probability of being eligible for DA in subsequent years, both for the focal group specifically and for the district as a whole (i.e., for any other student groups). These DA indicators are our primary outcome measures because they transform disparate achievement measures into binary variables that can be compared across districts, student groups, and indicators. We do consider a limited number of specific tests for heterogeneity:

- The impact of DA on future DA status for larger districts
- The impact of DA on future DA status for students with disabilities when they are the focal group

D.7.5 Impact of DA on Eligibility for DA in Future Years

Receiving DA does not reduce the likelihood that a district will be eligible for DA in the future, as can be seen in Table 13. For districts that became eligible in 2022, DA has no impact on the likelihood of future DA in the 2023, 2024, or 2025 assignment years. The effect sizes of between two to eight percentage point differences in DA assignment around the eligibility threshold are not statistically significant, with large p-values seen for all three outcome years.

Table 13. Change in Likelihood of Being Eligible for DA in Subsequent Years as a Result of DA, by Years of Data Analyzed, for All Districts

DA in Subsequent Year	Impact of Current DA Assignment	Standard Error	P-value	Bandwidth	Effective N Below Cutoff	Effective N Above Cutoff
2023	-0.02	0.13	0.87	0.53	196	117
2024	-0.08	0.12	0.50	0.68	257	156
2025	0.07	0.16	0.64	0.49	179	111

Table 14 provided the impact estimates on DA identification for the focal group in subsequent years. As with the prior results, there is no evidence that DA changes the probability of the focal group being eligible for DA in subsequent years. The effect sizes range from one to fourteen percentage points, but none are statistically significant.

Table 14. Change in Likelihood of Focal Group Being Eligible for DA in Subsequent Years as a Result of DA, by Years of Data Analyzed, for All Districts

DA in Subsequent Year	Impact of Current DA Assignment	Standard Error	P-value	Bandwidth	Effective N Below Cutoff	Effective N Above Cutoff
2023	0.14	0.12	0.25	0.48	174	107
2024	0.01	0.09	0.92	0.49	179	111
2025	0.14	0.11	0.19	0.50	181	112

The preceding models were not weighted by enrollment size and so provide the impact of DA on the average LEA, regardless of the size of the district. It may be that larger districts have systematically different responses to DA than do smaller districts, which would be masked by the preceding models that do not take enrollment into account. Tables 15 and 16 restrict the model to those LEAs with an enrollment in 22-23 of greater than 1,000 and also weight by enrollment size. As can be seen, the impact estimates are not notably different from the main models, but the standard errors are far larger, due in part to the restricted sample.

Table 15. Change in Likelihood of Being Eligible for DA in Subsequent Years as a Result of DA, by Years of Data Analyzed, for larger Districts

DA in Subsequent Year	Impact of Current DA Assignment	Standard Error	P-value	Bandwidth	Effective N Below Cutoff	Effective N Above Cutoff
2023	0.11	0.37	0.75	0.47	125	47
2024	-0.08	0.25	0.74	0.42	104	44
2025	0.10	0.30	0.75	0.57	156	56

Table 16. Change in Likelihood of Focal Group Being Eligible for DA in Subsequent Years as a Result of DA, by Years of Data Analyzed, for larger Districts

DA in Subsequent Year	Impact of Current DA Assignment	Standard Error	P-value	Bandwidth	Effective N Below Cutoff	Effective N Above Cutoff
2023	0.26	0.33	0.44	0.41	102	43
2024	0.27	0.32	0.39	0.60	165	57
2025	-0.15	0.28	0.61	0.37	82	41

The next set of results restricts the sample to only those LEAs whose focal group is students with disabilities. As discussed above, the plurality of districts were identified in 2022 because of the performance of students with disabilities – they were the focal group in half of the LEAs eligible for DA and roughly a third of districts not eligible for DA. Tables 17 and 18 contain the results for those districts.

Notably, the impact estimates are larger and all positive, which in these models mean that DA reduces the probability of subsequent DA by the percentage shown. However, the smaller samples lead to larger standard errors and so we can not reject the null that DA has no impact at traditional levels of confidence.

Table 17. Change in Likelihood of Being Eligible for DA in Subsequent Years as a Result of DA, by Years of Data Analyzed, for LEAs in which SWD are focal group

DA in Subsequent Year	Impact of Current DA Assignment	Standard Error	P-value	Bandwidth	Effective N Below Cutoff	Effective N Above Cutoff
2023	0.24	0.24	0.31	0.41	85	41
2024	0.35	0.26	0.17	0.32	66	36
2025	0.16	0.23	0.47	0.47	102	45

Table 18. Change in Likelihood of Focal Group Being Eligible for DA in Subsequent Years as a Result of DA, by Years of Data Analyzed, for LEAs in which SWD are focal group

DA in Subsequent Year	Impact of Current DA Assignment	Standard Error	P-value	Bandwidth	Effective N Below Cutoff	Effective N Above Cutoff
2023	0.26	0.19	0.18	0.55	125	48
2024	0.07	0.07	0.31	0.33	66	36
2025	0.23	0.13	0.08	0.46	101	44

D.7.6 Impact of DA on LCAP Reporting

Table 19 contains the impact of DA on how many actions are reported in LCAPs by year. We also separate actions by type – those that are focused on student attendance and those that target students with disabilities. As can be seen, none of the coefficients are statistically significant, suggesting that DA does not change reporting on the LCAP by marginally eligible districts in the categories that we've assessed.

Table 19. Change in number of reported LCAP actions as a result of DA, by year of LCAP, for all districts

Action Category	LCAP Year	Impact of Current DA Assignment	Standard Error	P-value	Bandwidth	Effective N Below Cutoff	Effective N Above Cutoff
All	24	5.14	8.49	0.55	0.50	127	76
Attendance	24	-0.06	0.06	0.33	0.27	89	66
SWD	24	0.01	0.00	0.11	0.30	104	71
All	25	1.72	3.48	0.62	0.54	167	102
Attendance	25	0.27	0.16	0.09	0.27	89	66
SWD	25	-0.02	0.09	0.82	0.38	121	91

Table 20 contains per pupil expenditure tied to actions as reported in the LCAP (not district expenditure data) by year. As with actions above, we also separate reported spending by that which is focused on student attendance and that targets students with disabilities. The results mirror those from Table 19 above, with no evidence that DA shifts reported per pupil expenditures, either overall or in the categories that we assess.

Table 20. Change in per pupil expenditures tied to reported LCAP actions as a result of DA, by year of LCAP, for all districts

Action Category	LCAP Year	Impact of Current DA Assignment	Standard Error	P-value	Bandwidth	Effective N Below Cutoff	Effective N Above Cutoff
All	24	-2674.27	7904.14	0.74	0.09	23	12
Attend	24	0.12	0.60	0.85	0.39	89	43
SWD	24	1.11	0.92	0.23	0.20	45	26
All	25	2797.77	1710.38	0.10	0.38	86	42
Attend	25	1.82	7.66	0.81	0.27	62	30
SWD	25	11.61	20.96	0.58	0.12	29	16

D.8 Unclear attribution of improvement under overlapping student-group labels

These models start with districts and student groups that were triggered in 2023-24. For each triggered student group-indicator pair, the outcome asks a simple question: was that same group still triggered on that same indicator in 2024-25? A lower stay-triggered rate means more apparent improvement. This outcome should be interpreted cautiously. Because the dependent variable is whether the same student group remains triggered on the same indicator one year later, it blends substantive improvement with label stability. Companion analysis of DA trigger sets shows that exact trigger signatures are highly unstable from year to year and that student-group composition is the dominant source of that instability.

In practice, a district may appear to have improved for one named student group even when the underlying students have shifted across overlapping student-group categories. The models reported here therefore are best read as evidence about the persistence of labeled trigger pairs, not as a clean estimate of improvement for wholly distinct student populations. For ELA, about 66.1% of triggered cases were no longer triggered in the next year. In the regression, a higher limited-action share was associated with higher odds of remaining flagged for this indicator (coef = 0.222, p = 0.030).

These results are sensitive to overlap in the labeled student-group architecture. Under the central overlap specification, the average nominal trigger count declines from 2.66 groups to 2.19 effective groups, indicating that part of what appears to be multi-group instability reflects repeated labeling of overlapping underlying students rather than wholly distinct populations. Consistent with that interpretation, high-overlap transitions show lower student group-indicator pair retention than low-overlap transitions (0.101 versus 0.155, p = 0.005), and indicator-code retention also declines (0.301 versus 0.360, p = 0.060). Taken together, these patterns suggest that some apparent instability in DA trigger persistence reflects relabeling across overlapping student groups, which complicates attribution of improvement when the outcome is defined as the persistence of the same labeled trigger pair.

D.9 The multi-dimensional support taxonomy reveals detail of school district resource allocation strategies that are obscured in standard school finance accounting

Coding for the action title and action descriptions extracted from the LCAPs used a classification approach that built from common types of supports and services that are offered in public schools today, e.g., instructional coaches, professional development, etc. A single thematic label is frequently not enough to characterize what a district is actually buying to support the students that would benefit from the action. The dual-category taxonomy improved this by separating the dominant intervention logic of an action from its most important adjacent support logic thereby giving it a new, greater dimensionality. Tests of statistical fit and coverage improved (see C.4.4 Thematic Coding of LCAP Actions).

In the current deduplicated 2023-24 and 2024-25 action file, 39 primary categories and 39 secondary categories generate 1,329 primary-secondary pairings. The most common combinations are not random. They reveal stable intervention bundles such as:

- English Learner Development | Professional Development (809 actions; $516.2 million)
- Mental Health/SEL | Counseling/Social Work (390 actions; $318.5 million)
- English Learner Development | Foster Youth/Homeless (303 actions; $1.91 billion)

These are not simply labels; they are the school district's targeted theories of action for selected student groups. They reveal that many school districts are not budgeting for sing-purpose intervention but for composite strategies that combine instruction, capacity building, directed intervention, and student group targeting within a single action.

Analytically this is important because standard school finance accounting, which California follows as does the rest of the states in the union, does not have the ability to capture such detail. In order to test this we code each action to the likely object, function, and goal using the standard codes in the California School Accounting Manual (CSAM) with a 98% match rate (non-matches were too broad and fit into multiple possible codes). The three primary codes used in reporting at the federal level are object (what was bought such as teachers), function (what area of public education such as instructional support), and goal (what program area such as special education). Even the lowest level of detail is too coarse to recover the strategic content of an intended action by a school district.

For example, isolates object codes 1100 and 1200 (teacher salaries and teacher support salaries), function 1000 (instruction), and goal 4760 (bilingual education). There are a total of two possible combinations of knowing how funds are planned to be spent. When isolating the LCAP actions to this same object, function, and goal combination in the dataset we find a total of 118 different support combinations (primary + secondary category) providing a much deeper and richer understanding of a school district's intent and the student group that will benefit from such actions.

To date, it has been rare that school finance researchers have been able to more clearly understand the intended strategies underneath the resource patterns through the standard accounting code structure. The contribution of the multi-dimension support taxonomy is therefore to shift the analysis from where the funding was in the accounting structure to which combination of actions the district intended to fund and to the benefit of which student group(s).

E. Discussion and Implications

E.1 Summary of Key Implications

E.1.1 DA shows no clear stand-alone effect on LEA planning, as reflected in the LCAP, or on student outcomes.

The paper's strongest takeaway is not that districts do nothing after DA, but that the study does not detect a clear stand-alone DA effect once the analysis becomes causal or holds portfolio structure constant. First, the regression discontinuity results show no statistically significant reduction in future DA eligibility for districts overall or for focal student groups. Second, the same design finds no significant change in the number of reported LCAP actions or in per-pupil action expenditures. Third, even in the broader planning models, the one-year and multi-year DA coefficients become small and statistically weak once district size, need, and portfolio structure are held constant. Taken together, the study supports a narrower conclusion than the accountability rhetoric implies: DA may change planning at the margin, but it does not appear to produce a large, independent shift in either LCAP-reported behavior or subsequent performance.

The evidence further suggests that DA is not primarily associated with a broad, undifferentiated reshuffling of district budgets. Instead, the most consistent audited spending differences are concentrated in pupil services and special education. This matters because it implies that the planning shifts visible in the LCAP sit inside a more durable expenditure structure tied to student support systems and disability-related service burdens.

E.1.2 Structural features of law and regulation constrain what districts can make visible and what they can move.

The findings suggest that at least part of the apparent mismatch between need and response reflects structural constraints rather than simple local inattention. Students with Disabilities are the clearest example. Their support is financed far more heavily through other state and local funds than through LCFF, and SWD-focused actions are often embedded in cross-program structures rather than isolated in special-education-only lines. That pattern is consistent with a heavily constrained policy environment in which districts must meet special-education obligations before they can freely reconfigure resources. The broader point is that California's support and planning systems operate on top of legal and fiscal constraints—special education maintenance-of-effort is one example—that can limit how visible or flexible district responses appear in the LCAP.

The students with disabilities-trigger results suggest that DA may be interacting with structural service obligations rather than only with the discretionary improvement strategy. If districts identified through students-with-disabilities triggers are systematically more special-education heavy, then at least part of the DA response may be constrained by preexisting obligations embedded in labor, benefits, and legally required service delivery. That pushes the policy conversation away from a simple "districts should target better" critique and toward a more grounded question: how much room do districts with large special-education burdens actually have to reconfigure spending in response to accountability pressure?

E.1.3 Required LCAP fields obscure district intent and make some student groups look absent when they are partly masked.

The study repeatedly shows that the LCAP's formal fields do not capture the full district theory of action. The strongest masking pattern is for Students with Disabilities and Homeless students: both appear far more often in narrative action text than in the structured beneficiary field. More generally, a DA trigger is associated with a much larger increase in narrative visibility than in formal-field visibility, which suggests that districts often signal concern in prose without carrying that concern into the coded field. The allocation results point in the same direction. English Learners are robustly above parity, homelessness is robustly below parity, but Low Income students are highly rule-sensitive because they are so frequently bundled with other groups in the same action. The implication is that the current template records some beneficiary relationships clearly and others only imperfectly.

E.1.4. California's finance, accountability, and support structures remain partially disjointed, creating mixed messages for district staff and other education partners.

The paper's combined findings suggest that California is still asking one system to do work that is organized across several different logics. The finance system records spending in broad accounting buckets. The accountability system identifies performance problems by student group and indicator. The support system asks districts to respond through an LCAP template that is simultaneously a planning document, an engagement document, and a compliance document. The result is predictable: districts often respond with broad portfolios, LEA-wide scope, and bundled actions even when the accountability signal is subgroup-specific. The 55 percent UPP threshold reinforces this dynamic by pushing districts above the threshold toward more LEA-wide actions and fewer limited actions. The dual-category taxonomy, in turn, shows that districts are planning through composite strategies that the accounting system itself cannot see clearly. For policymakers and practitioners, the practical lesson is that better alignment will require clearer expectations about evidence-based responses, clearer subgroup visibility rules, and a stronger bridge between planning language and audited financial records.

E.1.5 Subgroup allocation results are not equally stable across groups.

English Learners remain descriptively above their student share across all allocation rules we tested, while students experiencing homelessness remain consistently below theirs. Low-income students are the most rule-sensitive case, because they are frequently bundled with other student groups in the same action and their apparent resource position changes depending on the allocation rule applied.

E.2 Implications for Policymakers

The paper points to a design problem more than a simple implementation failure. California's accountability system identifies highly specific student-group and indicator problems, but the LCAP still allows districts to document their response through broad, multi-beneficiary, and often LEA-wide actions. A first policy implication is therefore to make subgroup attribution more explicit. The state could require districts to identify a primary beneficiary, allow secondary beneficiaries, and distinguish whether an action is principally targeted, jointly targeted, or infrastructure-serving. That would preserve local flexibility while making the planning record more interpretable and more comparable across LEAs.

A second implication is that DA should be paired with clearer response architecture, not just clearer identification architecture. The findings suggest that districts often respond to DA through familiar portfolios rather than indicator-specific intervention strategies. The state could therefore strengthen the System of Support by pairing each major trigger domain with more clear roles and responsibilities, evidence-based response menus, implementation examples, and short-cycle monitoring expectations. Relatedly, state leaders should revisit the interaction between the 55 percent unduplicated pupil threshold, Contributing rules, and LCAP scope categories, because those rules appear to push many districts toward broader LEA-wide documentation even when the accountability signal is subgroup-specific.

A third implication concerns data integration. Policymakers should not expect the LCAP alone to function as a clean audit of targeted spending. The strongest way forward is to build a tighter bridge among the accountability file, the LCAP planning file, and audited expenditure systems so that subgroup-specific planning claims can be interpreted alongside actual spending patterns. In practical terms, the state needs a more coherent reporting architecture in which finance, accountability, and support are aligned rather than only loosely connected.

E.3 Implications for Practitioners

District and county practitioners do not need to wait for a template change to improve the usefulness of the LCAP. The clearest practical move is to make the district's theory of action more visible in the executive summary. For each triggered student group or high-priority problem, practitioners should specify the focal need, the core intervention, the implementation mechanism, the scope choice, and the evidence they will use to judge whether the strategy is working. Even where the action is necessarily broad, the plan should say why a districtwide or schoolwide response is warranted and how the focal student group is expected to benefit.

Practitioners should also separate infrastructure from intervention. One recurring weakness in the evidence is that staffing, MTSS, counseling, and compliance-support actions are often blended together with focal-group support in ways that obscure the operative intervention. A stronger LCAP distinguishes the enabling platform from the subgroup-specific response and then tracks both. Doing so would make the plan more usable internally, make partner engagement more concrete, and make later interpretation of progress more defensible.

Finally, districts should treat bundled actions as something to explain rather than something to leave implicit. When an action serves multiple student groups, practitioners should state whether those groups are being served for the same reason, through the same mechanism, or only through overlapping infrastructure. That level of specificity is especially important for students with disabilities, students experiencing homelessness, and low-income students, whose support is most easily masked by current documentation rules.

E.4 Limitations

Several limitations should shape how the reader interprets the LCAP results. None of them eliminates the value of the analysis, but each narrows the claims the paper can make.

Planned allocations versus executed expenditures. The LCAP is a planning document. It records declared actions and planned action funds, not a verified ledger of what the district ultimately spent. The paper, therefore, identifies changes in districts' stated theory of action and planned allocations, not execution in the strict accounting sense. SACS totals help scale the action tables, but they do not, by themselves, validate every action-level amount.

Measurement and coding error. Action extraction, thematic coding, scope imputation, and group tagging introduce nontrivial measurement error. We mitigate that problem through de-duplication, confidence flags, alternative specifications, and robustness checks, and the main descriptive patterns survive those tests. Even so, some actions are necessarily misclassified, especially when districts use vague or boilerplate language.

Subgroup denominators and multi-group allocation rules. Subgroup share-versus-resource analyses remain sensitive to both the denominator data and the treatment of bundled actions. To reduce that problem, this paper uses year-specific district subgroup denominators and a main-paper backbone that combines directly observed single-group actions with a hybrid 50/50 allocation rule for bundled actions, while reporting equal, primary-only, and proportional bounds in the appendix. Even so, groups that are frequently named jointly—especially low-income students—remain more sensitive to allocation assumptions than groups whose targeting is more often directly observed.

A further limitation concerns overlapping student-group architecture in the state accountability system itself. Because the same students may be counted in multiple student groups, year-to-year changes in triggered group-indicator pairs may reflect both substantive improvement and relabeling across overlapping categories. Without student-level linked data, the present analyses can test the sensitivity of this problem but cannot fully separate those two sources of movement.

Template, legal, and regulatory constraints. Not every pattern in the LCAP should be interpreted as a free district choice. State instructions, Contributing rules, scope requirements, and the politics of subgroup naming likely shape what districts record. Explicit racial and ethnic targeting, in particular, may be understated in the formal dollar fields even when districts clearly discuss those groups elsewhere in the plan.

Limits of causal inference for the planning analyses. The regression discontinuity design provides causal leverage for the outcome analysis at the DA threshold and for assessing DA's impact on planned spending. Event studies, outcome-linkage models, and dose-response tests can suggest mechanisms, but they do not prove that a specific planned action mix caused subsequent change.

Overlap across student groups in the state accountability architecture. Exact student-level intersections are unavailable in the present dataset, so overlap must be modeled using bounded memo-based priors rather than observed counts of distinct students carrying multiple flags. As a result, the overlap measures reported here should be interpreted as sensitivity adjustments that bracket plausible duplication rather than as precise estimates of student-level intersections.

What these findings can and cannot support. These results can support claims about how districts describe their intended response to DA, how similar those responses are across LEAs, and which subgroups or indicators appear to receive greater or lesser planning attention. They cannot by themselves prove that districts later spent every dollar as written, that the LCAP fully captures local strategy, or that one portfolio is a unique causal pathway through which DA affects student outcomes.

The Regression Discontinuity is Valid for Marginally Eligible Districts. The most important limitation of the causal design is that the RDD provided valid inference "in the neighborhood of the eligibility cutoff." The lack of effects reported here accurately describe the (lack of) impact of DA on districts who just barely qualify for it. We are unable to determine the impact of DA on districts who qualify for it based on numerous student groups and indicators. While able to separate cause from correlation, the RDD is subject to greater statistical uncertainty than other designs. In this case, the standard errors are large enough that we are unable to detect small improvements in district performance or changes to LCAP reporting that may indicate positive effects of DA.

E.5 Future Research

The comments embedded in the draft and the companion regression memo point to a clear next phase of work: moving from documenting district planning responses to directly testing the mechanism.

First, if the paper's central mechanism question is whether DA changes district behavior, then the next step is to study the LCAP as a policy instrument rather than only as a data source. That means testing whether first-time DA identification changes the seriousness of community engagement, the elaboration of goals, the use of numeric targets, the degree of within-county or network duplication, and the extent to which districts revise rather than recycle prior text. Hibel and Beberman's measures of duplication, measurability, and goal elaboration provide a ready-made framework for that analysis.

A particularly important next step is to move from group labels to distinct students. Student-level CALPADS linkages, or at minimum LEA-year intersection tables across student-group flags, would allow future work to estimate how much DA trigger churn reflects true performance change versus changes in overlapping student-group labels. That step is essential for moving from label-level persistence models to more credible estimates of improvement for the students actually driving identification.

Second, future work should replace these proxy measures with observed intersection data. Student-level CALPADS records, or LEA-year intersection tables reporting the joint distribution of key student-group flags, would allow the overlap proxy to be replaced with true distinct-student counts and would substantially improve inference about whether instability in DA triggers reflects real improvement, compositional change, or relabeling across overlapping student groups. That step would also allow future analyses to estimate overlap-adjusted resource targeting with greater precision at both the LEA-year and indicator-specific levels.

F. Conclusion

Differentiated Assistance is designed to interrupt low performance by forcing a district to pay closer attention to the students and indicators it has not served well. The evidence in this paper suggests that the interruption is real, but modest. Districts do respond in the LCAP, yet they do so through a planning instrument that channels those responses into recurring categories, common portfolios, and sometimes ambiguous subgroup targeting.

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Appendices: Technical Details

Appendix 1: Action Coding for Academic/Non-Academic/Admin and Category Descriptions

Appendix 2: Overview of Regression Discontinuity Design

Appendix 3: Differentiated Assistance Evaluation Methods and Data

Appendix 4: LCAP Analysis and Action Code Taxonomy Descriptive Statistics

Appendix 5: Supplemental Statistical Tables for LCAP Analysis

Appendix 1. Action Coding: Academic/Non-Academic/Admin and Category Label

#	Acad / Non-Academic / Admin	Action Code	Category Label	Descriptive Terms or Phrases Associated with Action Code
1	Academic	ELD	English Learner Dev	English Learner Development, Newcomer Program
2	Non-Academic	ATT	Attend/ Absent	Attendance, Absenteeism, Chronic Absenteeism, SARB, Suspension
3	Academic	MATH	Math/STEM	Math, Science, Technology, Engineering
4	Academic	PD	Professional Development	Professional development, aides, classified staff, collaboration, PDC
5	Non-Academic	MH_SEL	Mental Health/SEL	Mental health, behavioral health, social-emotional learning
6	Non-Academic	COUNS	Counsel/ Guidance/Social Work	Counselors, Guidance, Social Workers, Psychologist, Therapy
7	Non-Academic	FAM	Family/Comm Engage	Family and Community, Parent Engagement, Community Liaisons, Community Schools, Community Building, Educational Partner, PTA
8	Academic	LIT	Literacy/Reading	Literacy, Reading, and Writing
9	Non-Academic	SAFE	School Safety/Climate	School Safety, Climate, PBIS, Student engagement
10	Academic	CURR	Curriculum/Materials	Curriculum, Materials, Pacing Guides
11	Academic	TUT	Tutoring	Tutoring, High Dosage Tutoring
12	Non-Academic	FH	Foster Youth/Homeless	Foster Youth, Homeless, Transportation, Housing
13	Admin	STAFF	Teacher/Staff/Admin Retention	Staff Retention, Teacher Retention, Recruitment
14	Academic	SPED	Special Education	Special Education, IEP, triennial
15	Academic	EXT	Extended/Expanded Learning	Extended, Expanded Learning, Additional Instructional Minutes
16	Academic	TECH	Technology / Digital	Technology, Digital Materials
17	Academic	CTE	Career Tech Ed	Career Technical Education
18	Admin	LEAD	Leader Develop	Leadership Development, Principal Development
19	Academic	CSR	Class Size Reduction	Class Size Reduction, Class Size, Ratios, Additional Staff, Lower Ratios
20	Academic	ENRICH	Enrich & Extracurriculum	Enrichment, Field Trips, Extracurricular, Physical Education, Culinary, Academic Supports, Saturday Academy, Academic Instruction, Electives
21	Academic	ASSESS	Assess/Data Systems	Assessment, Data Systems, Data Storage, Data Warehousing
22	Non-Academic	FACIL	Facilities & Maintain	Facilities, Maintenance, Classroom Furniture
23	Non-Academic	TRANS	Transportation	Transportation, Buses

24	Non-Academic	MTSS	Multi-Tiered System of Supports	MTSS
25	Academic	VAPA	Visual & Performing Arts	Visual and Performing Arts
26	Academic	CLSUP	Class Support/Aides	Class Support, Instructional Aides, Bilingual Aides, Intervention Aides, Paraprofessionals, Instructional Aides
27	Academic	ECE	Early Child/TK	Early Childhood, Transitional Kindergarten, Early Grade
28	Non-Academic	HLTH	Health Services	Health Services, Nurses
29	Admin	EQUITY	Equity & Culturally Responsive	Equity, Culturally Responsive, Diversity
30	Non-Academic	FOOD	Nutrition/Food Services	Nutrition, Food Services, Food, Snacks, Meals
31	Admin	COORD	Program Coordination	Program Coordination
32	Academic	ALT_ED	Alt / Adult Education	Alternative Education, Adult Education, Pathways, Dropout
33	Academic	COACH	Instructional Coaching / TOSA	Instructional Coaching, Coaching, Teachers on Special Assignment, TOSA
34	Admin	ADMINOPS	Administration / Operations	Administration, Operational Support
35	Academic	COL_CAR	College & Career	College and Career, Higher Ed, University, AP, IB, SAT, FAFSA
36	Admin	DISC	School Discretion	School Discretion, School Allocations
37	Admin	PLAN	Strategic Planning	Strategic Planning, Planning
38	Academic	SALARY	Base Salaries	Salary, Salaries, Benefits
39	Academic	INTERVENE	Intervention / Diff Instruction	Intervention, Differentiated Instruction, Targeted
40	nan	nan	nan	nan

Appendix 2. Overview of Regression Discontinuity Design

The central goal of DA is to improve the academic achievement of struggling students. Therefore, it is important to evaluate how students perform. However, there are several challenges. First, a difficulty with any quantitative analysis of DA's impact concerns the appropriate control group. But in this case, the control group is less than ideal. That is, districts eligible for DA are, by definition, different from those ineligible for DA. Districts that receive DA have at least one student group whose performance is below satisfactory levels in two indicators. So, comparing DA-eligible and non-DA-eligible districts in terms of impact comes with caveats.

Second, given that student achievement has a strong serial correlation (that is, a district's performance in one year is highly predictive of its performance the next year), one would expect the average outcomes of DA-eligible districts to be at least somewhat below those of districts that were not eligible for DA, even if the DA had a positive impact.

Additionally, several local contextual factors can affect student outcomes. That is, any comparisons between DA- and non-DA districts over time will risk conflating the impact of DA with other factors that change over time. Moreover, because of a statistical phenomenon called "mean reversion," outlier districts with extremely low or high performance in one year are less likely to be outliers in another year, solely due to the laws of probability rather than any action taken by the districts. Consequently, districts eligible for DA in one year will almost certainly have somewhat higher performance in the following year, even if DA has no effect on student achievement. To mitigate these challenges in analyzing the impact of DA, the research team employed a regression discontinuity design (RDD) to statistically estimate the causal effect of DA eligibility on districts' student outcomes.

The criteria for identifying districts for DA in California are far more complex than the accountability assignment rules in other states whose systems have been evaluated by RDD. In California's accountability system, each student group receives a performance color for each indicator, determined by a combination of that group's current performance and its change in performance from the prior year. If any student group in the district has two low colors (sometimes, but not always, red) across two priority areas (sometimes, but not always, a single indicator), then the district is eligible for DA. From this complex system, the research team identified which measure of student achievement, for each student group, determined DA eligibility for each district. In general, it is the second-lowest indicator score for the student group with the most negative, second-lowest indicator scores in the district. This is the score that will render a district eligible for DA if it is below (in most cases) the red-orange performance threshold and, conversely, will keep a district ineligible for DA if it is above the red-orange threshold. Conceptually, the RDD model compares districts just on the red side of the red-orange threshold to districts just on the orange side of the red-orange threshold. The difference between the two hypothetical districts is that one receives DA and the other does not.

Appendix 3. Differentiated Assistance Evaluation Methods and Coding

For the quantitative analysis, we used publicly available data from the CDE website. These included data from the California School Dashboard files for 2017, 2018, and 2019, as well as corresponding ESSA and CSI/TSI status files. Table C-1 shows the files used by year of availability.

Table C-1: Data Files Used for Differentiated Assistance Evaluation

Priority Area	Data	2017[29]	2018	2019
Pupil Achievement (PA 4)	Academic Indicator ELA	X	X	X
Pupil Achievement (PA 4)	Academic Indicator Math	X	X	X
Pupil Achievement (PA 4)	English Language Proficiency Indicator	O	O	X
Pupil Engagement (PA 5)	Graduation Rate	X	X	X
Pupil Engagement (PA 5)	Chronic Absenteeism	—	X	X
School Climate (PA 6)	Suspension Rate	X	X	X
Outcomes in a Broad Course of Study (PA 8)	Career & College Readiness Indicator	O	X	X

We obtained district-type information from the suspension data file. We used the largest sample size (i.e., largest denominator) for the “ALL” student category as a proxy for the population of each district. This number typically came from the suspensions file because suspensions can affect students in most or all grade levels, so this measure typically covers the largest number of students.

Data Sources

Data was matched across various files via the County-District-School (CDS) code. To form the analytic sample for the regression discontinuity, we kept only district records, excluding school-level and county office of education records.

We excluded observations within each indicator that did not meet the reporting standard or had a special rule applied that was not determined by the performance change and level. We also flagged and excluded groups in each district that had insufficient sample sizes to receive a color in the accountability model; specifically, foster youth and homeless student groups with fewer than 15 students, along with all other groups with fewer than 30 students. We also excluded observations that received:

- the “no test flag” (i.e., districts that failed to test at least 10 percent of their population);
- the “certify flag” (i.e., districts that failed to certify their discipline or suspensions data); or
- the “data error flag” (i.e., districts and schools that certified zero chronically absent students but had more full days of out-of-school suspension than the number of days reported as absences in the California Longitudinal Pupil Achievement Data System [CALPADS] for the Dashboard current year that qualifies for a color at their overall level or student group levels are automatically are assigned an orange performance level [box 180] if their earned color was originally blue, green, or yellow).

For each student group in each district, we identified and counted the number of indicators that received a “red” performance level for the priority area. This differs from DA eligibility, as a student group must have low performance in two priority areas to be eligible.

Identifying the Focal Indicator and Constructing the Running Variable

Because the indicator that determines DA eligibility varies across districts, we identified a focal indicator—i.e., the indicator that has either prompted DA eligibility or would prompt DA if it fell below a certain performance threshold. The student group possessing the focal indicator is called the focal group. The process for identifying the focal indicator and constructing the running variable was as follows:

Step 1: Center and standardize running variables

To identify the focal group and indicator, we needed to compare performance across indicators using different measures and scales. To achieve this, we standardized the measures by centering them and dividing them by their population standard deviations.

First, we calculated the standard deviation of the current year’s status values for each indicator i across all districts and student groups. The standard deviation is defined as:

$$x_{d_i} = \sqrt{[\Sigma_{j=1}^{n}(x_{jd} - \bar{x})^2]/n}$$

where X_{jd} is the current year’s math status value for the j_{th} student group in district d, and $\bar{X}$ is the mean of all the current year’s math status values. We refer to this value as sd_i for the i_{th} indicator.

Second, we centered the change scores at the lowest color boundary (on the change axis) for each status row by subtracting that boundary value from the score, and then we divided the centered change variable by its population (status) standard deviation. For small LEAs (with n ≤ 150) that use the 3 x 5 methodology, we centered the change scores at the lowest color boundary after excluding those in the first and last columns, then proceeded with the same steps, dividing by the population standard deviation. Dividing each centered change value by the appropriate indicator’s sd_i created variables that are all on the same scale, allowing us to compare scores across indicators. We refer to row-specific, standardized, recentered change values as row_ score_i for each row, and ith indicator.

Step 2: Rank standardized variables to identify the lowest and second lowest

For each student group within each district, we determined the lowest and second-lowest change scores. First, we grouped status rows by the lowest color in the row, so that rows with red as the lowest color are in a group (the "red group"), rows with orange as the lowest color are in a second group (the "orange group"), and so forth. Then, we ranked scores by status row groups, so that those in the red group were the lowest, those in the orange group were the second-lowest, and so on.

Next, we used the group's row_score_i values to determine change score ranks within row groups. For example, if students with disabilities were in the red group for the college/career indicator (CCI), the orange group for suspensions and chronic absenteeism, and the yellow group for all other indicators, their lowest indicator would be CCI, and the second-lowest would be the orange indicator (either suspensions or chronic absenteeism) with the lowest row_score_i value.

The focal group is the student group whose second-lowest indicator (within the student group)—i.e., the focal indicator—is the lowest across student groups. We identified the focal group and focal indicator for each district, and the focal indicator would become the running variable.

Adjusting for Special Cases

As part of the ranking process, we treated priority areas with multiple indicators as special cases and applied additional rules. Namely, those cases were:

- ***Pupil Engagement:*** This priority area utilizes either graduation or chronic absenteeism measures. A group meets the priority area by receiving a red performance level on either graduation or chronic absenteeism. Receiving a red performance level on both measures still counts as only one priority area. Consequently, if the lowest indicator is chronic absenteeism (or graduation rate), we excluded graduation rates (or vice versa) from consideration as the second-lowest indicator.

- ***Pupil Achievement:*** This priority area utilizes both ELA and math scores. A group must receive a red performance level on one subject score and orange (or red) on the other to meet DA eligibility for the pupil-achievement priority area. If either the lowest or second-lowest indicator for the focal group was ELA scores (or math scores), we included the third-lowest indicator in the ranking as well, since ELA and math fall under the same priority area. In this case, we treated ELA (or math) values as part of the red row group (so they were counted as a "lower score") and reranked them. We then used the third-lowest indicator score in place of the student group’s second-lowest score to compare across student groups within each district, while the other groups retained their original second-lowest scores.

Step 3: Construct the running variable for regression discontinuity.

To determine whether the district is in the potentially treated set (those eligible for DA or close to eligible) or the comparison set of districts, we considered the lowest color in the status row of the focal indicator. If the status row for their focal indicator included red boxes (or orange for math and ELA indicators), the district was in the potentially treated set. All other LEAs were in the comparison set. We then used the focal indicator's row_score_i as the running variable.

Descriptive Statistics

Districts

Tables C-2 and C-3 show the counts of districts by district type in the data files. Most are unified districts, followed by elementary districts. Unified districts are the largest, and 70 percent of students attend school in a unified district, followed by 20 percent in an elementary district and 10 percent in a high school district. The remaining district types are attended by fewer than 2 percent of students.

Table C-2: Count of Districts by Type

Total District Count	**995**	**991**	**936**
Elementary District	297	293	488
Elementary School	220	221	0
High School District	72	72	74
High School	2	2	0
Middle School	3	3	0
Unified District (Not COEs)	345	344	373
COEs (Labeled UD)	56	56	0
Missing district type	0	0	1

Table C-3: Share of Students in Each District Type

		2018	**2017**
Total Student Count	**5,858,050**	**5,923,489**	**5,840,575**
Elementary District	19%	19%	20%
Elementary School	1%	1%	0%
High School District	10%	9%	0%
High School	0%	0%	0%
Middle School	0%	0%	0%
Unified District (Not COEs)	70%	70%	71%

Student Population

We calculated the student populations for each student group by choosing the largest denominator across that group's measures. We aggregated this at the district and state levels. The measures are reasonably close to the statewide student demographic population data pulled from CDE's DataQuest database for the same year.

Table C-4 below shows the share of all districts with adequate sample sizes to receive a performance color for each indicator in 2018, by student group. For example, in 2018, only 2 percent of districts had a population of American Indian or Native Alaskan students large enough to receive a performance color for graduation rate or CCI.

Table C-4: Share of Districts With Sufficient Student Group Sample Sizes to Receive a Dashboard Performance Color for Each Indicator in 2018, by Student Group

	School Climate	Pupil Engagement		Pupil Achievement		Course of Study
	Suspensions	*Absences*	*Grad Rate*	*ELA*	*Math*	*CCI*
By Race/Ethnicity						
Hispanic / Latino	86%	78%	80%	79%	79%	80%
White	87%	79%	74%	79%	79%	74%
Asian	47%	40%	38%	40%	40%	38%
Black / African American	41%	35%	29%	33%	33%	29%
Filipino	36%	30%	24%	28%	28%	24%
Native Hawaiian or Pacific Islander	19%	15%	3%	11%	11%	3%
American Indian or Native Alaskan	27%	19%	2%	10%	11%	2%
Two+ Races	56%	48%	23%	41%	41%	23%
By Special Populations						
Socioeconomically Disadvantaged	91%	83%	87%	86%	86%	87%
Students with Disabilities	75%	67%	58%	68%	68%	58%
English Learners	74%	67%	56%	70%	70%	56%

Appendix 4. LCAP Analysis and Action Code Taxonomy Descriptive Statistics

LCAP Scaling and Feasibility

Given the labor-intensive nature of LCAP data extraction—even with LLM assistance—the research team adopted a scaled approach to data collection. Rather than attempting to extract LCAP data for all LEAs across all identification cycles, we prioritized a single LCAP plan year (corresponding to an 18-month treatment window) and focused extraction on the data elements most common and comparable across plans: identification of the student group targeted by each action, the budgeted expenditure amount, and—where available—the state indicator to which the action is aligned. This scaled approach reflects advice from early collaborators who emphasized the descriptive value of even a single cross-section of LCAP data before proceeding to causal inference.

Descriptive Versus Causal Inference

A key insight from this study is the importance of not underestimating the contribution of descriptive analysis. Even without a causal identification strategy, the LCAP data can provide a valuable descriptive picture of how DA-identified districts characterize and target their spending relative to non-DA districts. This descriptive picture—including analyses of teacher professional development spending, programmatic investments by student group, and the overall composition of DA-responsive actions—provides the empirical foundation for posing causal questions. The regression discontinuity design is the mechanism for moving from “what do DA districts do?” to “does DA cause districts to do it?”, but the descriptive work is a necessary precondition and a contribution in its own right.

LCAP Data Quality and Believability

A persistent concern throughout the data extraction process has been the believability and consistency of LCAP-reported expenditure data. Because LCAPs are self-reported planning documents, the figures they contain reflect intended rather than actual resource allocations (for the planned LCAP) or retrospective estimates of actual expenditures (for the annual update). We developed validation checks by comparing the total sum of planned expenditures in the LCAP to the SACS data for the corresponding fiscal year, e.g., 2023-24 LCAP year is equivalent to the 2023-24 fiscal year SACS data. All instances with exception of 3% of cases matched across those sources.

Data Collection Summary: DA Status and LEA Eligibility, 2022–2024

The data integrates CDE LCFF District/COE Eligibility Files from the 2022, 2023, and 2024 release cycles with LCAP and other LEA descriptive information.[1] This tracks 1,083 LEAs across all three identification years, recording each LEA's assistance status (Differentiated Assistance or General Assistance), the student groups that triggered DA eligibility, and the specific priority-area combination (coded A through K) indicating which state indicators each student group met. Researchers also captured the longitudinal DA status across six identification cycles (2017, 2018, 2019, 2022, 2023, and 2024), enabling classification of LEAs by the persistence of DA identification.[2] Table 3 presents the distribution of LEAs by assistance status across the three post-COVID identification cycles.

Table 3. LEA Counts by Assistance Status, 2022–2024 CDE Eligibility Files

Assistance Status	2022	2023	2024	3-Year Total
Differentiated Assistance	617	384	589	1,590
General Assistance	376	603	405	1,384
Eligible LEAs (DA + GA)	993	987	994	—
DA as % of eligible LEAs	62.1%	38.9%	59.3%	53.5% avg

As Table 3 shows, the proportion of LEAs identified for DA has fluctuated across the three post-COVID cycles, from a high of 62.1% in 2022 to 38.9% in 2023, and back to 59.3% in 2024 (which includes both Year 1 and Year 2 designations under the updated identification framework). On average, approximately 53.5% of eligible LEAs were identified for DA in each of the three years. The total file tracks 1,083 LEAs, of which approximately 993–994 are designated as either DA or General Assistance in any given year; the remainder carry other designations (Closed, No Designate) and are excluded from the analytic sample.

Table 4 presents the cross-classification of LEAs by their DA status across all three identification years, which is essential for constructing the analytic categories described in Section 2.2.

[1] California Department of Education, LCFF District/COE Eligibility Files, February 2023, December 2023, Nov. 2024.
[2] LEA counts include school districts, county offices of education, and charter schools that appear in the CDE eligibility files. Counts exclude LEAs designated as "CLOSED" or "NO DESIGNATE."

Table 20. LEA Cross-Classification by DA Status, 2022–2024 (N = 1,083)

2022	2023	2024	N (LEAs)	% of Total	Analytic Category	Category N
GA	GA	GA	344	31.8%	Never DA	344
DA	GA	GA	87	8.0%		
GA	DA	GA	29	2.7%	Single-Year DA	184
GA	GA	DA	68	6.3%		
DA	DA	GA	34	3.1%		
GA	DA	DA	25	2.3%		
DA	DA	DA	296	27.3%	Multi-Year DA	555
DA	GA	DA	200	18.5%	Intermittent DA	200

Table 4 reveals substantial variation in DA persistence. Of the 1,083 tracked LEAs, 344 (31.8%) were never identified for DA in any of the three post-COVID cycles. At the other extreme, 296 LEAs (27.3%) were identified for DA in all three years, forming the core of the "multi-year DA" analytic category (N = 555 when combined with LEAs identified in two consecutive years). An additional 184 LEAs (17.0%) were identified in exactly one year only. A notable pattern is the 200 LEAs (18.5%) that were DA in 2022, exited DA in 2023, and returned to DA in 2024—representing an "intermittent" DA pattern that may reflect cyclical identification dynamics rather than sustained improvement or sustained struggle.

Table 5 reports the frequency with which each student group triggered DA eligibility across the three identification cycles.

Table 21. Student Groups Triggering DA Eligibility, by Identification Year

Student Group	2022 N	%	2023 N	%	2024 N	%
Students w/ Disabilities	520	84.3%	171	44.5%	195	33.1%
Homeless	272	44.1%	121	31.5%	125	21.2%
Foster Youth	243	39.4%	99	25.8%	104	17.7%
English Learners	230	37.3%	116	30.2%	84	14.3%
Long-Term ELs	—	—	—	—	215	36.5%
Black/African Amer.	162	26.3%	74	19.3%	51	8.7%
Low Income	158	25.6%	68	17.7%	68	11.5%
Hispanic	99	16.0%	58	15.1%	39	6.6%

White	73	11.8%	26	6.8%	30	5.1%
American Indian	70	11.3%	22	5.7%	27	4.6%
Two or More Races	52	8.4%	20	5.2%	19	3.2%
Pacific Islander	30	4.9%	9	2.3%	8	1.4%
Filipino	1	0.2%	—	—	—	—
Asian	2	0.3%	—	—	1	0.2%

Note: Percentages represent the share of DA-identified LEAs in each year for which that student group triggered eligibility. An LEA may be identified on multiple student groups. Long-Term English Learners (LTEL) were added as a separate reporting category beginning in the 2024 identification cycle.

Several patterns in Table 5 merit attention. Students with disabilities (SpEd) is the most frequently triggered student group in all three years, though the rate declined sharply from 84.3% of DA LEAs in 2022 to 33.1% in 2024. Homeless youth and foster youth consistently appear among the top four triggers. The introduction of Long-Term English Learners (LTEL) as a separate reporting category in 2024 immediately placed it as the second most common trigger (36.5%), suggesting a previously masked source of DA identification. Racial/ethnic student groups—particularly Black/African American, Hispanic, and American Indian students—trigger DA at rates that vary substantially across cycles, reflecting both changes in dashboard performance and shifts in the eligibility methodology.[3]

DA-to-LCAP Data Alignment and Availability

LEAs were matched via CDS code for the temporal relationship between DA identification events and the LCAP plan cycles during which districts can respond. For the 2022 DA identification (based on 2021–22 FY outcomes, released in December 2022), the first LCAP response window is the 2023–24 FY LCAP, adopted in June 2023. It includes both the annual update (actuals from the prior year) and new goals and actions for the upcoming year. The second response window is the 2024–25 FY LCAP. The same logic applies to subsequent identification cycles.

The matching process confirms the following data availability for the study: DA identification files for 2022, 2023, 2024, and 2025; audited actual financials (SACS structure) available for FY 2022 through FY 2025; ELA and math state assessment results for 2021–22 through 2024–25; district LCAPs by county collected for FY 2024 through FY 2025; LEA demographic, enrollment, and unduplicated pupil count (UPC) data are available for FY 2025; and certificated and classified staffing data are available for FY 2022 through FY 2025. Data analysis notes that 273 school districts in the General Assistance category

[3] Student group identification is based on the CDE's priority-area coding system (values A–K), where each letter code indicates a combination of state indicators on which the student group met the criteria for DA eligibility.

for all three years (the “never DA” comparison group) have fewer than 2,000 enrolled students, a relevant consideration for analytic specifications that may need to account for district size

The 37-code action taxonomy used to classify LCAP actions. The evidence tier is assigned at the action-code level based on the literature synthesis and implementation parameters captured in the project codebook. Typical CSAM goal/function/object codes reflect expected accounting patterns for that intervention type (used for interpretation and future linkage).

Table 22. 37-code taxonomy with typical school accounting goal, function and object

Action code	Label	Typical CSAM goal	Typical CSAM function	Typical CSAM object
ELD	English Learner Development	4760	1000	1100/5800
PD	Prof Dev	0000/1110	2140/7410	1100/5200
FAM	Family/Comm Engage	0000/1110	2495/5000	2200/5800
LIT	Literacy/Reading	1110	1000	1100/4100
MH_SEL	Mental Health/SEL	0000/1110	3120/3130	1200/5800
COUNS	Counsel/ Guidance	0000/1110	3110	1200/5800
ATT	Attend/ Absent	0000/1110	3130	1200/2200/5800
MATH	Math/STEM	1110	1000	1100/4100
CURR	Curriculum/Materials	1110	1000	4100/4200
STAFF	Staffing & Compensation	1110	1000/7400	1100/5800
EXT	Extended/Expanded Learning	1110	1000/4000	1100/2100/5800
FH	Foster Youth/Homeless	0000	3110/3130	1200/5800
SAFE	School Safety/Climate	0000	3130/8100	2200/5800
TUT	High-Dosage Tutoring	1110	1000	1100/2100/5800
TECH	Tech/Digital	1110	1000	4300/4400
LEAD	Leader Develop	0000	2700/7100	1300/2300
SPED	Special Education	0000/6500	1100/5750	1100/1200/5800
CTE	Career Tech Ed	3800	1000	1100/4300/5100
ENRICH	Enrich & Extracurr	n/a	n/a	n/a
CSR	Class Size Reduction	1110	1000	1100
FACIL	Facilities & Maintain	n/a	n/a	n/a
ASSESS	Assess/Data Systems	0000	1000/2100	4300/5800
TRANS	Transportation	0000	3600	2200/5100
ECE	Early Child/TK	1110	1000	1100/2100
VAPA	Visual & Performing Arts	n/a	n/a	n/a
MTSS	Multi-Tiered System of Supports	n/a	n/a	n/a
COORD	Pgm Coor	0000	2700	1300/2300
HLTH	Health Services	0000	3140	1200/2200
EQUITY	Equity & Culturally Responsive	n/a	n/a	n/a
FOOD	Nutrition/Food Services	0000	3700	4300/5800
COACH	Instructional Coaching	1110	2140	1100/1300/5800
CLSUP	Class Support/Aides	1110	1000	2100
ALT_ED	Alternative Education	n/a	n/a	n/a

ADMIN_OPS	Admin Operations	0000	7000/8000	1300/2300/5000
COMM	Comms & Translate	n/a	n/a	n/a
MIGRANT	Migrant Education	n/a	n/a	n/a
OTHER	Unclassified	n/a	n/a	n/a

Core descriptive distributions underpinning the Findings section, including action frequencies, spending totals, and Contributing rates by action code.

Table C3. Highest Contributing rates by action code (top 10)

Action code	Contrib rate (actions)	Contrib actions	Total actions	Contrib rate (funds)
CSR	92.8	64	69	99.4
COACH	89.5	17	19	97.8
ELD	89	666	748	86.8
VAPA	86.4	38	44	98.2
TRANS	83.9	47	56	22.1
MTSS	83.9	26	31	95.2
FH	83.7	174	208	99.5
ALT_ED	82.4	14	17	74
TUT	82.2	162	197	88.8
ECE	81.5	44	54	63.1
COUNS	81.4	267	328	93.6
ASSESS	81	51	63	98.9

Table C4. Lowest Contributing rates by action code (bottom 10)

Action code	Contrib rate (actions)	Contrib actions	Total actions	Contrib rate (funds)
SPED	38.2	50	131	10.8
FACIL	43.3	29	67	9.9
MIGRANT	50	1	2	13.3
COMM	50	1	2	89.1
FOOD	57.9	11	19	83.9
EQUITY	58.3	14	24	58.6
ADMIN_OPS	62.5	10	16	68.4
ATT	67.3	198	294	19.9
HLTH	68	17	25	11.5
SAFE	69	138	200	47.3
OTHER	69.3	656	946	42.5
MATH	70.6	207	293	84.7

Technical outputs from the Part 1 statistical analyses (predictive model performance, cluster archetypes, correspondence analysis inertia, regression coefficients, and network bundle).

Table D4. Correspondence analysis inertia (first two dimensions)

Eigenvalue	Inertia explained (%)
0.01	30

0.008	25.5

Table D5. Tobit regression: predictors of strong-evidence spending share

Predictor	Coefficient	p-value
const	0.039	0.88
UPP_pct	-0.002	0.047
log_enroll	-0.086	0
DA_run_end_2024	-0.07	0.004
log_total_lcap_funds	0.107	0
DistrictType_clean_Elementary School District	-0.581	0.006
DistrictType_clean_High School District	-0.657	0.003
DistrictType_clean_Unified School District	-0.571	0.008
log_sigma	-1.274	0

Table D6. Ordered logistic regression: predictors of evidence strength

Predictor	Coefficient	p-value
UPP_pct	0.029	0.269
log_enroll	-0.163	0
DA_run_end_2024	-0.015	0.592
DT_Elementary School District	-0.543	0.419
DT_High School District	-0.712	0.294
DT_Unified School District	-0.606	0.369

Table D7. Linear regression: predictors of spending concentration (HHI)

Predictor	Coefficient	p-value
Intercept	0.793	0.114
C(DistrictType_clean)[T.Elementary School District]	-0.267	0.591
C(DistrictType_clean)[T.High School District]	-0.294	0.556
C(DistrictType_clean)[T.Unified School District]	-0.291	0.559
UPP_pct	-0.001	0.062
log_enroll	-0.005	0.599
DA_run_end_2024	-0.03	0.155

Appendix 5. Supplemental Statistical Tables for LCAP Analyses

5.1 Allocation-Rule Analysis Student-Group Tailoring and Resource Gaps

The analytical sample uses 953 LEAs, 1,633 LEA-years, and 32,492 deduplicated action rows. Total planned action dollars are $51,939,121,439, with $35,399,453,918 in 2023–24 and $16,539,667,521 in 2024–25. Specifications include:

- Single-group-only backbone: when one student group is explicitly listed, that group receives full attribution.
- Central estimate for bundled actions: hybrid 50/50 rule. Fifty percent of a bundled action is allocated to the first listed group and the remaining fifty percent is allocated across all listed groups in proportion to year-specific LEA-year student counts for the listed groups.
- Appendix bounds: equal split, primary-only, and proportional-by-enrollment.
- Year-specific denominators: 2023–24 Census Day counts are used for 2023–24 and 2024–25 Census Day counts are used for 2024–25. Low Income is proxied by the CDE socioeconomically disadvantaged count.

Broad 'All' or unspecified actions are not attributed to specific student groups. Instead, the LEA-year share of broad actions, share of bundled actions, and mean number of groups per action enter the regressions as controls. District-year-group regressions are weighted by total district enrollment and use district-clustered standard errors.

The enhanced empirical-weight model was a design that estimated the likely primary beneficiary of bundled actions using funded single-group actions only. Predictors include primary category, secondary category, DA indicator family flags, scope, contributing status, district type, UPP threshold, and year. The model performance results were: cross-validated accuracy = 0.711; macro-F1 = 0.460. The model is strongest for English Learners, Foster Youth, and Low Income, but thin for Homeless students and other rare categories. The model was then applied to bundled actions, centered a Dirichlet prior on the model-implied weights, and averaged results across 30 imputations (alpha concentration=25).

Results. Several notable results included:

- English Learners are the strongest robust positive descriptive result. In 2024–25, their resource share is above their student share under every deterministic rule and under the empirical-weight model.

- Homeless students are the strongest robust negative result. They remain below their student share under every deterministic rule and under the empirical-weight model, and their 2024–25 regression coefficient is robustly negative across the appendix rules.
- Low Income remains rule-sensitive. In 2024–25 the descriptive gap is negative under equal split, hybrid 50/50, primary-only, and the empirical-weight model, but positive under the proportional rule.
- Foster Youth appear descriptively overrepresented under every deterministic rule, but that result is highly denominator-sensitive because the statewide student share is very small. In the regression, the FY25 coefficient is not stable in a substantively useful way.

Resource gap is defined as the attributed funding share minus the student-group share of enrollment, in percentage points.

Student group	**Student share (%)**	**Equal gap**	**Hybrid 50/50 gap**	**Primary-only gap**	**Proport-ional gap**	**Empirical-weight gap**	**Classification**
English Learners	17.4	19.1	34.4	60.0	8.9	15.1	Robust positive
Foster Youth	0.5	29.6	6.5	12.1	1.0	14.6	Robust positive
Homeless	4.0	-3.8	-3.9	-4.0	-3.9	-3.9	Robust negative
Low Income	63.8	-30.5	-22.7	-53.7	8.4	-11.4	Rule-sensitive

Under the hybrid rule, English Learners and Low Income students are still predominantly funded through bundled actions, which is exactly why Low Income remains allocation-rule sensitive. Homeless students are not mainly a bundling problem; they are a visibility problem because they are rarely named at all.

Student group	**Single-group share (%)**	**Bundled share (%)**	**Listed primary share (%)**	**Weighted mean no. groups**
English Learners	12.6	87.4	96.9	2.70
Foster Youth	11.4	88.6	95.6	2.64
Homeless	36.0	64.0	62.1	2.28
Low Income	7.5	92.5	22.9	2.80

For descriptive empirical-weight results for 2024-25, English Learners remain above their student share; Homeless students remain far below; Low Income remains below under the empirical-weight mean allocation.

Student group	Student share (%)	Mean resource share (%)	Mean gap (pp)	2.5th pct	97.5th pct
English Learners	17.4	32.5	15.1	13.9	16.7
Foster Youth	0.5	15.1	14.6	13.9	15.6
Homeless	4.0	0.0	-3.9	-4.0	-3.9
Low Income	63.8	52.4	-11.4	-12.9	-10.1

Pooled 2024–25 regression coefficients. In the multiple-imputation resource-gap regression, the pooled 2024–25 coefficient is effectively zero for English Learners, strongly negative for Homeless students, and positive for Low Income. This indicates that the descriptive parity result for English Learners is robust in level but not in the year-effect interaction, while Homeless remains negative in both senses.

Student group	Pooled coefficient	Pooled SE	p-value
English Learners	0.009	0.027	0.749
Foster Youth	-0.215	0.023	0.000
Homeless	-0.033	0.008	0.000
Low Income	0.271	0.019	0.000

Any High-Need family. At the broader family level, the weighted mean UPP is 65.3% in 2023–24 and 66.7% in 2024–25. The weighted mean share of contributing dollars in actions naming any of English Learners, Foster Youth, or Low Income is 68.3% in 2023–24 and 93.5% in 2024–25.

Figure 15. 2024–25 resource gap by student group and allocation rule

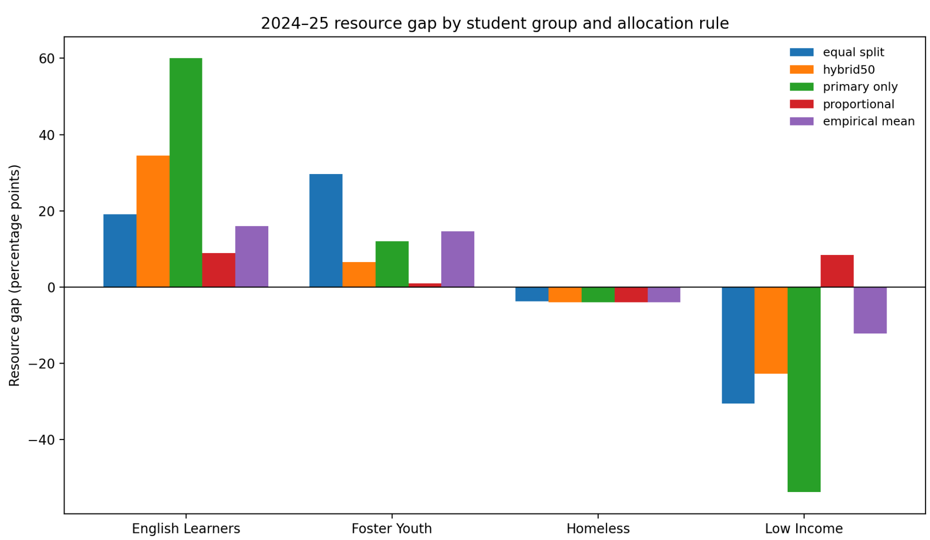


Figure 16. Regression sensitivity: 2024–25 resource-gap coefficients by rule

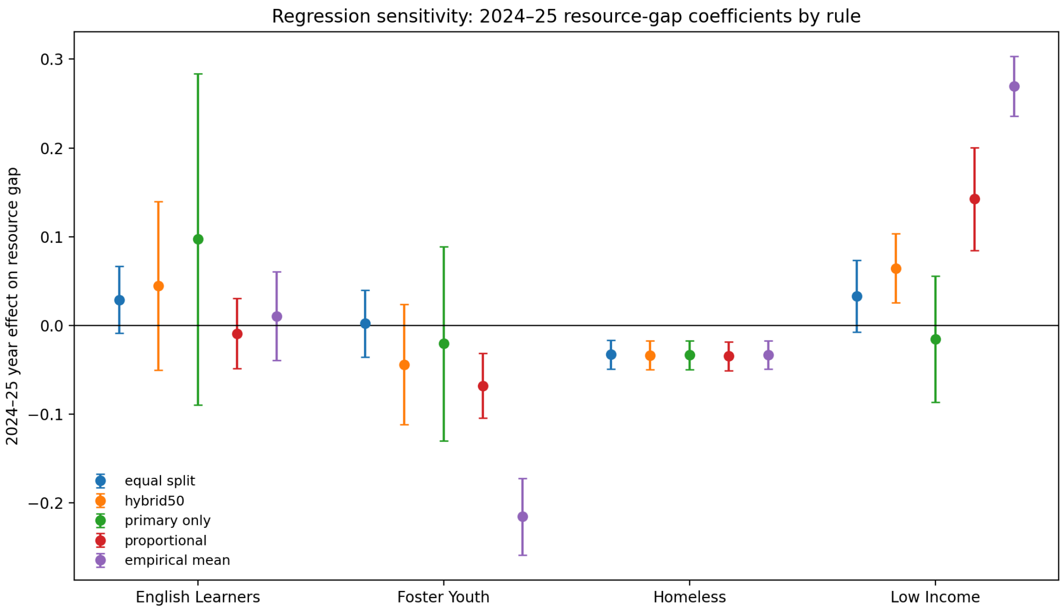
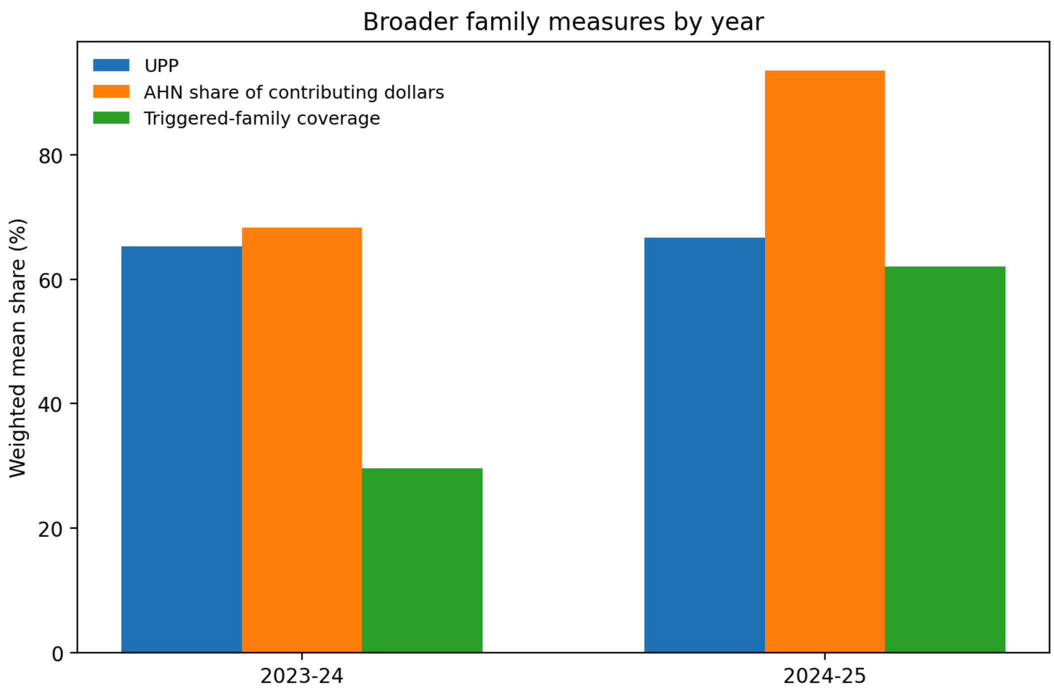


Figure 17. Broader family measures by year



5.2 Overlap Proxy Sensitivity for DA Trigger Duplication

1. Proxy construction

For each DA LEA-year, I reconstructed the set of triggered student groups from the underlying DA status workbook and assigned pairwise overlap priors based on the trigger memo. The central specification uses the memo's explicit student-level overlap rates when available and a 15.9 percent fallback for unspecified pairs. The conservative version sets unspecified pairs to zero. The upper version raises unspecified levels of within-cluster overlap for the demographic-economic cluster and, more modestly, for the vulnerability cluster and disability-linked pairs.

The main derived measures are: (a) average pairwise overlap (APO), (b) effective distinct group count (EDG), and (c) duplication share, defined as 1 − EDG / nominal group count. A denominator-informed weighted APO was also calculated for the LEA-year LCAP sample using year-specific district counts for 2023-24 and 2024-25.

2. Key statistical results

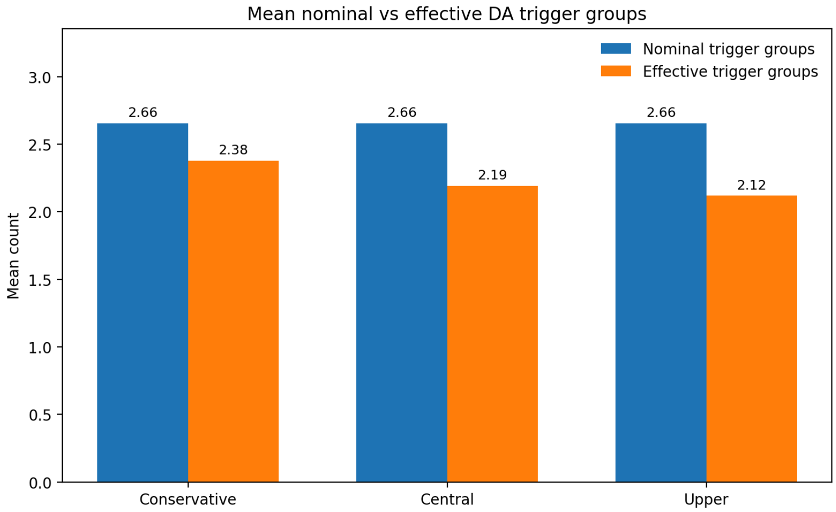
Across 2022–2024 DA LEA-years in the official trigger file, the mean nominal trigger count is 2.7. Under the central overlap specification, that falls to 2.2 effective groups, implying an average duplication share of 11.3%. Under the same central specification, the share of LEA-years with at least two triggered groups declines by 41%, and the share with at least three triggered groups declines by 45%.

In year-to-year DA transitions, high-overlap LEA-years show materially weaker pair retention than low-overlap LEA-years (0.101 vs. 0.155, $p=0.005$). Indicator-code retention is also lower in high-overlap transitions (0.301 vs. 0.360, $p=0.060$). This supports the idea that overlap introduces label churn into measures of student group persistence.

The transition moderation models tell the same story. In the pair-retention model, the interaction between nominal trigger count and duplication share is positive and statistically significant ($\beta=0.177$, $p=0.003$), as it is in the indicator-code retention model ($\beta=0.271$, $p=0.008$). The interpretation is that nominal trigger count is a noisier measure of burden when overlap is high; once duplication rises, the marginal meaning of "one more group" changes.

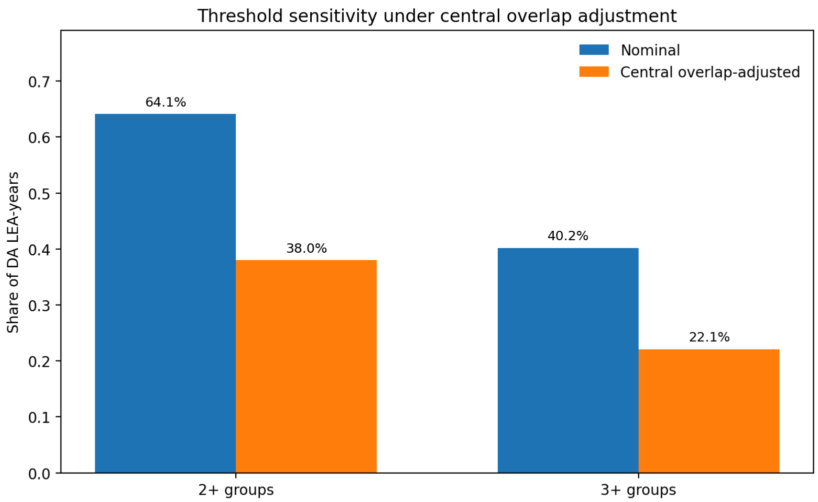
In the DA-only LCAP sample, high-overlap LEA-years show lower LEA-wide action share (0.409 vs. 0.484, $p=0.002$) and lower LEA-wide funding share (0.459 vs. 0.538, $p=0.006$). By contrast, the limited-action share is not materially different by overlap status. That means overlap seems to matter more for interpreting breadth than for overturning the core targeting patterns altogether.

Figure 18. Mean nominal vs. effective trigger-group counts



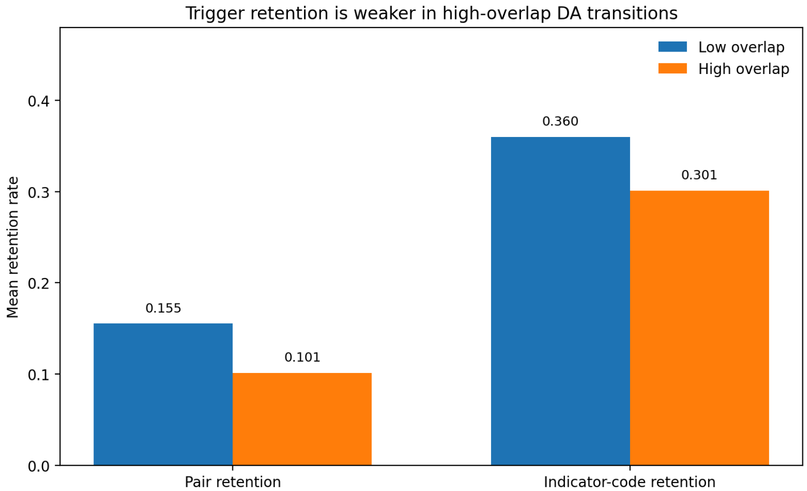
Source: author calculations from uploaded DA, CDEnroll, and LCAP files.

Figure 19. Threshold sensitivity under the central overlap adjustment



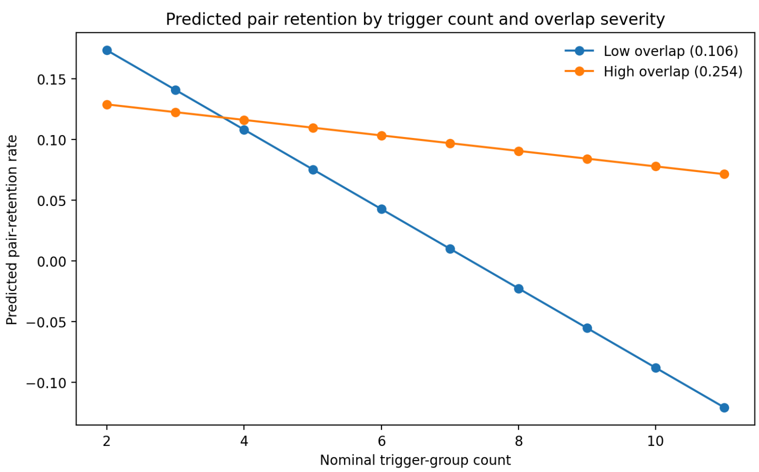
Source: author calculations from uploaded DA, CDEnroll, and LCAP files.

Figure 20. Pair and indicator retention in high- vs. low-overlap transitions



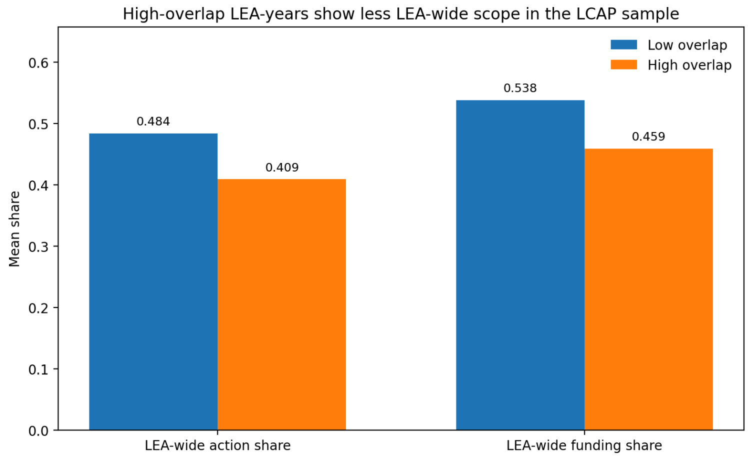
Source: author calculations from uploaded DA, CDEnroll, and LCAP files.

Figure 21. Predicted pair retention by trigger count and overlap severity



Source: author calculations from uploaded DA, CDEnroll, and LCAP files.

Figure 22. LEA-wide scope in the DA LCAP sample by overlap severity



Source: author calculations from uploaded DA, CDEnroll, and LCAP files.

5.3 UPP 55 Percent Threshold and Action Scope

This analysis investigated whether districts above the LCFF unduplicated pupil percentage threshold of 55 percent write their LCAP actions differently from districts below that threshold. The two outcomes are binary action-scope measures: whether an action is written as Limited and whether it is written as LEA-Wide. The key predictor is a district-year indicator for being above 55 percent UPP, merged from the 2023–24 and 2024–25 LCFF summary files.

The models are robust linear probability regressions estimated on 25,280 de-duplicated action records. Each model controls for analysis year, LEA size bin, urbanicity, district type, and lagged DA status. Because the dependent variables are 0/1 indicators, the coefficients can be read directly as percentage-point differences in the probability that an action is written with that scope.

Outcome	**Coef.**	**SE**	**95% CI low**	**95% CI high**	**Interpretation**
Limited action	-0.046	0.006	-0.057	-0.034	About 4.6 points less likely above 55% UPP
LEA-wide action	0.024	0.007	0.010	0.037	About 2.4 points more likely above 55% UPP

The simple scope shares and the regression results are doing slightly different work. The descriptive shares show the raw scope mix within each year and UPP band. The regression adjusts for year, district type, LEA size, urbanicity, and lagged DA status. That adjustment matters because districts above and below 55 percent UPP are not otherwise comparable on several of those dimensions. After those adjustments, the threshold still predicts fewer limited actions and more LEA-wide actions.

The tables below summarize the supplemental and next-round models discussed in the finding's sections. They are designed to line up directly with the event-study, outcome-linkage, evidence-alignment, thematic, chronic-absenteeism, students-with-disabilities, indicator-response, dose-response, and UPP-threshold analyses reported in Sections D.9 through D.12.

5.4 Testing for masked student groups in LCAP reporting

These analyses examine whether student groups that appear weakly represented in the formal LCAP beneficiary fields are in fact under-addressed by districts, or whether they are partially obscured by the structure of the reporting template. The empirical concern is straightforward. The LCAP formally centers unduplicated-pupil logic and contributing-action justification, which privileges English Learners, Low Income students, and Foster Youth. Yet districts often describe a broader set of student groups in their action titles and narratives, including students with disabilities, homeless students, long-term English learners, and racial or ethnic student groups. A single-outcome model cannot distinguish between genuine omission and reporting-induced masking. To address that problem, we estimated a two-part visibility and targeting design and then extended it to an indicator-specific panel.

The first dataset is a district-year-group panel. Each observation represents a district, year, and student group. For each observation, we coded four outcomes: whether the student group appears anywhere in the action title or description, whether it appears in the structured beneficiary field, the share of associated action dollars conditional on visibility, and the scope of the action conditional on visibility. The structured field was operationalized using the UPC Group variable, and “All” or “All Students” was not treated as group-specific formal visibility. Explanatory variables included district-year student-group share, differentiated-assistance status, whether the district was above the 55 percent unduplicated-pupil threshold, group type, year, and district controls available from the ELSI export. The 55 percent threshold indicator was constructed directly from the LCFF summary files.

The second dataset is a district-year-group-indicator panel. Here the unit of analysis is the district-year-group-indicator combination, using math, suspension, and graduation files. This panel is designed to test whether masking varies across accountability domains. It also sharpens the distinction between general district concern and indicator-linked concern. The panel includes indicator-specific trigger bundles, visibility measures, associated target-share measures, and severity indicators based on available accountability information. The academic trigger bundle is not math-only. In the source coding, ELA, math, and English learner progress are grouped together in the academic differentiated-assistance bundle. Accordingly, the math trigger effect should be interpreted as an academic trigger rather than a pure math.

The descriptive results provide the clearest evidence of masking. In the district-year-group panel, the structured field is dominated by the three LCFF-privileged student groups. English Learners appear in the formal field in 82.2 percent of district-year observations, Low Income students in 82.8 percent, and Foster Youth in 80.8 percent. These same student groups also receive the largest associated shares of

LCAP dollars. By contrast, several other student groups appear far more often in the action narratives than in the structured field. Students with disabilities appear narratively in 61.3 percent of district-year observations but formally in only 8.7 percent, producing a narrative-only rate of 53.6 percent. Homeless students appear narratively in 36.1 percent of district-year observations but formally in only 2.6 percent, for a narrative-only rate of 34.0 percent. Long-term English learners, Hispanic students, and Black students show the same basic pattern, though with lower overall visibility levels than students with disabilities. This is the core descriptive signature of masking: districts are naming these student groups in text, but not carrying them into the structured field at comparable rates.

The regression results from the district-year-group panel move in the same direction. A one-point increase in student-group share is associated with about 0.14 percentage points more narrative visibility. Differentiated-assistance status is associated with approximately 12.8 points more narrative visibility, 2.3 points more formal visibility, and 2.4 points more associated LCAP dollar share. The central point is not just that accountability pressure increases attention, but that it increases narrative attention much more than formal-field attention. In practical terms, districts appear to respond to accountability signals by writing student groups into their action language without necessarily translating that attention into the structured beneficiary field.

The district-year-group-indicator panel strengthens this conclusion and shows that masking is not uniform across domains. Graduation is where the narrative-only pattern is most pronounced. Students with disabilities have a graduation-related narrative-only rate of 56.7 percent, Homeless students 44.7 percent, and long-term English learners 27.6 percent. In the stacked accountable-row models, the presence of a differentiated-assistance bundle that includes the indicator is associated with about 11.0 percentage points more narrative visibility, 1.9 points more formal-field visibility, and 1.1 points more target-share. This again indicates that accountability-linked pressure increases visibility primarily through narrative text. Notably, this narrative association is smaller for the formally privileged groups by about 7.9 percentage points, which is consistent with the idea that those groups are already built into the formal reporting architecture and therefore have less room for an additional narrative-only effect.

One of the more important domain-specific results appears in suspension. Red or orange suspension performance is associated with roughly a 2.2-point reduction in narrative visibility. That is, the most severe suspension cases do not appear to generate more explicit textual naming of student groups. This does not necessarily mean districts ignore those groups, but it does suggest that the most consequential discipline problems may not become more visible in the narrative record. That finding deserves caution, but it is directionally important because it implies that the visibility problem may be greatest precisely where a clearer accounting would be most useful.

Even with those limitations, the evidence supports a clear conclusion. The under-representation of several student groups in structured LCAP fields should not be interpreted automatically as evidence that districts are not thinking about those groups or designing supports for them. A meaningful share of the problem is mechanical. The template and its unduplicated-pupil logic encourage formal coding around English Learners, Low Income students, and Foster Youth, while other student groups remain more likely to appear in narrative language alone. The implication for interpretation is important: some apparent gaps in student-group targeting are at least partly reporting artifacts. The implication for policy is equally important: improving the structured capture of student-group visibility would yield a more accurate picture of district strategy, particularly for students with disabilities, Homeless students, long-term English learners, and racially identifiable student groups.

5.5 Coefficient and p-value tables on various regression analyses

Table 5.1. Event-study coefficients around the first DA identification

Outcome	Comparison to first post-identification year	Coefficient	p-value
Limited-scope share	Pre (-1)	0.192	0.194
Limited-scope share	Second year (+1)	-0.239	0.053
Mean evidence score	Pre (-1)	-0.076	0.777
Mean evidence score	Second year (+1)	0.041	0.818
Attendance-focused spending share	Pre (-1)	0.306	0.088
Attendance-focused spending share	Second year (+1)	-0.118	0.264

Table 5.2. Outcome-linkage, evidence-alignment, text-based thematic models

Model	Key term	Coefficient	p-value
Outcome linkage	Subgroup allocation share	-0.023	0.332
Outcome linkage	Mean evidence score	-0.023	0.00061
Evidence alignment	DA status	-0.046	0.143
Attendance language	DA status	-0.01	0.390
Trauma / mental-health language	DA status	-0.001	0.946
Inclusion / disability language	DA status	-0.041	0.072
Acceleration / intervention language	DA status	-0.022	0.160

Table 5.3. Chronic-absenteeism and students-with-disabilities models

Model	Key term	Coefficient	p-value
Attendance-focused spending share	DA status	0.012	0.565
Attendance limited-scope share	DA status	-0.048	0.080
SWD-focused spending share	DA status	-0.064	0.000317
SWD limited-scope share	DA status	0.073	0.170

Table 5.4. Indicator-specific response, dose-response, and UPP-threshold models

Model	Key term	Coefficient	p-value
Indicator-specific response (ELA)	limited_share	0.222	0.030
Pooled dose-response	limited_share	-0.156	0.045
UPP threshold: limited-scope model	UPP_above55	-0.041	0.000578
UPP threshold: LEA-wide model	UPP_above55	0.037	0.013

Table 5.5. Top co-targeted student-group pairs

Group 1	Group 2	Actions together	Spend together ($)
English Learners	Low Income	15362	20,987,191,475
Low Income	Students with Disabilities	54	148,912,150
English Learners	Homeless	76	108,909,057
Homeless	Low Income	67	80,652,902
English Learners	Students with Disabilities	57	25,497,583

Table 5.6. Students-with-disabilities coding summary

Coding dimension	Category	Actions	Spend ($)
Change bucket	Increase	6757	12,673,856,193
Change bucket	Maintain	12911	23,613,666,431
Integration bucket	Cross-program / integrated	14182	24,903,813,984
Integration bucket	Special-education exclusive	7911	17,674,657,167
Special-education phase	5. Services / Supports	17608	31,264,335,960
Special-education phase	3. Eligibility / Evaluation	2283	6,101,312,924