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Zero-Sum Rights: Student Needs, Parental Intervention, and Hidden Rationing in K-12 Education

Johnson, Rebecca Ann

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Zero-Sum Rights: Student Needs, Parental Intervention, and Hidden Rationing in K-12 Education

Rebecca A. Johnson

A Dissertation
Presented to the Faculty
of Princeton University
in Candidacy for the Degree
of Doctor of Philosophy

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by the Department of
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Abstract

While rationing brings to mind ICU beds and transplant waiting lists, K-12 school districts face a similar dynamic where students' need for help outstrips supply. This dissertation investigates how two forces intersect to shape rationing in U.S. school districts. First are policy categories that identify groups of students—students with disabilities; students struggling to learn English; students in poverty—to prioritize for extra help. Second are parents, who may have unequal tools to monitor schools' rationing decisions and unequal power to intervene.

Chapter One provides a framework for how these forces intersect to shape the rationing of resources. Chapter Two investigates how school districts that face cost pressure but that are (1) prohibited from changing *which* categories they prioritize and (2) prohibited from changing *how* they decide who falls into a category, nevertheless ration resources by using discretion to decide that fewer students fall within the disability category. Chapter Three focuses on New Jersey, the state with the largest drop in disability categorization, and finds that districts where parents monitored disability-related decisions were less likely to ration access to the disability category.

Chapter Four expands the lens on monitoring. First, focusing on monitoring *attempts*, it shows how the inequality we see in New Jersey extends to three other states. Second, the Chapter uses computational text analysis to investigate inequality in *what* parents use monitoring for—most notably, either to protest rationing or to protest school disciplinary decisions.

Finally, while Chapters Three and Four suggest that one way to curb hidden rationing is to increase parent monitoring of school decisions, Chapter Five shows that raising the level of monitoring *within one* category might have spillover effects on students in other categories. Using a regression discontinuity design (RDD) applied to a policy change in California, the Chapter finds that resources meant to prioritize other student categories in districts are partially diverted to cover the costs associated

with the disability category.

Overall, the dissertation explores what happens when policies that direct social service bureaucracies to prioritize certain categories are coupled with insufficient funding. This combination leads to hidden rationing that puts those without vigorous advocates at risk of losing out.

Acknowledgements

Global pandemics have a way of both putting the tribulations of the dissertation journey into perspective and making one incredibly appreciative of the people who have selflessly dedicated their time to making this journey possible.

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To Sara McLanahan: you've served as a model of how to combine care about the policy implications of research with a commitment to scholarship; from your early thoughts during the JDP seminar about the relevance of implementation studies to the many opportunities you've given me to develop wide-ranging interests with the Fragile Families group. Your unfailing mentorship during each critical juncture has been a highlight of my time at Princeton, and it seems fitting that I'll soon overlap with your family in Hanover.

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Introduction

In March of 2019, federal authorities announced indictments as part of *Operation Varsity Blues* of dozens of wealthy parents charged with committing crimes to give their children a leg up in elite college admissions (Department of Justice, 2019). Some of the parents, in addition to taking steps like bribing coaches, were charged with faking their child's learning disability to get extra time on the SAT and other tests. The college counselor at the root of the scandal helped them by facilitating access to psychologists who would be more likely to provide favorable diagnoses (Department of Justice, 2019).

The *Varsity Blues* scandal highlights the intersection of class, policy categories, and access to resources. Being categorized as having a disability can grant access to important goods—in this case, extra time on high-stakes exams. The scandal suggested that one of the primary forms of inequality was *false positives among the wealthy*: wealthy parents able to fake a child's disability, resulting in extra help for children who do not need it.

Yet around the same time that these parents were faking their children's disability, the Department of Education was investigating the Texas Education Agency (TEA) for implementing policies that resulted in the opposite type of classification error: false negatives, or children who *did* need extra help not being categorized as having a disability. A *Houston Chronicle* investigation revealed that, beginning in 2005, the TEA started penalizing school districts that categorized more than 8.5 percent of their students as having a disability. In turn, Texas fell from categorizing 11.6 percent of students as having a disability in 2004 to 8.6 percent in 2016 (Department of Education, 2018). The Department of Education's investigation found that, rather than occurring on its own, the drop toward the 8.5 percent target reflected false negatives, or children who needed the help that a disability diagnosis

could provide not receiving the diagnosis.[1] And investigations around *why* the target was set to 8.5 percent, especially when states had an average disability rate of closer to 15 percent at the time, pointed to cost pressure as the culprit. A 2004 report prepared by the legislature's Committee on Public Education discussed caps as a tool for cost containment:[2]

> Another method that states use to control special education costs is to impose caps either on the number of students who can be identified as eligible for special education services or on the amount of available state dollars. Nine states impose caps on the number of students served to a specified percentage of enrollment, which ranges from five percent in Alabama to 12.7 percent in Washington. Texas does not impose a strict cap on special education program enrollment...(House Committee on Public Education, 2014, p.48)

The result, over 25,000 fewer students categorized than if the legislature had not imposed a cap,[3] was concentrated among needy students like English Language Learners (Isensee, 2017). In sharp contrast to the wealthy parents of *Varsity Blues*, who navigated bureaucracies to secure advantage, the parents in Texas struggled to secure basic services for their children.

These two scandals provide different portraits of social class and policy categories. In the college admissions scandal, the already-advantaged fake membership in a category to get further ahead. In the Texas disability scandal, the needy fall further behind when organizations ration access to categories. This dissertation argues that public concern, currently concentrated on the first abuse of categories, should instead center on how cash-strapped organizations using categories to engage in hidden rationing of resources.

While my dissertation focuses on one type of organization—state governments and school districts—and one type of category—categories that identify groups of students who

[1] More specifically, the investigation noted that "Reductions in the percentage of children found eligible to receive special education and related services would not violate the IDEA [Individuals with Disabilities Education Act] if every child suspected of having a disability was properly identified, located, and evaluated in accordance with [the law] (Department of Education, 2018)."

[2] The legislature had asked for recommendations on ways of "reducing state and local administrative costs to increase resource allocation for direct services to students" (House Committee on Public Education, 2014, p.48). Yet while the charge was how to divide the same pie differently—spend less money on overhead; more money on services to students—the recommendations focused on a quota as a tool for general cost containment

[3] This number should not be viewed as the causal impact of the quota on rates. Instead, it was derived in the monitoring report by assuming that, but for the quota, Texas would have maintained pre-quota categorization rates of around 11 percent of students

need extra help—it contributes to three broader literatures on inequality and the American welfare state.

First is the literature on how categories condition access to help. Unlike more universal welfare states that grant assistance as a matter of residency or citizenship (Esping-Andersen, 1990), the U.S. welfare state targets help to specific social categories deemed deserving: mothers with dependent children; veterans; those experiencing homelessness (Katz, 1989; Starr, 1992). In Chapter One, I provide a framework for how categories compare to other methods for rationing resources. This framework shows that although states use policy categories to reduce discretion over who gets what, discretion sneaks back in at two stages and is exercised when organizations face continued cost pressure. First is continued discretion over *which* categories to prioritize, a more well-studied tool of rationing (e.g., Tach and Edin, 2017). Second is, within the formal policies that prioritize categories, on-the-ground decisions about (1) who belongs to a category, and (2) whether and how many resources reach category members. The framework shows the important role that potential beneficiaries of a resource have in reducing this discretion.

Second, in schools, the beneficiaries of resources are students, with parents serving as their surrogate advocates. A wealth of research highlights socioeconomic inequalities in this advocacy, showing how higher-SES parents are better able to shape on-the-ground decisions in schools in their child's favor (Lareau, 2000, 2011; Calarco, 2018). Yet the bulk of this research—conducted as ethnographies focused on a small number of schools—tends to view these schools outside of their budgetary context.[4] This budgetary context, state and local formulas that earmark school resources for certain categories of students, alters the background against which inequalities in advocacy take place. In turn, while a large

[4]As I discuss in greater detail in Chapter three, the authors sometimes mention general budget shortfalls—for instance, Lareau (2011) discussing the "very limited" budget at one of the schools she studied, and the lack of a PTA to make up state funding shortfalls. However, within the same district or school, there can be *over-time* changes in budget pressure that help us separate effects of these budget shocks on resource decisions from effects of the socioeconomic composition of a district's parents. And research on how the fiscal and political context around schools impacts on-the-ground decisions has tended to focus on one aspect of this context: accountability mandates that incentivize or penalize schools financially based on test performance (e.g. Booher-Jennings, 2005, 2006). The present work builds upon that research to focus on another part of the political and fiscal context: budget earmarking.

literature investigates the effects of these formulas on student performance (Jackson et al., 2014; Lafortune et al., 2016), much less research (1) investigates the moral ideas implicit in these formulas (Chapter One) and (2) how *formal* prioritization policies intersect with on-the-ground pressure by parents (Chapters Two through Five).

Finally, one challenge in investigating on-the-ground pressure by parents is a gap in data. Ethnography yields nuanced details of these interactions, but the small samples limit inference about the *impact* of interactions on school decisions. While parents' pressure on schools comes in many forms—exchanges during parent-teacher conferences; texts and emails; formal organizing—this dissertation studies one form of pressure: formal challenges to decisions about resources or school discipline. In turn, while research in "computational social science" (Lazer et al., 2009) has yielded new methods for analyzing interactions, little existing research focuses on this context (Evans and Aceves, 2016).[5] By applying these methods to study interactions between administrators representing school districts and parents seeking help for their child (Chapter Four), this dissertation helps spread these new tools to the study of street-level bureaucracy.

[5]In particular, the examples in Evans and Aceves (2016) fall in to two other categories: interactions between two official state actors (e.g., politicians interacting in a debate) or interactions between two non-state actors (e.g., interactions in workplace settings or speed dating).

Chapter One: Contextualizing the Case: Categories as Tools for Rationing

1.1 Overview

While Texas school districts under pressure to contain costs were categorizing fewer and fewer students, another legal storm was brewing around another costly decision. After a school district has categorized a student as having a disability, what depth of resources does the district owe them? Put differently, although more resources are optimal, when can a district claim to have done enough?

In January of 2017, the U.S. Supreme Court heard oral argument in *Endrew F. v. Douglas County School District*. Endrew (Drew), a child born in 1999 and subsequently diagnosed with Autism Spectrum Disorder (ASD) and Attention Hyperactivity Disorder (ADHD), had made it past the first hurdle in access to resources: he had been categorized as having a disability by the Douglas County School District. This category gave him access to an Individualized Education Plan (IEP), a legally-binding contract negotiated and signed on a yearly basis between Drew's parents and the school district. In the IEP, the district agreed to provide Drew with services.

But what depth of resources did the district owe Drew? Drew's parents argued that Drew was entitled to more resources than the district's public schools were willing or able to

offer. As the parents put it to a reporter, "If he was able to show up to school and say 'good morning,' that was good enough for them [Douglas County School District]" (Aguilar, 2016). Frustrated by the district's efforts, the parents rejected the district's proposed contract of services (the IEP) for Drew's fifth grade year and enrolled him at Firefly Autism House, an autism-focused private school that specializes in providing Applied Behavior Analysis (ABA) and where tuition approaches $70,000 per year. The parents' request for reimbursement, and the district's denial, led first to a state-level hearing and then to litigation over the content of Drew's contract.

District professionals, in refusing to reimburse the costs of attending Firefly, argued that the district might not have done everything, but it had done enough. A series of lower-court judges sided with the district professionals.[6] Each judge in his or her decision recognized that Firefly's more intensive services, which included a 1:1 student-teacher ratio and detailed charts of Drew's progress that the school shared with Drew's mother on a daily basis, were perhaps *optimal* for Drew. But each judge concluded that the district's services were *sufficient*.[7] For instance, the state Administrative Law Judge (ALJ) argued that, "There is no question that [Student] has made progress at [Private School]... But the fact that [Student] was making greater behavioral progress at [Private School] does not mean that [Student] was not receiving a FAPE at [School #2]" (Colorado Office of Administrative Law, EA 2012-0006). Later, the tenth Circuit held that:

> This is without question a close case...It is clear from the testimony at the due process hearing that Drew is thriving at Firefly. But it is not the District's burden to pay for his placement there when Drew was making some progress under its tutelage. That is all that is required (*Endrew F. v. Douglas County School District*, (10th Cir., 2015))

In the lead up to the Supreme Court oral argument, most organizations filing amicus briefs took the side of Drew and his family.[8] The briefs supporting Drew argued that "some

[6] A state-level Administrative Law Judge (ALJ); a federal district court judge; and a panel of judges on the U.S. Court of Appeals for the Tenth Circuit.

[7] More formally, each judge ruled that the district had met its obligation to provide Drew with a Free and Appropriate Public Education (FAPE) under the Individuals with Disabilities Education Act (IDEA).

[8] Ten out of the 14 briefs were filed on behalf of the plaintiffs (Drew's family); 4 out of the 14 the defendant (the school district).

progress" was not enough. Those filing on the district's behalf had to make the less popular argument that it was. To do so, they pointed to the fact that the $70,000 would come from a finite budget—giving enough to Drew to help him thrive might not leave enough for other students with disabilities whose parents were less effective advocates or for students without disabilities:

> Both of these actions [giving parents more incentives to file complaints and more private school placements] would divert significant resources from school districts' efforts to educate other students with disabilities and those without...Driving up private placements and encouraging litigation would harm the education of all students (Council of the Great City Schools, 2016, p. 6-7).

The districts thus argued that they need to ration resources to make sure that all students get enough, even if it means that no student will thrive.

The case highlights how formal policies to prioritize certain students leave room for on-the-ground discretion in the resources that organizations actually provide. Were the services at Drew's original school sufficient, or did he need more personalized attention? Courts tried to limit the discretion of Douglas County educators and administrators by establishing uniform standards. Drew's parents tried to limit discretion as well by acting as his private attorney general, investing substantial time and resources into arguing that he had a right to more than he was given.

In the rest of this Chapter, I show how two features of the case—policy categories used to earmark resources; parents advocating to make sure their child gets priority—fit in to four general moral logics of prioritization in social policy. I use the word "moral" because the policies make often implicit normative assumptions about who deserves help, even if these assumptions are embedded in details of the policy.[9] I use the word "logics," drawn from the institutional logics literature (Alford et al., 1985; Thornton and Ocasio, 2008), because the moral ideas become embedded in both formal policies and on-the-ground practices of key stakeholders in social policy: federal governments setting broad allocation rules; state

[9]For instance, as I discuss in Chapter Five, federal Maintenance of Effort (MOE) requirements that districts spend at least X percent in a current school year of what they spent in the prior school year, with X sometimes varying for different categories of students, implicitly rank the relative priority of these students during budget cuts.

governments that refine those rules and often finance their promises; local bureaucracies whose workers interact directly with potential beneficiaries.

In the remainder of the Chapter, I first outline a framework for ways that decision-makers can ration resources. The framework highlights two constraints on rationing. One constraint comes from policy categories, where decision-makers must prioritize category members. Another constraint comes from potential recipients of a resource, who might argue that they were unjustly denied that resource. I apply this framework to school districts that face difficult rationing dilemmas when deciding which students get what. Finally, I show how rationing in schools has the potential to exacerbate inequality because of its hidden nature: districts that face budget pressure but that are legally-prohibited from making cost-conscious decisions need to ration in ways that are less visible to both regulators and parents.

1.2 Rationing: a framework

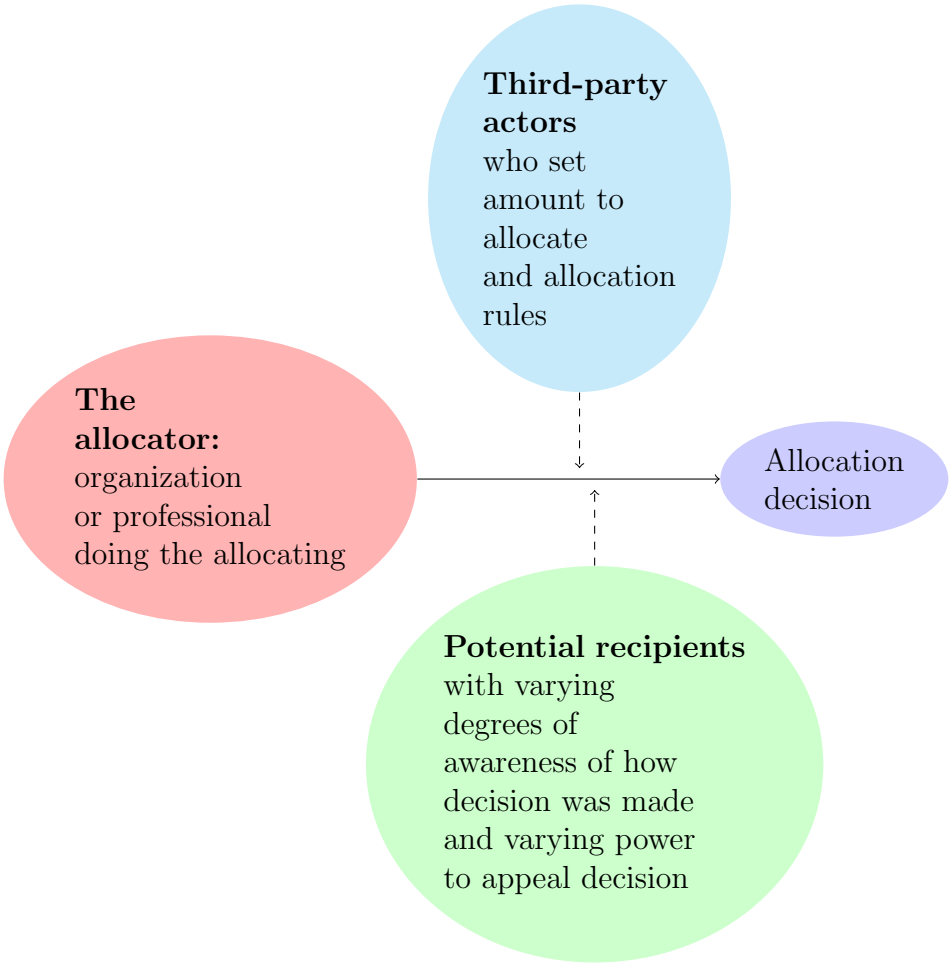
The case of school districts allocating limited resources to students with competing needs is one among many cases of rationing, defined broadly as decisions about who gets what when not every potential recipient can have resources to the point of satiety (Elster, 1992). While there are many ways to classify rationing decisions–the nature of the good being rationed (Walzer, 2008); the form that scarcity takes;[10] the type of organization forced to ration–the present framework focuses on two aspects of an allocation process. First: which actors are involved in rationing? Second: how much discretion do they have over rationing decisions?

1.2.1 Actors involved in rationing

Figure 1.1 presents a stylized diagram of how organizations allocate scarce resources, highlighting actors that Elster (1992) notes are involved in this process. The first set of actors are those responsible for rationing. Admissions committees allocate scarce spots at uni-

[10]For instance, are there natural limits to the resource or is the scarcity due to higher-level allocation decisions? (Elster, 1992).

Figure 1.1: Actors involved in rationing



versities, the United Network on Organ Sharing (UNOS) allocates kidneys, private firms allocate jobs. In the school district case, these allocators include district administrators responsible for school budget choices that shape the broad distribution of resources within a district, and teachers who allocate less tangible goods like attention and time.

The second set of actors are potential recipients of the resource being rationed. In school districts, the potential recipients are school districts at one level of allocation and students at another level of allocation, usually proxied by parents and guardians.

The final set of actors relevant for rationing are what I call third-party actors that do not make the rationing decisions themselves but instead affect features of the process like the criteria allocators use or how much of a resource is available to allocate.

1.2.2 Reducing discretion over rationing: general framework

Figure 1.1 highlights the relationship between those who make rationing decisions and two sets of parties that try to control those decisions. In turn, different real-world rationing examples vary in what role, if any, others play in constraining rationing.

Figure 1.1 suggests a 2 × 2 table of different constraints that those rationing a resource can face, with some cells more well-populated than others. Focusing on examples in each cell, first are allocation processes where both parties place weak constraints on allocations. Professionals at firms who allocate scarce jobs fall into this cell: the professionals face minimal constraints on these decisions from either third-party actors or potential recipients (Rivera, 2016). From third-party actors, firms can allocate according to whatever criteria they choose as long as these criteria do not violate anti-discrimination statutes like those enforced by the Equal Employment Opportunity Commission (EEOC). Meanwhile, potential recipients of a job are rarely given a reason for an unfavorable allocation decision at various stages in the process (e.g., if they do not receive an interview; if they do not receive an offer) and have no formal rights to appeal this decision.

Table 1.1: Different combinations of constraint allocators face

	Strong constraints from potential recipients	Weak constraints from potential recipients
Strong constraints from third-party actors	**School categories**	Physicians in HMOs allocating treatments; Local orgs allocating housing vouchers; UNOS allocating kidneys
Weak constraints from third-party actors	Parents intervening in decisions in private schools	**Firms allocating jobs; private universities allocating admissions**

While firms ration jobs under weak sets of constraints from both parties, in other cases, the allocator faces strong constraints from third parties but weak constraints from potential recipients.

For instance, physicians employed by HMOs or other managed care organizations can

face strong constraints from third-party administrators on rationing—for example, a physician may need prior authorization before prescribing an expensive therapy. But patients denied a therapy by a physician have few formal tools to appeal. While patients can file malpractice claims to challenge certain medical decisions, the grounding of these claims in tort law creates a stringent threshold for showing that a medical organization's withholding of services warrants court intervention.[11]

The opposite cell reflects rationing marked by weak constraints from third parties but strong constraints from potential recipients. Examples include private organizations that face few constraints from third-parties and more constraints from potential recipients of a good–for instance, private schools face many fewer constraints from the federal government than public schools, but may face equal pressure from parents trying to influence allocations.

The fourth cell encompasses allocation processes where the allocator faces strong constraints from both third-party actors and the potential recipients. Constraints from third parties include requiring the allocator to use explicit criteria to allocate the resource rather than leaving criteria unspecified.[12] Other constraints include requiring that the allocator makes a minimum number of allocations or allocates the resource to a minimum percentage of applicants.

Notably, there is not only *between*-process variation in where an allocation process falls

[11]For instance, in *Wickline v. California*, a patient sued Medi-Cal for granting a four-day extension of a hospital stay after surgery when the physician requested eight days. The patient developed an infection shortly after discharge that resulted in the amputation of her leg, which the physician argued an eight-day extension could have prevented. In *Wilson v. Blue Cross*, parents sued an insurer who restricted their son's depression treatment to ten days when the physician recommended at least four weeks; the harm that triggered the suit was the son's suicide after his discharge (Perdue and Baxley, 1995). Meanwhile, patients whose physician prescribes a therapy but who are denied reimbursement by insurance have some appeal rights: they can file appeals that the insurance company reviews or appeals to an external medical review board (Office, 2011). However, a Government Accountability Office (GAO) audit of this process suggests that only a small proportion of coverage denials–0.5% in one estimate–are appealed, despite the fact that, once filed, over 30 percent of appeals are successful(p. 22).

[12]Sometimes the third party defines these criteria and then requires that allocators follow them–for instance, the Social Security Administration defines criteria for what counts as a work-limiting disability and requires local Disability Determination Offices to apply these criteria. In other cases, the third party allows the allocator to set the formal criteria themselves as long as the allocator follows a certain procedure to choose those criteria.

but also *within*-process variation over time. Hospitals once allocated kidneys under few constraints from either third-party actors or potential recipients. The "God committee" at Seattle Hospital, for instance, once weighed factors like the potential recipient's contribution to the community and faced few pressures to use more clearly-defined criteria. However, since that time, the United Network on Organ Sharing (UNOS) has shifted to allocating kidneys using an explicit formula that places strong constraints on how transplant teams allocate the organs. While this is an example of the same process shifting from fewer constraints on allocators to more constraints on allocators, other allocation processes have shifted in the opposite direction. For instance, one form of "privatization" involves governments entering into contracts with private organizations–either nonprofits or for-profit entities–to administer some aspect of a government-financed allocation (e.g., assessing eligibility for the resource) (Starr, 1988).[13] This form of privatization has generated criticism by those who argue that allocators in these private organizations will face fewer constraints in making these decisions than the government agencies that once allocated the resource (Gilman, 2001).

1.2.3 How categories impact rationing

Policy categories introduce another step in the rationing process that Figure 1.1 depicts.[14] Categories are legally-binding constraints on whom an actor can allocate a resource to and are often grounded in notions of need or desert: the elderly; veterans; mothers with dependent children; those with disabilities. Economists have noted the prevalence of categories for both cash and in-kind transfers in U.S. social policy (Akerlof, 1978; Currie and Gahvari, 2008). Akerlof (1978) outlines the structure of categories: rather than granting different sizes of transfers based on a continuous measure of need, the categories often involve binary distinctions where those who qualify for the category get some quantity of the resource[15]

[13]This corresponds to the third meaning, discussed in Starr (1988) p. 16-17 of: "instead of directly producing some service, the government may finance private services, for example, through contracting-out or vouchers."

[14]For shorthand, in the remainder of the dissertation, I call these categories. But they differ from social categories like gender in that they are used for some official state purpose.

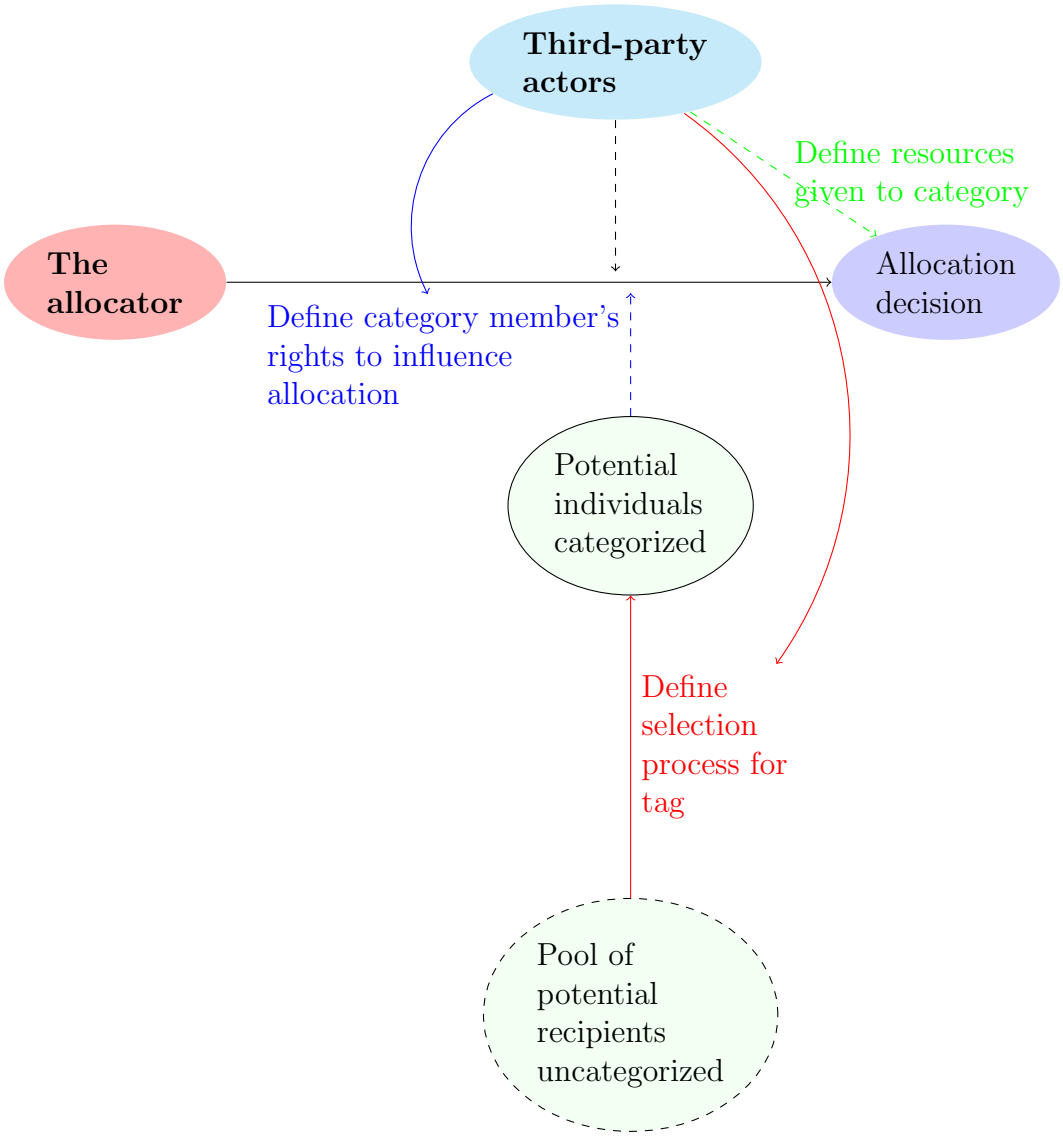
[15]This quantity can vary in magnitude or be equal across recipients

and those who fail to qualify for the category get nothing.

In turn, categories constrain rationing. Imagine two allocators. One is a bureaucrat within the Social Security Administration. The other is a wealthy philanthropist. Each has been giving cash transfers to elderly individuals to help these individuals survive without formal employment. Each allocator, after reading about increasing longevity and about an increasing share of workers employed in knowledge or service occupations rather than disabling forms of manual labor, decides that he should start allocating the cash transfers not only by age but also by an individual's degree of impairment, such as struggles with walking and driving. The bureaucrat, constrained by the role of categories in the allocation of cash assistance to the elderly,[16] is not free to change how he rations. The wealthy philanthropist, facing few constraints on how his foundation allocates grants, can do so.

[16]In particular, people qualify for social security benefits by a combination of an age minimum and a minimum number of work credits.

Figure 1.2: Actors involved in rationing: the role of categories



This example highlights how third-party actors use categories to constrain discretion. First, third-party actors often define *whether* categories are used to filter the pool of potential recipients into those with tags that give them rights to resources—for instance, should a bureaucracy use categories or a lottery? Then, if the method is categories, the third party often defines which categories are prioritized—for instance, should able-bodied adults receive help or only those whose inability to work is "no fault of their own"? Finally, third parties define how individuals should get categorized. For instance, is the category is an easy-to-assess attribute like age or a more complex, value-laden one like disability (red ar-

row in Figure 1.2)?

Second, third-party actors often define the scope of resources associated with the category. For instance, do Medicare benefits include prescription drugs? Which foods and beverages can individuals receiving Supplemental Nutrition Assistance Program (SNAP) benefits purchase (green arrow in Figure 1.2)? Third, third-party actors often define what rights category members have to influence allocations (blue arrow), either by protesting a denial of an allocation or, once allocated, protesting its termination. In other words, what rights do potential category members have to appeal an unfavorable allocation decision? These appeal rights are important for maintaining the legitimacy of allocation processes, but authors like Lipsky (2010) argue that these appeals are often made "costly to use, rarely successful, and, if successful, certainly not well-publicized." This means that appeals can promote legitimacy without placing actual strains on benefits provision.

To make the concepts in Figure 1.2 more concrete, consider how the shift from Aid to Families with Dependent Children (AFDC) to Temporary Assistance to Needy Families (TANF) as part of the 1996 welfare reform reconfigured each of the components. The first shift was in how the federal government defined the qualifying categories (red arrow). The federal government not only adopted a more restrictive tag of its own that added work requirements, but also weakened its influence on eligibility (weaker red arrow). The government allowed states to define categories more restrictive than the federal categories, such as setting more stringent work or time limits or calculating asset exemptions differently (Gais, 2001).[17] The second shift was in the resources category members were entitled to (green arrow). States continued to have latitude in setting the generosity of benefits associated with the category, though the block grant financing I discuss in greater detail below placed pressure on states to reduce the generosity of these category-associated resources.

Finally, commentators argue that the shift not only changed which individuals had access to the category and the depth of resources category members were promised, but also changed the appeal rights available to category members (blue arrow), who struggled to

[17] More recently, Kentucky, through a waiver from the Department of Health and Human Services, has generated controversy through attempts to add work or financial/health literacy requirements to the tag entitling individuals to Medicaid.

retain access to help even if an agency made mistakes in categorization decisions(Gilman, 2001; **?**).In particular, in *Goldberg v. Kelly*, the Supreme Court ruled in 1970 that although the U.S. Constitution lacks a positive right to welfare, welfare benefits are a form of property and, as a result, holders of the benefit are entitled to the "due process protections of prior notice and a hearing" before the government terminates their benefits. These due process rights are grounded in a recipient's "legitimate expectation of an entitlement." Yet later case law clarified that this legitimate expectation is contingent upon the process used to allocate the benefit. Cases like *Eidson v. Pierce* asserted that individuals lack property rights, and thus lack due process protections, for benefits like housing vouchers where parties involved in the allocation process have substantial discretion in deciding who accesses the benefit.[18] Gilman (2001) argues that the partial privatization that accompanied welfare reform–states contracting out to private firms essential functions of benefits allocation like eligibility terminations and terminations for non-compliance–might have undermined due process protection for benefit holders by undermining the benefit's entitlement status. In turn, Eubanks (2018) shows that even when Indiana adopted an automated welfare eligibility process that erroneously deemed individuals ineligible, the weakness of due process rights—the automation process was managed by a non-state contractor shielded from liability—meant a long delay in getting help.

1.2.4 Fiscal federalism and categories

The AFDC to TANF example foreshadows another aspect of how categories constrain rationing: how categories intersect with the financing of a resource in U.S. federalism. Welfare reform not only narrowed *who* was prioritized but also changed how the benefits attached to the category were financed. With AFDC, the federal government matched at least one-half of every dollar that a state spent on benefits for those eligible with a federal contribution, allocating more to poorer states and during times of rising caseloads. TANF shifted to block grant financing that involved three changes: the grant's amount was fixed to a histor-

[18]That ruling, issued by the 7th Circuit, is somewhat contradicted by rulings in other Circuits that place limits on the role that the presence of discretion in allocations can play in limiting property interests in a public benefit.

ical level,[19] states needed to contribute substantially more to financing category members' services than in the past, and states had more flexibility to define what resources to give category members (Edin and Shaefer, 2015; Schott and Floyd, 2017).

Framed in terms of Figure 1.2, block grants changed aspects of the link between categories and rationing (green arrow)–for instance, states could spend large portions of the grants not on direct cash transfers to category members but on broader supports potentially useful for the *class* of tag-holders like childcare initiatives. More troublesome for inequality, states could also use category-associated federal budget allocations to fill budget holes for other state services with little relationship to the needs of category members (Edin and Shaefer, 2015; Schott and Floyd, 2017). The federal government thus weakened *both* its role in defining the category and its associated rights and resources *and* its role in financing the category.

This example shows one potential relationship between fiscal policy and categories: a third party (often the federal government) weakens its influence on a category[20] and also weakens its role in financing the resource. Table 1.2 outlines other potential relationships.

Table 1.2: Relationships between a third party's role in influencing a category versus devoting resources to the category

	Role of third party in influencing a category's definition, rights, and resources	
	Strong role	Weak role
Robust third-party financing of tag	Funded entitlements	NA
Minimal third-party financing of tag	Unfunded entitlements	Discretionary goods

The case I discuss in the next section falls in the lower left-hand cell: the federal government (a third party) has a strong influence on the category but finances few of its associated resources. I call this an *unfunded entitlement*.[21] In unfunded entitlements, the federal gov-

[19] States were allowed to choose between one of three "base periods" in the 1990s.

[20] With influence defined as the three roles in Figure 1.2: defining the category, defining resources that attach to the category, defining category members' rights.

[21] We can think of *unfunded entitlements* as a subset of more commonly-discussed *unfunded man-*

ernment treats the resource as an entitlement–everyone who belongs to the category gets access to the resource and category members have strong rights to protest resource denials–but requires state and local governments to finance the entitlement.

In contrast, most cases fall in the upper left-hand cell of Table 1.2. For instance, the federal government has a strong role in influencing the categories used to access Social Security benefits, setting detailed rules about aspects like work credits. But the federal government pairs this strong influence with robust financing of the resource, paying out benefits through a Social Security Trust Fund that is protected from fluctuations in yearly budget allocations. Similarly, while benefits like SNAP are financed out of federal budget allocations rather than a protected trust fund, the program's structure–federal financing of benefits for all individuals who meet the eligibility conditions for accessing the resource–makes SNAP a funded entitlement.

Constitutional restrictions make unfunded—or more precisely, weakly funded—entitlements rare. Most notably, the Spending Clause and associated case law limit the federal government's ability to change the structure of social benefits without providing funding for these changes.[22]

dates. The latter term typically refers to the federal government placing requirements on sub-national units–state governments; local governments; private firms–without allocating sufficient funding to cover the costs of complying with the requirement. As Dilger and Beth (2011) discusses, there is much debate over what counts as an unfunded mandate and most agree that rather than a binary classification, there is a continuum that stems from both the stringency of the mandate, the amount of funding the government allocates to cover its costs, and the degree of coercion states face in accepting the mandate and some funds versus declining. These unfunded mandates cover a broader array of decisions than those about allocations. For instance, the federal government might require states to enforce child support payments more vigorously but allocate few funds to that stronger enforcement (Dilger and Beth, 2011).

[22]Indeed, a recent example highlights the constraints that make unfunded entitlements rare. The Patient Protection and Affordable Care Act (ACA) proposed a new federal constraint on how states define the tag required to qualify for Medicaid. States previously varied widely in how they defined the tag. While nearly all states excluded most non-disabled adults without dependent children from coverage, states also varied in the income requirements among parents, with some covering parents with incomes up to 100% of the federal poverty level and others excluding parents who earned over 50% of the federal poverty level (Kenney et al., 2012). The ACA required that by 2014, states shift to a more generous set of categories and cover all individuals under the age of 65 with incomes below 133% of the federal poverty level, including non-disabled non-parents. If states did not accept these expanded categories, they would not only lose funding that would help cover the costs of the expansion but would also lose existing federal funding for Medicaid. In *National Federation of Independent Business (NFIB) v. Sebelius*, the Supreme Court ruled that despite the generous federal funding to cover the costs of more categories–federal financing of 100% of expansion costs in the first two years with a gradual phasing down to 90% of the costs by 2020–the expansion's terms

Unfunded entitlements raise questions about inequality. What happens when the federal government defines a category broadly, promises generous resources associated with the category, and gives category members strong rights to influence the receipt and magnitude of those resources, while financing few of the costs of these promises?[23] While many herald the inequality-reducing promise of each of these steps–more expansive categories for social benefits; more generous resources attached to categories; stronger rights to receive and retain these resources–this case helps us explore implications of making these promises amidst insufficient resources to fulfill them.

were unconstitutionally coercive. Part of the court's reasoning was that the proposal constituted a "shift in kind" in the definition of who should qualify for Medicaid rather than just a "shift in degree." The Supreme Court held that the federal government's proposed shift from a limited set of discrete categories to access Medicaid–the blind, elderly, disabled, and low-income families–to a more expansive set of categories, accompanied by the withholding of federal matching funds for states that did not accept the expanded tag, was an unacceptable form of coercion. The ruling highlights the challenges the federal government faces in playing a strong role in shaping categories for priority without fully financing those changes. In addition, some statutes try to discourage unfunded mandates or entitlements. For instance, 1995's Unfunded Mandates Reform Act (UMRA) allowed the Congressional Budget Office (CBO) to estimate the potential costs of "unfunded mandates" on local governments and private firms when scoring legislation. Analyses suggest mixed effects of UMRA on reducing the incidence of unfunded mandates (Dilger and Beth, 2011).

[23]In the U.S., this party is often the state legislature or other, sub-national levels of government. Zackin (2013) argues that although the *federal* Constitution does not offer individuals positive rights to resources like housing, education, and healthcare, these positive rights are present in many state constitutions. Advocacy groups use these state constitutions to make rights claims–in the next section, I discuss how social movements use rights to an adequate education outlined in state constitutions to press state legislatures to redistribute resources between school districts. Relatedly, cases like *Callahan v. Carey*, where a class of 10,000 homeless men sued New York City housing officials arguing that the lack of shelter space violated a provision of the state constitution, targeted the same level of government that outlined the right (Haywood, 2002). Internationally, some Latin American countries have outlined a positive right to health–most notably, Brazil gives individuals a right to file litigation if denied, for instance, reimbursement for a particular prescription drug (Biehl et al., 2009). Again, the level of government that defined the scope of the right (the federal government in the Brazilian constitution) bears the fiscal responsibility of fulfilling it. Hyman (1999) describes how some U.S. state legislatures considered something approaching a positive right to specific healthcare resources during debates in the 1990s over whether managed care would result in patients being inappropriately denied needed healthcare services. At the federal level, a 1997 commission during the Clinton era proposed a Bill of Rights that would have contained a "Complaints and Appeals" clause that would give healthcare consumers a right to a "fair and efficient process for resolving differences with their health plans." That bill, and a later one proposed in 2001, never passed, leaving patients with a weaker set of rights in the form of malpractice claims where the denial of care must cause significant harm before it triggers an actionable claim.

1.3 The specific case: rationing in school districts

Existing research largely focuses on rationing in medicine: kidneys; ICU beds; expensive, life-saving therapies. Yet stakeholders in education also face rationing dilemmas: state governments dividing finite dollars across school districts; school districts rationing access to higher-performing schools in a district or extra staff like counselors and school psychologists (Condron and Roscigno, 2003); teachers rationing finite time and attention (Booher-Jennings, 2006). And as a coalition of schools supporting the District's rationing decisions in Drew's case argued in their amicus brief, these rationing dilemmas unfold as budgets tighten:

> Ever since the 2008 recession, public school districts have been under extraordinary pressure...Petitioner's proposed standard is a financial load that public school district budgets simply cannot bear (Council of the Great City Schools, 2016, p. 27-28).

Dealing with this budget pressure, what methods do school districts use to ration? These methods are often hidden or implicit, since rationing is particularly difficult to discuss openly in a context where the beneficiaries are children and where, as Jencks (1988) notes, no one argues "about whether educational opportunity should be equal"(Jencks, 1988, p. 518). Instead, rationing occurs via decisions about how to operationalize educational opportunity in concrete policies. As Jencks (1988) puts it: "the enduring popularity of equal educational opportunity probably derives from the fact that we can all define it in different ways without realizing how profound our differences really are"(p. 518).

The purpose of this section is to map the different prioritization methods that stakeholders in education use to the ideas about how to operationalize educational opportunity that they reflect. Before discussing the two methods that this dissertation focuses on—a mix of categorical and beneficiary-driven prioritization—I review two other methods that are also used: lotteries and predictive models.

1.3.1 Abandoning prioritization: lotteries

Lotteries reflect a prioritization logic that involves abandoning notions of priority. The other moral logics try to operationalize who deserves a resource, whether through a model (predictive model-guided prioritization); manually-chosen categories reflecting need (categorical prioritization); or requests for help (beneficiary-driven prioritization). In contrast, lotteries give everyone who enters an equal shot at priority. Framed in terms of Jencks (1988)'s different notions of educational opportunity, lotteries correspond to *democratic equality*: each student is given an equal shot at a resource.

In education, pure lotteries are rare. Instead, they are often either (1) combined with eligibility criteria that only allow certain categories of student to enter the lottery (thus collapsing into a form of categorical prioritization), or (2) structured to give certain students higher odds in the lottery. For instance, the federal No Child Left Behind legislation initially required that charter schools that receive certain federal funds use a lottery when they have more applicants than seats (Skinner, 2014; Berends, 2015). Yet the U.S. Department of Education later clarified that oversubscribed charter schools could use a weighted lottery giving higher odds to students in categories like economic disadvantage, disabilities, and limited English proficiency (Frankenberg et al., 2010). Similarly, for high-stakes decisions like how much overall funding a district gets from the state budget, states have never proposed giving wealthy districts the same amount of funding as less-wealthy districts or using a lottery to decide which district gets more. Instead, debates occur over how to operationalize what Jencks (1988) calls "humane justice." As he describes, humane justice is the broad commitment to giving more help to schools or students to compensate them for barriers they face in achieving similar outcomes as others:

> If some students need special help to develop the skills or character traits society values, society must give them whatever help they need. If, for example, some children need unusually good schooling to compensate for an unusually unfavorable home environment or unusual physical handicaps, society must make sure they get it (Jencks, 1988, p. 522)

1.3.2 First way of operationalizing humane justice: predicting need using many attributes

As Jencks (1988) highlights, there are many attributes of a student that might mean they need extra help: a challenging home environment; physical or mental disabilities; earlier schooling that was insufficient. One way that states and districts could prioritize these students is to (1) choose an outcome they want to avert (e.g., a student dropping out of high school; a student failing a state exam); (2) model each student's risk of that outcome using many attributes (e.g., their family income; health issues; performance in previous school years); and (3) prioritize the students whom the model flags as higher need.

Early Warning Systems or *Early Warning Indicators* are one variant of this approach (Porter and Balu, 2016). These often focus on directing extra help to students at risk of failing to graduate. While they started as models, many evolved into simple checklists that school administrators could easily use. As Knowles (2015) puts it: "any administrator can implement the system with just a few data elements and a spreadsheet of student names"(p. 20). For instance, the Chicago On-Track System distills a student's need for extra help in order to graduate into two components measured at the end of a student's freshman year. Students who satisfy both criteria are flagged as on-track/low-risk; students who fail either are flagged as off-track (Allensworth et al., 2018):

1. Has the student has accumulated five full course credits (enough to be promoted into tenth grade)?

2. Does the student have one or fewer F's in a core subject?

Thus, the predictive measure of need ends up prioritizing students in two categories: those who did not earn enough credits to pass the grade and those with two or more F's. More recently, school districts are considering adopting predictive models that, rather than separating students into "in need" versus "not," score students along a more continuous spectrum of need (Lakkaraju et al., 2015; Porter and Balu, 2016; Princeton AI Ethics, 2018; Sansone, 2019). These models have yet to be widely implemented by states or districts,

so I do not discuss them. However, in the Conclusion Chapter, I highlight how the forms of algorithmic bias that have halted their uptake in social services (Princeton AI Ethics, 2018)—opacity about why someone is prioritized; a lack of due process rights to protest decisions—plague schools' current, pre-algorithmic prioritization methods.

1.3.3 Second way of operationalizing humane justice: categorical prioritization

Predictive model-guided prioritization first defines an outcome that extra help is meant to avert. By contrast, with categorical prioritization, states and districts start not with an outcome to avert but categories of students whom common sense identifies as needy. Framed in terms of Jencks (1988), each category reflects slightly different operationalizations of humane justice, or attributes of students that give them a moral claim to extra help.

As Section 1.3.4 discusses in greater detail, categories can guide resource allocations at three levels. Most important are from state budgets to local school districts. States use formulas that, in addition to taking into account factors like the district's ability to fund schooling from local sources like property taxes, give districts more money for certain categories of students. While Chapter Five discusses the landscape of these categories in greater depth, the three most common ones reflect different ideas about who deserves compensatory help. First are students with disabilities—both severe ones like Drew's and less severe ones—with 47 out of 50 states providing some extra funding for this category (EdBuild, 2020). Here, the idea of equity is giving extra help to students whose learning-related disabilities put them further behind. Yet as the *Endrew* case highlights, these resources end up helping a mix of students—those who, with the extra help, can plausibly "catch up" to other students in their grades and those who, due to the severity of their disability, are given help that is unlikely to serve that utilitarian function.

Second are students who are English Language Learners, with 46 out of 50 states provid-

ing some supplemental funding (EdBuild, 2020).[24] Rooted in civil rights laws prohibiting discrimination on the basis of national origin, the ELL category is viewed as a means of correcting remediable challenges; the idea is that once the student becomes proficient in English, the extra help is no longer needed.

Finally, 32 out of 50 states provide some extra funding for students living in poverty, either defined by Free or Reduced Price meal eligibility or by narrower definitions of poverty like families receiving SNAP or TANF assistance (EdBuild, 2020). In contrast to the disability and ELL categories, which give extra help on the basis of the student's own attributes to try to close gaps, extra funding for students in poverty is rooted in ideas that schools that educated larger concentrations of these students needed more help in compensating for the student's family background. The federal origin of the category is Title I of the Elementary and Secondary Education Act of 1965 (ESEA), which, as part of Lyndon B. Johnson's "War on Poverty," gave districts with higher concentrations of "educationally deprived" students extra funding (Cascio and Reber, 2013).[25] States have followed suit and now give extra help to districts either in proportion to their share or whose share exceeds a threshold (EdBuild, 2020). Here, equity is not giving an individual student extra help to compensate for a mutable attribute but instead giving districts and schools extra help to compensate for less mutable characteristics of the families they serve.

Thus far, school districts' categorical prioritization resembles other social policies. Certain categories are deemed deserving; others are not.[26] The categories thus not only reflect need—which districts, schools, and students need extra help?—but also considerations like the student's blamelessness for that need. In addition, as with other social policies, the categories mix need with practicability—for instance, categories for students in poverty prioritizing students whose families are *actively receiving* welfare benefits like TANF, rather

[24]Throughout, I use capitalization to indicate that the designations are part of formal administrative categories.

[25]In practice, "educationally deprived" was operationalized as the share of a district's students living in poverty based on the 1960 Decennial Census.

[26]For instance, although a student failing a state exam is a risk factor for later issues, few states structure funding to prioritize schools with high concentrations of poorly-performing students; instead, states often try to incentivize better performance.

than students whose families are eligible for these benefits.[27]

Yet four features of categories in schools make them a more potent source of inequality than in other policy settings. First, rather than category members receiving resources directly as soon as they are disbursed, resources intended to compensate schools for the presence of categorized students are allocated first to school districts who then have some discretion over how to spend them. This creates the potential for a "leaky pipeline" where resources intended to help students in certain categories are diverted to help others. Second, students with different categories have different formal rights to stem this leaky pipeline and to influence the resources attached to the category. Third, students in the disability category have the power not only to shape *whether* they receive resources but also to shape the *magnitude* of these resources. Finally, the federal legislature and judiciary that attaches these strong rights to the category finances few of the associated rights claims. I discuss each in turn, highlighting gaps in existing research on each of these features and potential implications for inequality.

1.3.4 Feature one: the potential for a leaky pipeline between resources intended for students in a category and these students

Many social welfare programs give resources directly to individuals who prove they are members of the targeted category: for instance, the Social Security Administration gives resources directly to individuals with the tag of elderly; the U.S. Department of Agriculture gives resources directly to individuals who meet the income category used in SNAP.[28] But allocations to students in categories go through two distinct allocation processes, which Fig-

[27]The reason this helps with implementation is that it allows districts to automatically assess eligibility from those other data systems rather than asking families to actively report this information.

[28]One could object, citing Lipsky (2010), that front-line workers in local bureaucracies–for instance, bureaucrats in "Food Stamp" field offices–are involved in allocating even these more "direct" goods. But while these offices are involved in *administering* the program, they give the resource to all individuals with the tag as opposed to having a resource that they must allocate between tagged and non-tagged individuals.

ure 1.3 depicts. First, federal, state, and local governments allocate funds to districts that are adjusted upward for the presence of students in various categories (green box). These categories have the strongest influence on state budget allocations, which compose roughly 45 percent of funding to districts (with local sources making up another 45 percent and the federal government roughly 10 percent).[29] The majority of research on how categories affect inequality focuses on changes to this level of allocation. In particular, a wealth of research focuses on school finance litigation, which arose in the 1970s through networks of public interest lawyers and legal advocacy organizations (Corcoran et al., 2004; Lafortune et al., 2016; Jackson et al., 2014).[30] The litigation used provisions in state constitutions–often involving a right to an *adequate* if not equitable education–to try to change the formulas states use to allocate resources between districts. The litigation focused on changing the benefits attached to a category (green arrow in Figure 1.2). But the changes occurred for *broad classes* of category members.[31] The cases claimed to advance the interests of "all public school students" (*Serrano v. Priest*),[32] children in "poor urban districts" (*Abbott v. Burke*), or other similarly broad parties. By changing state policies like the weights attached to categories such as whether or not a student lives in poverty, social movements used these rights to resources in order to influence *between-district* resource allocations.

Once resources from state, federal, and local sources enter the "black box" of school districts (Miles et al., 2004; Gordon and Pasachoff, 2018), what shapes whether extra resources either (1) intended for categorized students, or (2) meant to compensate schools for

[29]These proportions vary substantially across districts, with lower-SES districts receiving a higher proportion of funding from state and federal sources.

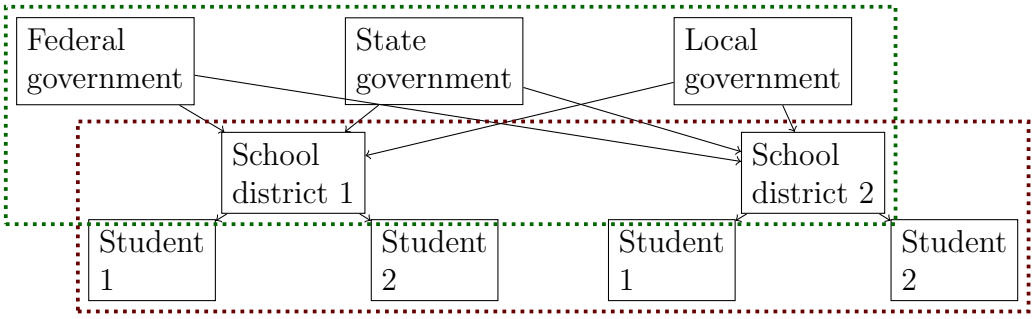
[30]After a failure in *San Antonia Independent School District v. Rodriguez* to ground these school finance cases in the equal protection clause of the U.S. constitution, the private enforcement strategy in school finance litigation was to use provisions in state constitutions to make arguments against the link between local property wealth and per-pupil financing.

[31]For instance, New Jersey's *Abbott v. Burke* was initially filed on behalf of twenty families, with Raymond Abbott, a student from Camden, listed first. Likewise, while *Serrano v. Priest* in California was filed by John Serrano, the parent of a public school student, Serrano himself was approached by a Ford Foundation-funded public interest attorney who was looking to develop a school finance case to challenge California's formula (Fischel, 2003).

[32]More precisely, the case, which became a class action when John Serrano was joined by families students from the Los Angeles Unified School District, was filed on behalf of "all public school pupils in California, 'except children in that school district, the identity of which is presently unknown, which school district affords the greatest educational opportunity of all school districts within California.'"

the presence of these students, are spent for these students' benefit? The red box in Figure 1.3 highlights this level of allocation. In turn, there is little research on how policies that earmark resources for categorized students play out on the ground. Existing research shows that higher-SES parents are more adept at securing resources for their children (Lareau, 2011; Calarco, 2018), but little research studies how these negotiations interact with budget pressures. In turn, on-the-ground negotiations by parents like Drew's create the potential for a "leaky pipeline" between resources that school districts receive and how they spend those resources.

Figure 1.3: **Two levels of resource allocations**. The green box describes allocations *to* school districts; the red box describes allocations *within* school districts. Depending on the size of the district, there is another layer–district allocations to schools within the districts–with disparities emerging in larger districts that operate many schools.



1.3.5 Feature two: federal government grants different formal rights to members of different categories

In turn, Drew's case highlights how some parents can supplement *informal* strategies they use to influence school decision-making—interacting with the child's teacher; requesting meetings with school leadership—with formal due process rights to appeal resource denials. Yet the formal tools that parents can use vary widely between students. In contrast to other entitlements, where category members may receive a different *magnitude* of a resources in proportion to characteristics like household size but all individuals have the same *formal rights* to shape aspects of benefit allocation like appealing a termination of benefits, school districts are unique in that they serve populations with different formal rights to shape

resource allocations.

The students with the strongest formal rights to shape resource allocations are those who qualify for a disability category, now defined under the Individuals with Disabilities Education Act (IDEA). The federal government plays a strong role in defining the category and its associated rights and resources.[33] The most notable right is to an IEP like the one Drew's parents were protesting. IEPs result from a negotiation between parents and a school district, described in greater detail in Chapter Two, where a parent or teacher can request that a child be evaluated, experts weigh in on whether the child's difficulties fall into one of thirteen federally-recognized disability categories, and the district decides whether the IEP should be issued.

1.3.6 Feature three: these formal rights include the ability to influence the size of allocations

IEPs and associated resources have important differences from many of the other entitlements—Medicaid; TANF; SNAP—discussed in the previous section. One is that similar to non-means-tested entitlements like Social Security and Medicare, family income plays no role in either eligibility for the benefit or the resources associated with the benefit. Thus, in contrast to entitlements like SNAP where the depth of resources is inversely related to a category member's income–for SNAP, benefits start at a maximum allotment for households with zero income and then are scaled back as a household's income rises–there is no mech-

[33]The IDEA's precursor, 1975's Education for All Handicapped Children Act (EAHCA), was passed during a historical era marked by what Epp (1998) characterizes as a "rights revolution" marked by increased demands for legislatures and courts to protect the rights of various minority groups. Particularly important for special education's advent and the contours of its private enforcement system was 1954's *Brown v. Board of Education*. Disability rights advocates recognized that *Brown*, by extending the Constitution's "equal protection clause" to argue that the federal government should take proactive action to provide minority students with equal opportunities to majority students, could be used as a template to argue that the federal government should take proactive action to provide a specific type of minority—students with disabilities—equal opportunities to non-disabled students within the public school system (Yell et al., 1998). The final legislation, modeled after two successful class action suits that disability rights advocates had filed in Pennsylvania and D.C., granted federal and state administrative agencies some power to enforce the statute's provisions. For instance, the Department of Education's Office of Special Education Programs (OSEP) was granted the power to investigate school districts flagged through various means as being non-compliant.

anism for scaling benefit size in inverse proportion to a family's ability to allocate personal resources to a child's disability.

Second is that in contrast to most benefits where a formula is used to determine benefit size–for instance, one that adjusts for household size; one that adjusts for pre-retirement earnings–the emphasis on the IEP as an *individualized* contract means that parents and school districts negotiate over the magnitude of the benefits. For instance, a parent or advocate for the child may propose 60 minutes of speech therapy a week, a district counters with 20 minutes, and the IEP ends up somewhere in between (Caruso, 2004). Thus, while categories like those for entitlements such as Medicaid and SNAP are accompanied by some rights to influence allocations–for instance, the right to a hearing to challenge an inappropriate denial of access to the resource; the right to a hearing to challenge a termination–the category of disability is accompanied by strong rights to influence not only the *presence or absence* of an allocation but also the *magnitude* of these allocations.

The formal rights that accompany the disability category compare favorably not only to the rights attached to other entitlements but also to the rights to resources held by two other classes of students: students in other categories (e.g., ELL; FRPL) and students without any priority categories. As I explore in greater detail in Chapter Five, categories like ELL come with some rights to influence resource allocations. For instance, parents can submit complaints to the Department of Education's Office for Civil Rights (OCR) or the Department of Justice's (DOJ) Educational Opportunities Section of the Civil Rights Division. However, these complaints can only challenge district-wide patterns of non-compliance with the relevant statutes and do not address an individual child's share. Meanwhile, parents of students without priority categories are left with few formal mechanisms to shape resource allocation decisions. For instance, parents upset with the Oakland Unified School District's decision to allocate scarce budget resources to "high-priced consultants" rather than mental health care for students traumatized by neighborhood violence voiced anger at a school board meeting, but had few formal tools to protest this allocation decision (Katsuyama, 2016).

1.3.7 Feature four: amidst strong formal rights given to the disability category, limited federal resources to fund rights claims

The federal government as a third-party actor has a strong influence on the category of disability. The federal government defines which disabilities compose the category, adding additional disabilities such as autism in re-authorizations of the statute. The federal government defines the resources that category members are entitled to not through a formula but instead through requiring that districts allocate resources that deliver a certain level of benefit to the category member. And while districts need not allocate resources that *maximize* outcomes for category members, they must provide resources that meet a certain substantive level of benefit established in case law, and that the *Endrew* case increased.

Finally, the federal government gives category members strong rights to influence resource allocations. The most notable shift in these rights was through amendments to the statute that incentivized the use of legal tools to shape resource allocations: the Handicapped Children's Protection Act in 1986 allowed parents who prevailed in due process hearings or litigation against a district to recover attorney fees from a district, but not vice versa (Public Law 99-457). Viewed in terms of the previous section's framework, the category of disability falls in the quadrant of strong constraints on those rationing—in this case, district administrators taking the entire budget into account—from both the federal government as a third party and from potential recipients of the resource who can protest not only the denial of *any* resources but also the denial of *specific* resources like a particular form of therapy.

While the federal government as a third party thus sets high standards for entitlements associated with the disability category, the federal government funds few of the costs of these entitlements. While the federal government was supposed to fund 40 percent of the costs of special education services, allocations have hovered closer to 10 percent, making the entitlement nearly unfunded. Instead, the vast majority of funding comes from state and local governments, the latter diverting revenue intended for general education students

to students in the category. As I discuss in greater detail in Chapter Two, case law has also reaffirmed that costs are supposed to be "off the table" when districts are making resource allocations to students with the category of disability. As one lawyer involved in the *Endrew* case put it, and as the Supreme Court agreed:

> There are going to be some extreme cases, and the Court saw one several years ago in the *Garrett F.* case, which involved a situation where a child with a ventilator needed full-time nursing services, and the Court quite clearly said that even there, where the school district was saying that was going to cost $30 to $40,000, the Act does not permit cost to trump what the Act otherwise requires (Transcript of Oral Argument at 10, *Endrew F. v. Douglas County School District*, 2017 (No. 15-827))

Thus, the rights associated with the category of disability are "trump cards" that override considerations like cost and balancing allocations between district students.

What is known about how the intersection of these three features—districts with budget pressure; formal policies that tell administrators to prioritize certain types of students; parents who press for their own child's priority—affects between-student inequalities? Most existing research, written by legal scholars, points to the potential for various forms of inequality from unfunded entitlements within schools. Most notable is Kelman and Lester (1997). Using close conceptual analysis of statute and case law surrounding the IDEA, the authors point to the gap between the observed reality of school allocations–some students are given legal entitlements to priority in resource allocations; other students are given no such entitlements–and normative intuitions about how priority should be granted. While the treatment has some empirical examples–for instance, the authors conduct interviews with school administrators that reveal dynamics such as middle-SES districts facing the most resource squeezes because they could neither rely on property taxes nor on Title I funds–the authors themselves note that their focus is more on how the due process rights that parents are given *could* distort resource allocations rather than "whether and which parents and children are able to exercise their due process rights"(p. 16). More recently, Pasachoff (2011), reviewing the due process system under the IDEA, notes inequalities that might stem from deputizing some parents to act as private attorneys general, but highlights a need for empirical research on the form that these inequalities take.

1.4 Roadmap of the remaining chapters

We began by contrasting two uses of categories: wealthy parents in *Varsity Blues* faking their child's membership in a category to get a leg up; disadvantaged parents in Texas struggling to access categories that would give their child basic services. Drew's case falls in between these two extremes. His disabilities were real and profound, but his parents acknowledged that few parents would have the time and persistence to mount such a vigorous fight with the district to get him a specific set of services. And the $70,000 price tag on those services, over 10 times the average per-pupil expenditures in the district, raised alarms among districts struggling to give something to everyone.

The present chapter tries to reconcile these three cases by showing the role that categories play in rationing. Categories reduce the discretion of the administrators in Drew's district by earmarking money for students like him. But when districts lack adequate funding to comply with these earmarking requirements, administrators likely engage in hidden rationing—or letting costs influence decisions without openly acknowledging the role of costs. The remaining chapters investigate how this hidden rationing unfolds.

Chapter Two investigates how organizations that face cost pressure but that are (1) prohibited from changing *which* categories they prioritize and (2) prohibited from changing *how* they decide who falls into a category, ration resources by using discretion to decide that fewer students fall within the disability category. This shows that when policymakers prioritize categories whose boundaries are fuzzy—whose disability is severe enough to count? What living arrangements count as being homeless?—one form of hidden rationing is for organizations to raise the threshold for membership in a policy category.

While Chapter Two shows *that* districts facing cost pressure ration resources by rationing access to categories, Chapter Three investigates whether the burden of rationing is equally or unequally distributed. Drew's case highlights how some parents can monitor district decisions about resources and intervene to protest by filing formal complaints against a district under the IDEA. The Chapter argues that monitoring *before* the cost pressure has a causal impact on what happens *after* the cost pressure. Districts where parents monitored

decisions were less likely to ration access to the disability category.

Chapter Three focuses on monitoring in one state: New Jersey, the state that tightened budgets. Chapter Four expands the lens on monitoring in two ways. First, focusing on monitoring *attempts*, it shows how the between-district inequality we see in monitoring extends to three other states. Second the Chapter examines attempts that go to a hearing and that leave a written record of *what* the monitoring focused on. It shows inequality not only in *whether* parents monitor to reduce district discretion, but also *what* they use this monitoring for—most notably, to either protest rationing or to protest school disciplinary decisions.

Finally, Chapters Three and Four could suggest that one way to curb hidden rationing by school districts is to increase parent monitoring of school decisions. For instance, advocacy groups could provide more training to parents of students with disabilities to decrease inequalities in monitoring. Yet Chapter Five shows that raising the level of monitoring *within one* category might have spillover effects on the resources given to members of *other prioritized categories* whose parents have fewer formal rights to intervene in school decisions. The Chapter, after investigating *why* different rights were attached to different categories, explores *how* this creates diversion where resources intended for categories with weaker tools for monitoring get diverted to members of the disability category.

Chapter Two: Budget Pressure and Discretion to Ration Categories

2.1 Introduction

> *The record does not establish that the Student has an inability to learn or an inability to maintain satisfactory relationships in school. The Student has passed all of her classes and gets along with adults and peers at her school. There is nothing in the record suggesting 'inappropriate' behavior from the Student in school. While there is some testimony to the effect that the Student has a general pervasive mood of unhappiness at home, there is insufficient evidence of this behavior at school to trigger the IDEA classification here* (DC Hearing Officer Determination, April 2014)

In Drew's case, the parents and school argued over whether Drew should receive expensive services. But they agreed that Drew had a disability, and there was no dispute that he fell into that category.

In the quote above from a dispute in DC, a mother argued that her child had a disability that the district failed to recognize. The district responded that although the student displayed a "pervasive mood of unhappiness at home," her behavior at school meant she should not be classified as disabled. The hearing officer sided with the district. As a result, unless the parent appealed in Federal District Court, her daughter would not be getting extra services.

How do the fiscal pressures that districts face—mandates to prioritize students if they fall into a category; insufficient funding to do so—affect decisions about whether a student falls into a category? The present Chapter delves more deeply into how organizations can use categories to ration. Using the case of school districts, it highlights a new rationing mechanism—*rationing by threshold-raising*—that applies to other social policies like determining which students count as homeless or which food stamp applicants are looking for work.

The Chapter builds upon research that shows how governments use categories to allocate social policy benefits (Skocpol, 1992; Starr, 1992; Mohr, 1994; Steensland, 2006). It argues that the majority of existing research focuses on how policymakers and organizations ration resources by changing *which categories* a policy prioritizes. However, organizations may also ration resources by deciding that *fewer individuals* fall into a social category. For categories like "age over 65," organizations have minimal discretion when deciding who falls into the category. Yet for categories like "has a disability," "homeless," or "looking for work," organizations may have broad discretion.

The Chapter studies how, under cost pressure, professionals and street-level bureaucrats ration resources not by changing *which categories* a policy prioritizes but by using discretion to decide that *fewer individuals* belong to the same category. This discretion matters for access to resources. Discretion over who counts as having a disability shapes access to disability-related cash assistance (O'Brien, 2015); discretion over who counts as "homeless" conditions access to public housing (Warren et al., 2017). Focusing on the disability category, and policies that introduce cost pressure, the Chapter shows that cost-containment policies cause districts to narrow the boundaries of the disability category covertly and decide that fewer students have a disability. They do so not by changing the formal definitions for who counts as a category member—a more covert form of rationing using categories. Instead, districts do so by raising the invisible threshold at which students' problems count as severe enough for the category.

In doing so, the Chapter contributes to two broader debates. The first is on categories' dual nature as sources of stigma versus currency to access important goods. Applied to

disabilities in schools, most research and policy, called the "disproportionality" literature, has framed the disability category as largely *undesirable* and focused on potential *overallocation* to subgroups like African-American males (e.g., Artiles, 2003; Losen and Orfield, 2002; Skiba et al., 2005; Blanchett, 2006; Sullivan and Bal, 2013; Albrecht et al., 2012). The Chapter highlights nuances in this form of educational stratification. Several developments can make disability categories a desirable good that schools might underallocate to less-advantaged groups of students: the costs of disability services straining school budgets (Rosenthal, 2016; Krent et al., 2018; DeMatthews and Knight, 2019); categories like autism creating a respectable diagnosis for white, middle-class parents (King and Bearman, 2009; Eyal et al., 2010; Eyal, 2013);[34] or the appeal of category-related resources like extra time on standardized testing to parents concerned with downward class mobility (Belkin et al., 2019).[35] Thus, if advantaged parents "fight to get" a disability diagnosis for their child (Dumit, 2006), administrators might *underallocate* categories to students whose parents face structural barriers to mounting a vigorous fight (Lareau, 2000, 2011; Haskins and Jacobsen, 2017; Calarco, 2018; Baldwin Clark, 2018).

Second, the Chapter helps connect work on the fuzzy boundaries of social categories (e.g., Zerubavel, 1996; Bowker and Star, 2000) with work in fiscal and political sociology on budget pressures (Hacker, 2004; Brodkin and Majmundar, 2010; Moynihan et al., 2014; Herd and Moynihan, 2019). The Chapter outlines a mechanism–*threshold raising*–where organizations that face resource constraints covertly raise the invisible thresholds used to

[34]Autism was added as an "official" IDEA disability category as part of the 1990 re-authorization. While the disorder makes up anywhere between 1 percent and 8 percent of special education placement depending on the state and year, (Zirkel, 2011) finds that autism-related litigation makes up a disproportionate amount of litigation. Reviewing all federal court decisions (distinct from the much more frequent due process hearings analyzed in Chapters Three and Four), Zirkel finds that: "autism litigation trended up from approximately 12–45%" of all cases during the period he studied (1993-2006), while autism enrollments ranged from 0 to 5 percent. He summarizes that: the "proportionality ratio of autism litigation to autism enrollments was more than 10 : 1." In other words, IEPs associated with autism generate 10 times the amount of litigation one would expect if litigation tracked prevalence on a 1:1 basis.

[35]There is no academic research of which I am aware that studies this issue. However, recent work shows that high-SES parents engage in more *overall* investments of money and time in children in states with higher levels of income inequality (Schneider et al., 2018). Parent investment of time in the process of securing a disability diagnosis for their child might be one type of investment that fears about downward mobility motivate.

group individuals into broader social categories.

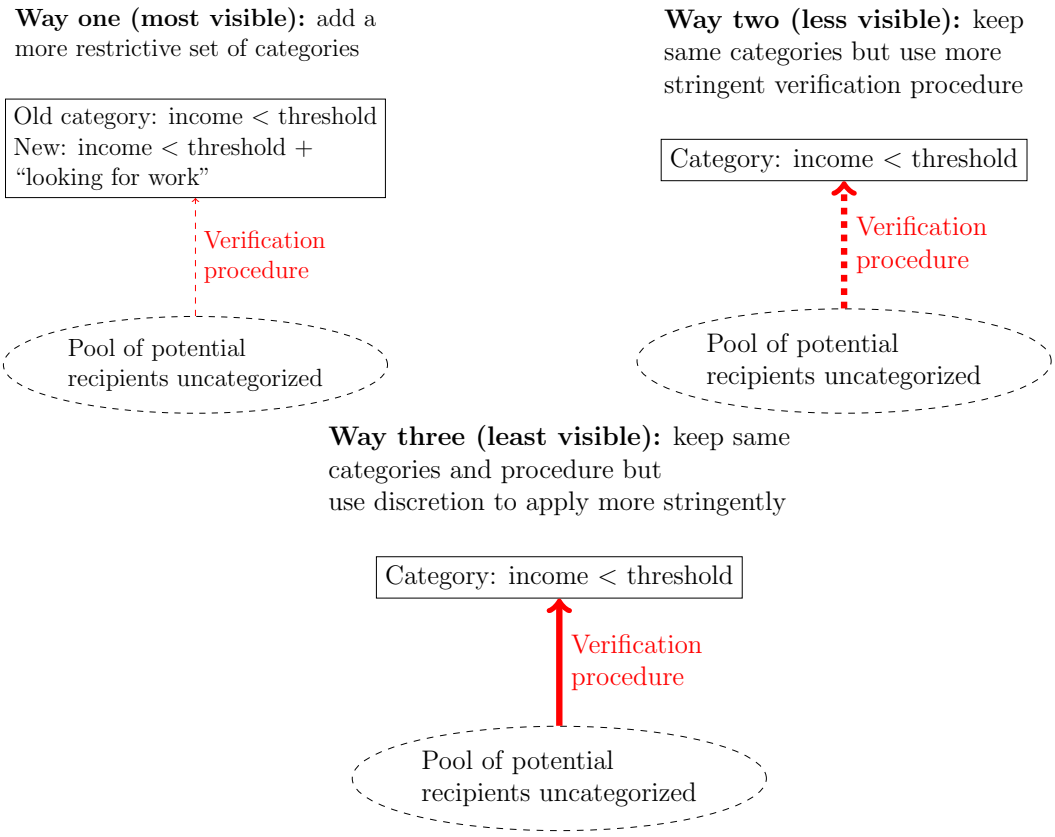
The remainder of the Chapter proceeds as follows. First, I build upon Chapter One's framework to show three ways that bureaucracies and other organizations can use categories to ration access to resources. I show how the most hidden form of rationing is when a policy's categories and procedures for deciding who falls within a category remain the same, but when on-the-ground actors make accessing a category subtly more challenging. Then, focusing on school districts, I show the dilemmas that emerge when they face budget pressures to prioritize students with disabilities. I then move to the analysis, which investigates whether increased budget pressure causes districts to ration access to the disability category.

2.1.1 Rationing resources by using discretion to decide who belongs in a category

There are three ways that changes to categories can be used to allocate *fewer* resources. First are changes to *which categories grant access to a resource*–for instance, changes to exclude unauthorized immigrants from policies like Medicaid and Social Security (Fox, 2016). Second, for the same categories, actors can implement a more stringent *selection process* or verification procedure for assessing whether the individual displays the categorized attribute–for instance, how frequently do applicants need to re-verify their income (Brodkin and Majmundar, 2010; Herd and Moynihan, 2019)? How burdensome is the documentation process (Brodkin and Majmundar, 2010; Herd and Moynihan, 2019)? Finally, for the same category and for the same verification procedure, there may be room for discretion that leads to variation in the *strength of filtering*–for instance, discretion in deciding whether a small error in paperwork documenting income leads to a benefits denial (Eubanks, 2018).

Past research largely focuses on the first use of categories for rationing, investigating *which categories* policymakers use, *why* they use those categories, and *how* policymakers change prioritization by changing the categories required to access a policy. Scholars argue

Figure 2.4: **Three ways that policymakers or organizations can use categories to allocate fewer resources**



that U.S. social policy is structured around two broad ideas of worth: the deserving poor and the undeserving poor (Katz, 1989, 1996; Mohr, 1994; Gilens, 2009; Steensland, 2006; Brown, 2013). The deserving poor are thought to have characteristics that entitle them to more generous social assistance. The undeserving poor are framed as lacking those characteristics or possessing others like undocumented status or a felony conviction that "pollute" otherwise pure categories (Brown, 2013; Curtis et al., 2013). In turn, policymakers translate the broad idea of *deserving poor* into a set of specific categories.[36] Focusing on categories in school systems, Domina et al. (2017) note the presence of categories like disability or Free and Reduced Price Lunch status that help direct compensatory resources to certain students. Recently, Saatcioglu and Skrtic (2019), focusing on status rankings *within* disability categories, show how white migration to a previously low-status disability category

[36]These categories vary across policies, within the same policy over time, or within the same policy but across states/sub-national entities.

was accompanied by the district allocating more resources to those categorized students.

Rationing via this path can thus occur through increasingly stringent definitions of who counts as "deserving" that manifest in layering additional categories onto a policy's existing one (leftmost panel in Figure 2.4). For instance, "culture of poverty" arguments by Murray (2008) and others proposed a definition of "deserving" where individuals needed to be actively looking for work to merit cash assistance (Danziger, 2010). States translated these moral ideas into specific categories that reflected an emphasis on work–for instance, only exempting mothers from work for the first 12 months of a child's life or reducing the extent to which postsecondary or language education counted as work exemption (Gais, 2001; Danziger, 2010; Tach and Edin, 2017).

Yet this first form of rationing–changes to the categories a person needs to belong to in order to qualify for assistance–is a highly-visible policy change. For instance, proposed changes to SNAP that would make it harder for "able-bodied adults without dependents" to access prompted public outcry. As a result, policymakers fearing backlash or who face legal constraints might resort to two, more covert forms of rationing (Hacker, 2004; Herd and Moynihan, 2019).

The second form of rationing is keeping the same categories but changing the formal procedures organizations use to decide who falls into the category, a strategy that has received some attention (Hacker, 2004; Brodkin and Majmundar, 2010; Herd and Moynihan, 2019). Rationing by changing the formal procedures organizations use to decide who falls into a category is an example of what Herd and Moynihan (2019) call *administrative burden*. Their example of eligibility determinations for SNAP benefits highlights how policymakers, under the guise of trying to prevent program fraud, increased the documentation that applicants needed to provide to certify they were low income.[37] This form of rationing is less visible but still detectable in policy or in administrative procedures. The ability to be tracked and detected increases the chance of backlash by affected constituencies.

[37]As another example, concerns about rising rates of Supplemental Security Income (SSI) and Supplemental Security Disability Insurance (SSDI) claims, especially for mental disorders, led not only to changes in 1996 reforms to how disability was defined (e.g., the exclusion of drug or alcohol dependence from allowable adult disorders) but also new procedures to more stringently assess the extent to which mental disabilities impaired behavior (Social Security Office of Policy, 2018).

Therefore, cost pressure might lead to a third, *least visible* form of rationing that has received much less attention: professionals and street-level bureaucrats use discretion to decide fewer individuals belong in the social category. Put in terms of Starr (1992), these intermediary actors might apply a more stringent filter for judging which specific cases belong in the broad categories the policy prioritizes.[38] And categories vary in their ambiguity, creating room for discretion in deciding who is a category member (Zerubavel, 1996; Bowker and Star, 2000).[39] Generally, categories like "aged 65 or older" involve less discretion in deciding who qualifies.[40] Other categories allow for more discretion. For the category of refugee, decision-makers have discretion when deciding whether a refugee faces a true threat of persecution upon return to their home country. For disability, decision-makers have discretion about where along a continuous spectrum of need to draw the binary threshold that gives a person a claim to assistance (Kelman and Lester, 1997; Dorfman, 2017).

As the following analysis shows, this discretion means that organizations facing cost pressures may ration not by changing *which categories* they prioritize or the *formal procedures* they follow when deciding who is low-income or has a disability. Instead, organizations may ration by using discretion to decide that fewer individuals fall into the category. Thus, while categories reduce discretion by specifying *whom* organizations should prioritize for a resource and *how* to prove that you belong in a category, they do not fully eliminate discretion. Instead, categories can push discretion *earlier in the process* as professionals and bureaucrats exercise discretion when deciding who is a category member.

[38]Starr (1992) focuses on official classifications, defined as "categories officially adopted or approved by the state and incorporated into law and administration"(p. 263). Categories are one form of official classification–categories that shape access to one type of good (social policy benefits). States use other types of official classifications to distribute other types of goods and consequences; for instance, Starr (1992) and Mora (2014) discuss how the category of Hispanic that united ethnic groups not previously thought to belong to a homogeneous category emerged as a means of political mobilization.

[39]Saatcioglu and Skrtic (2019) note a similar characteristic of categories–malleability–but define malleability as the ability for a category to change positions within a status hierarchy.

[40]Though this is not universal–for instance, age is highly relevant for refugees from Syria seeking asylum in Western European nations and being below 18 can help an individual's chances of asylum. In the absence of birth records, or when the veracity of these records is in doubt, bureaucracies have struggled to assess who falls above versus below this threshold (e.g., Sauer et al., 2016).

2.1.2 Dilemmas districts face under budget pressure

In turn, discretion has higher stakes when there are fewer resources to go around. And as Chapter One highlighted, disability services in schools are a *weakly-funded entitlement*—districts must provide services to all students who need them and cost concerns cannot trump these requirements. Here, I show the specific regulations that might cause districts to ration covertly.

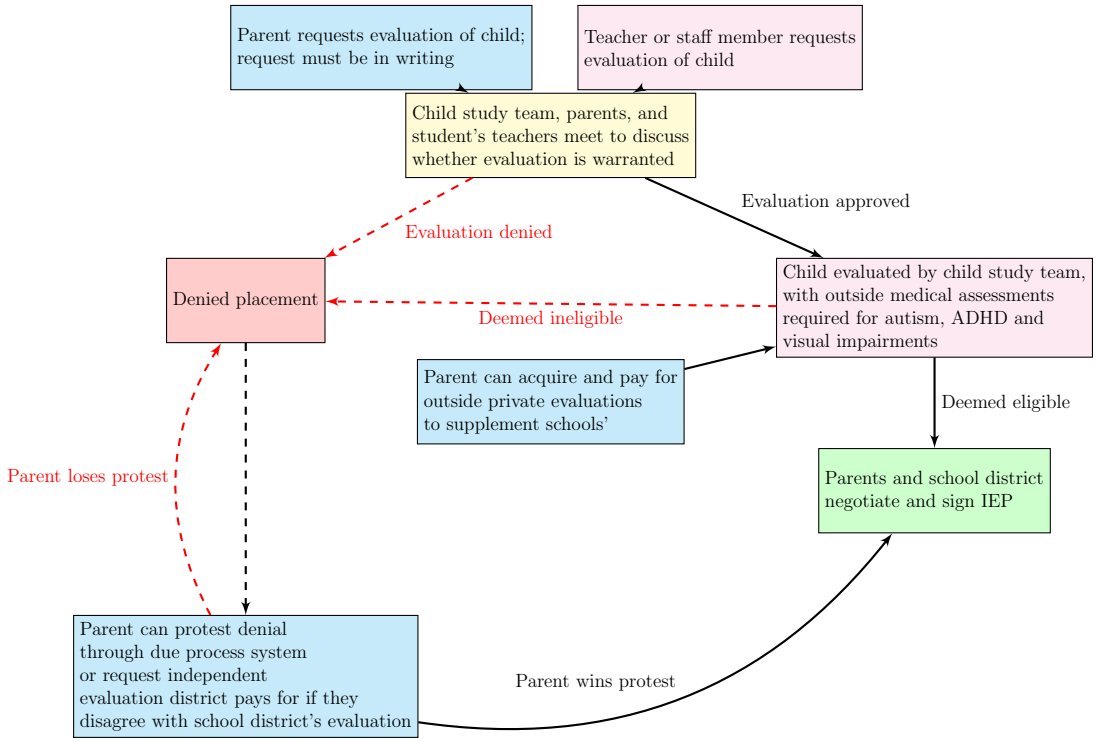
First, the federal government specifies strict procedures that districts must follow when deciding whom to categorize. Districts are under a broad "child find" mandate. Administrators are told not to wait for students and parents to come to the district requesting services for a disability; instead, districts are obligated to try to proactively find all students who might fall into the category.[41] In addition, school districts and states must follow a highly-specific procedure that Figure 2.5 outlines, and they must use a uniform set of thirteen disability categories–e.g., speech/language disorders; autism; deaf-blindness–to categorize students.

Second, the federal government limits discretion through defining what resources a district must provide in an IEP. The government requires that districts provide an "appropriate" set of services in the "least restrictive environment." The federal government also outlines rigid procedures that districts and parents must follow when deciding what counts as "appropriate"–for instance, is 20 minutes of speech therapy appropriate or does the child need 40 minutes?[42] Finally, if negotiations sour over *whether* a child has a disability or *which services* the child should receive, parents are given the right to file a free due process

[41] More formally, states and districts must "identify, locate, and evaluate" all students with disabilities and who are in need of special education services. This obligation extends to "children with disabilities who are homeless children or are wards of the State, and children with disabilities attending private schools, regardless of the severity of their disability"(20 U.S.C. § 1412(a)(3) (2006); 34 C.F.R. § 300.111(a), 2012).

[42] Many social policies use a formula to determine the magnitude of resources an individual receives–for instance, one that adjusts for household size or pre-retirement earnings. In contrast, the emphasis on the IEP as an *individualized* contract means that parents and school districts negotiate over what resources a child is owed by the district. For instance, a parent or advocate for the child may propose 60 minutes of speech therapy a week, a district counters with 20 minutes, and the IEP ends up somewhere in between (Caruso, 2004). Qualitative or normative work highlights how inequalities in parents' facility with this bargaining process might translate into inequalities in resource allocations (Kelman and Lester, 1997; Pasachoff, 2011; Baldwin Clark, 2018).

Figure 2.5: Interactions involved in deciding which children fall into the disability category



hearing (DPH) complaint like the one Drew's parents originally filed. The rights trump cost considerations by the district.

Question: do districts ration the disability category when they face heightened cost pressure?

How might district administrators balance the tension between (1) budget pressures that create incentives to ration and (2) legal and moral taboos against overt rationing?

Returning to the earlier three forms of rationing in Figure 2.4, district professionals are barred from *rationing by formally changing what counts as a categorized disability.* For instance, districts cannot eliminate more costly disabilities like autism from the 13 listed disabilities.[43] Likewise, districts are barred from *rationing by changing the formal process they use to categorize students.* For instance, they cannot choose to only categorize students

[43]Baldwin Clark (2018), noting the over-representation of white middle-class children in the autism category, uses the diagnosis as an example of opportunity hoarding by white middle-class parents.

who are referred by their teachers for evaluation and not those referred by parents. This leaves the third form of rationing in Figure 2.4: rationing by exercising discretion within the same formal policies.

In turn, districts have discretion over several decisions. First is *whether* to categorize a student as having a disability. Districts facing cost pressure might decide, for instance, that a child's attention difficulties are not severe enough to warrant an IEP. Second is, conditional on categorizing a student as having a disability, what specific disability diagnosis to provide – for instance, learning disability versus speech/language disorder versus emotional disturbance. Districts facing cost pressure might decide, for instance, that a child's problems are more likely to fall into a category like learning disabilities that generally involve lower resource expenditures. Finally, conditional on categorizing a student as having a disability and providing a specific label, districts have discretion when deciding what services to provide and the setting the student should be educated in. Districts facing cost pressure might decide, for instance, that a child no longer needs a one-on-one aide or that he or she should be educated in the public school rather than a specialized special needs private school. While all forms of rationing may occur in response to cost pressure, there are no systematic data on the content of IEPs for students already categorized and, in the present study, the mechanism operates at the level of *whether* the child has a disability rather than *which disability he or she has*. Thus, by examining the first type of rationing–rationing by exclusion from the category that gives the student access to *any* IEP resources–we reach a conservative estimate of whether districts ration in response to cost pressure.

While other studies note the *presence* of this discretion over categorization (Domina et al., 2017), and note how this discretion can be used to ration resources for children who lack vigorous parent advocates (Baldwin Clark, 2018), the present Chapter quantitatively studies how cost pressure causes districts to *use* this discretion to categorize fewer students.

Studying the causal impact of cost pressure is difficult at the district level. Because cost pressure is often endogenous to unobserved and observed characteristics of a district's parents, the present Chapter exploits exogenous state-level shifts that change the cost pressures associated with providing services to students with disabilities. State contributions to

districts typically start with a "base rate" where a district is given a set amount of money for each *enrolled* student, regardless of the student's disability status or other attributes–for instance, a district may be given $10,000 per student on the basis of its average daily membership (ADM). States where districts face less cost pressure with each additional student they categorize use *weighting financing*, where they weight a categorized student as a multiple of a general education student for the purposes of the state allocation to the district. For instance, New York uses a single-pupil weighting system where each IEP student, regardless of his or her disability, is weighted as 1.41 times that of a general education student. So if a district received $10,000 from the state for each general education student, it would receive $14,100 for each special education student (Ahearn, 2010, p. 36).[44] Districts in these states face *less pressure to ration the disability category.*

The Chapter exploits shifts between *weighting financing* and *block grants*. With block grants, a state's allocation to a district is largely not sensitive to the number of students the district categorizes as having a disability. Appendix Table 6.8 outlines nuances within these two general categories.

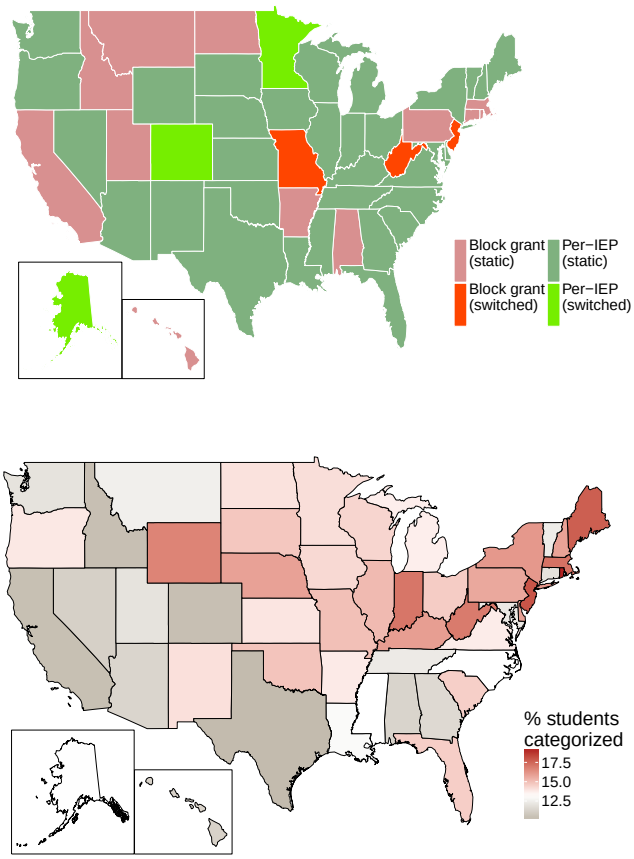
The present Chapter largely focuses on states that switch to block grants. While these regimes take various forms outlined more fully in Appendix 6.8, most important about these formulas is that they compound the cost pressure that districts face from the unfunded federal mandates that govern what they owe students. While passed by legislatures across the ideological spectrum–e.g., both Alabama and California shifted to block grants

[44]Other states use multiple pupil weighting systems. For instance, in South Carolina, students classified under autism are weighted as 2.57 times that of a general education student, while the "emotionally disabled" are weighted as 2.04 times, which would translate into $25,700 versus $20,400 respectively compared to a general education student allocated $10,000. These IEP-related weighting factors are often accompanied by weighting factors for students with other forms of need. The most common weighting factor is one for low-income students where students in certain poverty categories (e.g., Free or Reduced Price Lunch (FRPL) eligible) are weighted as a multiple of a base student (e.g., a 1.2 weight would translate into $12,000 for that student), with 30 out of 50 states in a recent review using this factor. 27 states also have English Language Learner (ELL) multiples. In addition to these student multiples, states sometimes use a "tax effort" multiple where a district is rewarded more if it sets a higher property tax rate on its local base. The purpose of these multiples is to try to ensure that state budget allocations do not supplant local contributions to schools. Other multiples include those to small districts due to failures of economies of scale and those that adjust for cost of living within the district. For a non-technical overview of state education financing formulas, see: `http://www.elc-pa.org/wp-content/uploads/2013/02/ELC_schoolfundingreport.2013.pdf`. For more technical treatments and analyses, see: Lafortune et al. (2016)).

in the mid to late 1990's despite different legislature party composition–block grants generally reduce state budget expenditures on IEP students. In particular, since the grants mean that districts receive a lump sum that is not sensitive to either how many students the district identifies as having a disability or the intensity of services a district provides to each IEP student, the formulas place cost pressure on districts. In turn, districts facing this cost pressure are prohibited from changing *which disabilities* help a student qualify for a category or the *formal procedures* they use to assess students. Yet the previous discussion and Figure 2.5 highlight that discretion might shift to the decision about which students have a disability.[45]

[45]The child's teacher has discretion at the stage: should a child be *evaluated at all* for a disability? When a child is evaluated, disability categories like "emotional disturbance" fail to map on to a single medical diagnosis and include criteria such as the child exhibiting "inappropriate types of behavior or feelings under normal circumstances" that allow for discretion in interpretation by school professionals and parents *Code of Federal Regulations, Sec 300.8, Child with a disability.* In addition to ambiguity in the regulations that define the general criteria, states are given the discretion to define their own criteria for each disability category as long as it meets or exceeds the federal criteria set forth in the CFR. MacFarlane and Kanaya (2009) find that this state-level discretion has a small impact impact on prevalence rates of autism within special education, with states that adopt more generous criteria for autism that includes Asperger's and other autism spectrum disorders exhibiting higher prevalence but their analysis is correlational rather than causal and the effects are modest. If a child's evaluation suggests a disability, the "child study team," which in New Jersey is composed of a school psychologist, a learning disabilities teacher-consultant, and a school social worker, has discretion at the stage: does the evaluation indicate the child's disabilities merit receipt of special education services through an IEP, receipt of a Section 504 plan under the Rehabilitation Act, which parents have come to refer to as an "IEP-lite" due to its decreased rights (Author interview, October 25th, 2016.), extra resources provided but that lack the formal rights to resources that come with an IEP, or no extra resources for the time being.

Figure 2.6: *Top panel*: shows the financing formulas in each U.S. state during the period under study. *Bottom panel*: shows the rates of categorizing students as having a disability in each state in a midpoint year of the period prior to any of the financing formula changes (2006-2007 school year).



Highlighting this room for discretion in which students are categorized as having a disability, the right panel of Figure 2.6 shows the percentage of students in each state categorized, with between-state variation that is likely not fully reducible to underlying differences in disability status. The possible presence of this discretion leads to the following hypothesis, which the analysis investigates:

> ***Hypothesis***: shifts to block grants cause districts/states to decide that fewer students have a disability

2.2 Does cost pressure cause districts to decide that fewer students fall into the disability category?

2.2.1 Data

To study cost pressure's effects, we can exploit the fact that six states changed their financing regimes during the period under study (left panel of Figure 2.6), with Appendix A detailing legislative confirmation of these changes, Appendix Table 9.36 outlining data sources for the dependent and control variables, Appendix Figure 6.49 presenting correlations between the control variables, and Appendix Table 6.11 presenting descriptives.

2.2.2 Methods and results

Fixed effects analysis

Two sets of methods and results support the claim that cost pressure causes districts to ration resources by rationing access to the disability category. Appendix A presents the full state/year fixed effects specification, which identifies the effects of financing regime changes solely among states that switch their formulas in either direction during the period under study (1999-2000 school year to 2010-2011 school year); standard errors are clustered at the state level (the treatment unit). Table 6.13 shows that a shift to block grants, a form of fiscal retrenchment that increases cost pressure, is associated with a reduction of 0.885 percentage points in the percentage of students categorized as having a disability ($p < 0.05$). The results are robust to a variety of specifications, including estimating the causal effect without any state-level controls (Table 6.14 in the Appendix). Appendix Chapter 5.4.1 summarizes these analyses, which also include separating switches to block grants from switches away from block grants (Table 6.15) and estimating a placebo test that shows no changes in categorizing in the three years prior to the block grant and significant drops in the years following (Table 6.16). The Appendix also discusses factors that increase the chance

that the timing of the financing changes is plausibly exogenous to changes in categorization that might have led states to deliberately adopt block grants.

To quantify the magnitude of these effects, Table 2.3 presents on average how many fewer students would be categorized as having a disability in states of different sizes that adopt block grants. The Table shows results that are not just statistically significant but also substantively meaningful. A medium-sized state decides that 6000 fewer students have a disability. In response to Hypothesis One, increased cost pressure, combined with discretion about categorization, causes districts to ration resources by deciding that fewer students have a disability. The results and their magnitude confirm and extend those of Dhuey and Lipscomb (2011)'s analysis of block grants in the 1990's by showing that the second wave of these reforms, which occurred among a distinct set of states, had similar effects. The analysis that follows expands upon their findings in two ways: first, by using new synthetic control techniques to address possible violations of state-year fixed effects' identifying assumptions; second and more importantly, by presenting the first investigation in the next Chapter of *which districts* engage in stronger versus weaker rationing of the disability category.

Table 2.3: Fixed effects results: substantive significance of effect of block grants

State's place in distribution of student enrollment in 2008-2009 school year	Total student enrollment	Count of fewer students placed in special education
Cutoff for bottom 25%	280,809.50	2485
Median student enrollment	677,451.50	5994
Cutoff for top 25%	1,124,811.50	9954

Synthetic control analysis to confirm causal interpretation

The state-year fixed effect analysis provides suggestive evidence that the federal government's use of policy categories does not *fully eliminate* discretion. Instead, this moves discretion earlier in the process to decisions about *who belongs to a category.* But for the

results of state-year fixed effects models to be unbiased, the weighting states that *did* shift to block grants (treatment states) and the weighting states that did not shift to block grants (control states) can have different levels of categorization in the years leading up to the policy's passage. But the analysis assumes that the trends in the years leading up to the policy's passage were roughly parallel in order to estimate how the policy's passage then affects these previously parallel trends.

In the case of financing formula changes, we might worry that the states that choose to switch financing formulas make this choice after observing particular trends in categorization. For instance, states might switch to block grants because they are experiencing particularly rapid increases in disability rates in the years prior to switching their financing formula. If this is the case, the control group used in the analysis may produce biased estimates of each financing change's impact. This suggests that a more conceptually accurate control group, focusing on switches to block grants, might be the following:

Treatment: a state that switches from weighting to block grants

- **Control**: weighting states at risk of this switch that resemble trends in categorization rates of a treatment state prior to the treatment state switching its policy

Synthetic control analysis helps us accomplish this aim of matching states that switch formulas with control states that mirror the pre-policy trends in special education rates of states that shift their financing formula (Abadie et al., 2015), implemented using the "synth" package in `R` (Abadie et al., 2011). Appendix A describes the process in greater detail. Focusing on New Jersey, we begin by observing a particular 1) level of disability categorization and 2) trend in disability categorization prior to New Jersey's switch to a block grant. Then, rather than selecting one control state that resembles this level and trend, we take a "donor pool" of control states that were at risk of shifting to a block grant (and thus had weighting financing during the entire observed period). We then estimate the weights by finding the solution to the constrained optimization problem where the equation being minimized is the mean gap between the treatment state's categorization rates and a

weighted control's categorization rates in the pre-treatment period, and the constraint is that the weights on the states must be non-negative and sum to one.[46]

After a synthetic control is constructed using these two sets of weights, I investigate whether, after the adoption of block grants, categorization in the treatment state diverges from rates in the composite state that resembles the treatment state's pre-treatment trends. To confirm that this divergence is due to the effect of the policy and not due to chance, I conduct placebo testing. The purpose of these placebo tests is to examine whether these placebo states experience a post-policy divergence as large as the treatment states. If not, we can be more confident that the post-policy divergence witnessed in the treatment state occurs as the result of the policy rather than chance. More formally, the placebo tests calculate the following ratio, where Y represents the rate in the treatment unit (the real treatment state or a placebo treatment) or the weighted control unit ($Y_{\text{synthetic control state}} = \sum_{j=1}^{J} Y_{statej} * weight_{statej}$) where j refers to each state with a non-zero weight, and in the following equation, N_2 = number of post-treatment years and N_1 = number of pre-treatment years:

(A) Post-policy root mean squared prediction error (RMSPE) (first year of policy to 2011):

$$\sqrt{\frac{1}{N_2} * \sum_{i=\text{First year of policy}}^{2011} (Ytreat_i - Ysynth_i)^2}$$

(B) Pre-policy root mean squared prediction error (2000 to last year pre-policy):

$$\sqrt{\frac{1}{N_1} * \sum_{i=2000}^{\text{Last year before change}} (Ytreat_i - Ysynth_i)^2}$$

(C) Post to pre ratio: A / B

[46] We begin with a vector for the treatment state that contains the pre-treatment characteristics, which in our case, are both the special education rates (Y) and observed covariates (Z) specified above: $X_1 = (Z_1, \bar{Y}_1^1 ... \bar{Y}_1^m)$ where m represents different linear combinations of pre-treatment outcomes. Similarly, for the donor pool states, synth creates a matrix with the same observed covariates and pre-treatment outcomes: $X_0 = (Z_0, \bar{Y}_0^1 ... \bar{Y}_0^m)$. Then, the algorithm finds two sets of weights that minimize the distance between the treated unit and synthetic control: first, a weight on the relative importance of each covariate (with the dependent variable likely to be weighted the highest) and second, a weight on each state to form the synthetic control. This was implemented using R's "synth" package, with the program's default algorithms used for the optimization part of the procedure (Nelder Mead and BFGS)

If the policy did have an effect in the treatment state, we would expect the state's post to pre ratios to be among the largest in these placebo tests, since we expect the treatment to cause a divergence in disability categorization rates for a treatment state in the post-policy period.

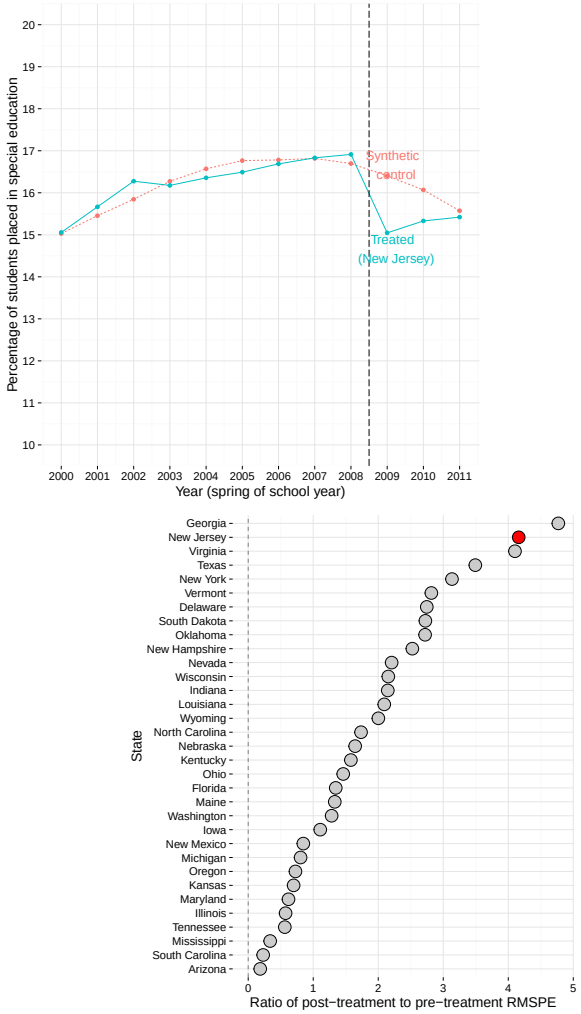
The figure that follows depicts the results with a dashed line dividing the period into *pre-treatment* school years (to the left of the line) and *post-treatment school years* (to the right of the line).[47] Figure 2.7 presents the results of the synthetic control analysis of New Jersey, Appendix Figure 6.53 of Missouri, and Appendix Figure 6.54 of West Virginia. Taken as a whole, New Jersey seems to be the only state out of the three where adoption of block grants caused a clear drop in disability categorization relative to synthetic control, as illustrated in both the graphical depiction of New Jersey's post-policy trend and the results of the placebo test. More specifically, New Jersey's RMSPE ratio is ranked second out of 33, indicating a less than 0.06 chance (2/33) that its post-capitation drop in special education rates is due to chance.

In contrast, and highlighting the advantage of synthetic control relative to state-year fixed effects that often have an ambiguous counterfactual (Imai and Kim, 2019), the graphical depictions for Missouri and West Virginia show a different pattern. In those states, the shift to formally adopting a block grant *temporally followed* drops in categorization. Though further research is needed, one interpretation for these different patterns is that while New Jersey's treatment spurred new organizational practices, the treatment in these other two states might have served as a post-hoc legislative approval on changes in categorization produced by other changes in organizational practices. As an example of other changes that can produce drops in categorization, a recent federal investigation focused on Texas, which Figure 2.6 shows has one of the lowest rates of categorizing students (Rosenthal, 2016).

Appendix A presents more details of the synthetic control construction and estimates; it also summarizes the RMSPE results of financing regime switches in the opposite direction

[47]Since the formulas go into effect at the beginning of a school year, there is no "gap year" in between when the new financing formula is enacted and when the formula goes into effect. However, some formulas do have phase-in periods where the formula is gradually escalated to full implementation, which would lead to attenuation in the results (since the policy is only partially enacted in the first couple treatment school years) rather than increase the magnitude of the results.

Figure 2.7: Synthetic control analysis of New Jersey shows a sharp drop in New Jersey in the post-block grant period relative to its synthetic control, a good match with the synthetic composite in the pre-treatment period, as well as a ranking of 2/33 on the RMSPE ratio placebo test.



(shifts from capitation to weighting), which causes increased rates of categorization in Alaska but not the other two states.

2.3 Conclusion

Organizations often seek to limit decision-makers' discretion. Chapter One outlined how social policymakers limit bureaucrats' discretion by specifying *which categories* are eligible for a policy, *how to assess* who falls into the category, and *what rights and resources* cat-

egory members receive. The present Chapter asked: what happens when bureaucrats face cost pressure but are barred from formally changing which categories they prioritize or how they decide who is a category member?

In line with research on more hidden forms of rationing (Hacker, 2004; Herd and Moynihan, 2019), I find that discretion moves earlier in the process. Bureaucrats use discretion to decide that fewer individuals belong in a social category. Thus, while past research on educational stratification sometimes treats categories as control variables that serve as proxies for demographic status (e.g., IEPs; Free or Reduced Price Lunch Status (FRPL); English Language Learner (ELL)), the present Chapter shows how an important axis of stratification might be *who accesses* the prioritized category in the first place.

The findings about vulnerability to *losing* one's category membership amidst cost pressure aligns with recent calls to focus on how schools' categorization of students impacts inequality (Domina et al., 2017). More specifically, Domina et al. (2017) note that schools "retain varying degrees of autonomy over the ways in which" categories like disability are enacted (p. 317), but do not explore how budget pressures may mean that administrators use this autonomy to tighten a category's boundaries.

2.3.1 Broader contributions and scope conditions

The results focus on one type of organization–school districts–and one category: disability. The Table below highlights how organizations, facing different forms of pressure, may engage in other category-related strategies (Edelman, 1992; Suchman and Edelman, 1996). The present findings highlight one strategy, which I call *threshold raising*. Districts must assess whether a student's disability, which can often fall along a continuous spectrum of severity for disorders like the behavior challenges in autism or attention difficulties in ADHD, falls into a binary disability category. Faced with cost pressure, they may implicitly raise the threshold for category membership.

Other examples in the disability realm might include disability examiners using more stringent thresholds to decide whether an applicant really needs SSI/SSDI amidst public perceptions of fraud or "overuse"(Schwartz, 2018). This threshold raising might have conse-

quences for inequality due to the increasing importance of disability-linked cash and in-kind services (Hansen et al., 2014; O'Brien, 2015; Dorfman, 2017). In the immigration realm, those who adjudicate applications for asylum in the U.S. and Western Europe, facing political and public backlash but no formal changes in the category of "refugee," might also implicitly raise the threshold an applicant needs to cross when proving the severity of her fear of persecution (Ramji-Nogales et al., 2011).

Organization	**Decision**	**Pressure involving social categories**	**Form of symbolic compliance**
Immigration bureaucracies	Whom to offer asylum	Grant asylum to fewer applicants	Raise an implicit threshold for binary categorization
Elite universities	Whom to admit	Increase percentage of first-generation/low-income students	Hidden heterogeneity (Jack, 2016)
Technology firms	Whom to hire/promote	Increase gender equality	Strategic aggregation
School districts	Which disability label to give	Increase racial equality	Categorical manipulation (reranking of status hierarchy)(Saatcioglu and Skrtic, 2019)

The threshold approach applies to categories like disability or refugee where decision makers begin with a continuous attribute and decide who falls into the binary category. Organizations might use different strategies when they face pressure that involves less ambiguous categories like age > threshold, gender, or income < threshold. One is exploiting hidden heterogeneity. For instance, Jack (2016) shows how the broad category of "first-generation/low-income" students contains two subgroups who face different challenges: the "privileged poor," category members who participated in diversity pipeline programs prior to enrollment, and the "doubly disadvantaged." Work on rankings and reactivity (Espeland

and Sauder, 2007) suggests that universities that face pressure to increase their percentages of first-generation/low-income students could exploit this hidden heterogeneity to admit the relatively privileged subgroup within the overarching category.[48]

Similarly, for categories less ambiguous than disability, organizations might engage in strategic aggregation. For instance, Blanche (2017) shows how technology firms under pressure to increase gender diversity report statistics at levels of aggregation that conceal underlying inequalities–for instance, reporting that 30 percent of employees are female to conceal the fact that 60 percent of the employees in customer support roles are female while many fewer of the employees in engineering roles are female.

This typology of different category-related strategies–threshold raising; exploiting hidden heterogeneity; strategic aggregation–can be applied to other cases where either public bureaucracies or private firms face pressure to prioritize a social category. In addition, the use of methods like synthetic control can expand the range of pressures on organizations that researchers can study. It does so by using a form of permutation inference to more reliably assess the causal effect of an $N = 1$ policy change, which are impossible to study under fixed effects methods that require many changes among units and that have an unclear interpretation when the changes occur during different time periods (Abadie et al., 2015; Imai and Kim, 2019). While extensively used in economics and political science (e.g., Maclean and Saloner, 2018; Athey and Imbens, 2017; Bechtel et al., 2018), the present Chapter is one of the first to apply the method to a sociological question.[49]

2.3.2 Limitations

The present analysis has limitations. One limitation is that discretion over deciding category membership likely varies across the IDEA's 13 disability categories. The boundaries of diagnoses like emotional disturbance, Other Health Impairment(often used for ADHD), or specific learning disability are fuzzier than the boundaries for categories like orthopedic

[48] Jack (2016) focuses on these students' experiences once they enroll at an elite university rather than admissions decisions.

[49] Brazil (2016) uses the method in a *Demography* paper to study the effect of riots on residential segregation.

impairments or deafness. While the administrative data used in the state-level analysis decomposes overall categorization into specific disability categories, the counts in some categories are too small to form reliable between-category comparisons of which categories are most impacted by cost pressure. Past research identifies *within*-category differences as an important source of racial inequality–for instance, Ong-Dean (2009), Baldwin Clark (2018), and Saatcioglu and Skrtic (2019) discussing the overplacement of African-American students into categories like emotional disturbance and underplacement into categories like autism. The present study cannot speak to this within-category form of inequality.

A second limitation is that the counts of categorization are a *stock* rather than a *flow* measure–that is, we only know the overall stock of students categorized as having a disability in a particular state-year or district-year. We do not know how many of these are students newly categorized. Thus, while cost pressure can lead to two forms of rationing– a student who is already categorized as having a disability "losing" this category during evaluation meetings; a student who is not yet categorized "failing to gain" a category they seek–we cannot disentangle these forms of rationing in the present data. Similarly, the results assume that losing access to an IEP is a form of rationing. But research focused on a high-performing charter school in Boston shows that students lose access to an IEP when they switch from the public school to the charter school, but receive compensatory resources *regardless* of their categorical designation that help outcomes (Setren, 2015). However, it is unclear whether those results generalize beyond the high-performing charter school context and, in general, the assumption that students receiving an IEP are likely to have access to more resources seems safe, especially for budget-pressed public schools.

The final limitation is that as Figure 2.5 highlights, there are many professional actors involved in decisions about which students receive an IEP. Teachers play a role through referring students. Parents play a role in requesting an evaluation or disputing the results of an evaluation that finds the student's disability is not severe enough. In New Jersey, IEP meetings need to have members of both a *Child Study Team*—a school psychologist; a school social worker; a learning disabilities specialist—and an IEP team that adds a general education teacher and a "representative of the school district, who may be a child study team

member, special education administrator or principal, and who (1) is qualified to provide or supervise special education; (2) is knowledgeable about the general education curriculum; and (3) is knowledgeable about the availability of the resources of the school district" (Hespe and Worthington, 2016). The analysis, which examines the *outcomes* from these meetings rather than the interactions that take place during them, cannot investigate, for instance, whether it is the school district representative who makes meetings more difficult following budget shocks. Future work—for instance, work that examines transcripts from these meetings before and after budget pressure—can investigate more specific mechanisms through which rationing gets enacted.

2.3.3 Concluding

With these limitations in mind, the Chapter shows that one form of hidden rationing occurs through discretion to change a category's boundaries. When the category grants access to a weakly-funded entitlement—in this case, disability services that are more costly for the district to provide under state shifts to block grants—the pressure is to narrow its boundaries and categorize fewer individuals. In other cases, organizations might have financial incentives to broaden a category's boundaries. The findings could potentially extend both to other categories in school districts—for instance, assessments of family income to determine membership in the Free or Reduced Price Lunch category—and categories used to condition access to other social welfare programs.

Chapter Three: Parent Monitoring and Unequal Discretion to Ration

3.1 Introduction

> *Following the September *** ARD [Admissions, Review and Dismissal] meeting Student's mother visited the *** and was very upset by what she saw and heard from the teacher. Student was ***. In her view nothing *** seemed conducive to the learning environment. The teacher told her about an incident when Student ***. On September ***, 2016 Student's parents provided the school district written notice of their intent to withdraw Student and place Student at *** - a private school. Student's mother was an active participant at every ARD meeting, made suggestions, shared information, asked questions, and was a strong advocate for Student's needs. Parental input was considered and solicited at every meeting.* (Texas Hearing Officer Determination, Student v. Georgetown Independent School District, April 2017).[50]

The previous Chapter showed that budget pressure in the form of block grants causes districts to categorize fewer students as having a disability. New Jersey was the state with the largest drop. This Chapter explores mechanisms behind that drop. If school professionals are able to use *discretion* to ration categories, districts may differ in the degree of discretion professionals have in these decisions. The Chapter thus focuses on New Jersey and investigates two questions. Do districts engage in similar degrees of rationing access to the disability category? And if districts vary in the extent to which they ration categories, what explains these outcomes? I find that parent monitoring *before the budget change*—monitoring like Drew's parents did of decisions about what he was owed—reduces rationing

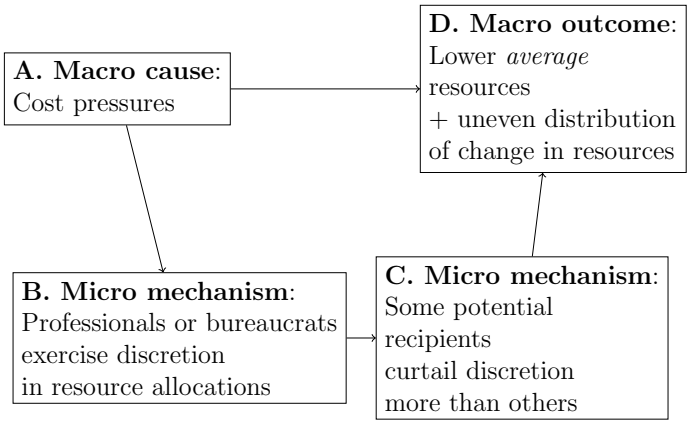
[50] *** indicate redactions the Texas Hearing Office makes before publicly posting the decisions.

after the budget change. This monitoring is a more significant predictor of differences in rationing than factors like the district's demographic composition or its fiscal health.

First, I present a general framework for how variation in monitoring can mean that organizations have different amounts of discretion to ration. Then, applying this framework to school districts, I argue that while a wealth of research focuses on inequalities in how closely parents monitor educators' decision, little research investigates whether this monitoring produces unequal outcomes when districts face budget shocks. I next turn to the analysis, which first shows *that* New Jersey districts varied in how much their categorization changed following block grants and then investigates whether the presence of monitoring reduced rationing.

3.1.1 Unequal monitoring of decision-makers leads to an unequal amount of discretion

Figure 3.8: Interactions and rationing outcomes



The previous Chapter focused on the top path in Figure 3.8. Cost pressure leads to lower average resources, in the form of fewer IEPs promising students extra help. The bottom path shows how this *overall* drop in resources following a policy change or cost pressure may be accompanied by *unequal drops* across subgroups. In the present case, where the resource is *access to a category*, some continue to get categorized; others do not. One mechanism might be that discretion varies across potential recipients of a resource. Some professionals

might have more discretion to ration resources by deciding that an individual does not have a disability or is not truly low-income. Some professionals might have less discretion. These differences in discretion might be related to the professional's or organization's *interactions* with potential resource recipients (Lipsky, 2010; Herd and Moynihan, 2019)–some potential recipients engage in more intensive monitoring of and intervention into professional decision-making, monitoring and intervention that reduces discretion.[51]

What forms might this monitoring of decisions take? And how might variation in monitoring cause variation in the degree of discretion that decision-makers have? Past analyses of professions generally focus on two close conceptual cousins of discretion–autonomy and authority–and how these vary *between* professionals (Parsons, 1939; Larson, 1979; Abbott, 1988; Starr, 2008).[52] In the present Chapter, I argue that discretion is attached to *decisions*

[51]Herd and Moynihan (2019), in their discussion of the role of unequal human capital in navigating the "administrative burdens" of policies, highlight the potential for this form of inequality. However, their analysis does not focus on specific ways that having the human capital to more closely monitor bureaucrats' decisions can reduce discretion.

[52]Despite their general focus on autonomy and authority, we can draw out implicit ideas about discretion from some of these previous theories. Parsons (1939) argues that professionals exercise authority over a "particular technically defined sphere"(p. 38), and because they restrict their authority to this bounded sphere, they can exercise authority over clients who may be "superior in social status, in intellectual attainments, or in moral character"(p. 38). Framed in terms of discretion, Parsons argues *that* professionals have discretion on decisions within a bounded area of technical competence and implicitly argues that this discretion is deserved on the basis of their technical competence. Starr (2008), focusing on American medicine, describes how physicians transformed a weakly-institutionalized form of authority that rested on the perceived competence or charisma of an individual professional into a more strongly-institutionalized form of authority that resided in the medical profession as a whole. Framed in terms of discretion, physicians' discretion over various decisions was hard-earned and historically contingent rather than "propelled solely by the advance of science and satisfaction of certain human needs"(p. 4). Finally, Abbott (1988) argues that professions engage in ongoing struggles to claim exclusive jurisdiction over certain tasks and problems, and that they make claims to jurisdiction to various audiences. For discretion, Abbott's analysis highlights that precisely *which decisions* a given profession or professional has discretion over shifts as professions engage in these jurisdictional struggles, but the struggle for "exclusive rights" over an area of work can be thought of as a struggle for discretion over decisions in that area of work. We can think of autonomy as a *profession* or *professional-specific* and *context-dependent* characteristic. For instance, U.S. physicians historically have had higher degrees of autonomy than U.S. public school teachers (profession-specific), but the same might not be true in Norway (context-dependent); in addition, a U.S. physician working as a solo practitioner might have greater autonomy than a U.S. physician working in an accountable care organization (professional-specific). While autonomy is thus a characteristic that attaches itself to a professional and that permeates all of that professional's decisions, I argue that discretion is a *decision-specific* characteristic (that is also *context-dependent*). For instance, a physician has greater discretion over which diagnosis to give a patient than over whether to withdraw life-sustaining treatment (*decision-specific*), and a physician's discretion over whether to withdraw life-sustaining treatment has decreased with the rise of "patient consumerism" (*context-dependent*).

rather than *professionals*. For instance, school professionals have more discretion over which students they allocate attention to in class (Booher-Jennings, 2005, 2006) than over how severely they can discipline students (Arum, 2005). Defining discretion as a decision-level characteristic means that discretion can vary across potential recipients of an allocation.

3.1.2 Linking monitoring to aggregate resource outcomes

Yet returning to Figure 3.8, part of the challenge in studying how monitoring of professional decisions affects aggregate rationing outcomes (C $\implies$ D) is observing this monitoring on a large-enough scale to see how it moderates pressure on organizations. Ethnographic studies that zoom in on a few organizations have yielded rich evidence of nodes B (professionals exercising discretion in allocating some resource) and C (some potential recipients curtailing this discretion more than others). In particular, focusing on parents, higher socioeconomic status (SES) parents engage in greater monitoring of professional decisions that impact their child, monitoring that reduces discretion (Hays, 1998; Heimer and Staffen, 1998; Eyal, 2013; Lareau, 2000, 2011; Haskins and Jacobsen, 2017; Calarco, 2018).[53] Focusing on disability specifically, Baldwin Clark (2018) uses qualitative interviews to show how White parents with higher levels of cultural capital translate this capital into favorable disability diagnoses for their children. Saatcioglu and Skrtic (2019) use qualitative interviews to show how parents concerned about the influx of Black students in the wake of a desegregation order in the 1970s used their cultural capital to move their children into a disability category (learning disability 3) that granted them access to separated classrooms.

These ethnographies or interview studies usually use parent socioeconomic status or race/ethnicity as the axis of variation. In doing so, their findings either mix together two correlated features or focus on parent class rather than school cost constraints: (1)

[53]Lareau (2000) highlights revealing details of parental intervention into these classrooms such as how higher-SES mothers volunteer in classrooms as a way to monitor teacher performance and collect evidence to bring to principals to complain in the case of unsatisfactory performance (p. 65). Heimer and Staffen (1998)'s ethnography of parental monitoring of medical professionals in neonatal intensive care units (NICU's) shows important details such as one parent renting a room at the hospital in order to be there to watch her child's care "like a hawk" after a medical mistake (p. 252), though the authors emphasize that use of these tools is not strictly confined to upper-middle class parents.

how effective is the parent at monitoring and influencing school decisions (an individual attribute) and (2) what cost constraints do those at the school or in the district face in saying "yes" to a parent request. Lareau (2011) studies two schools: "Lower Richmond," a school in the city with predominantly working-class White and Black students, and "Swan," a school in the suburbs with predominantly middle and upper-middle class White students. As she describes, the two had very different budget constraints:

> Teachers at Swan have access to more supplies than do their counterparts at Lower Richmond; there is a photocopier for their use and ample paper and art materials. Referrals to special education are less common and less bureaucratic. Parents must formally agree (by signing a permission form) to have their children tested for learning problems, but the paperwork generally takes weeks, not months, to be processed ((Lareau, 2011, p. 21)

Yet in the discussion of the findings, which show that higher-SES parents at Swan are more effective in securing resources than lower-SES parents at Lower Richmond, these budget constraints that might lead, for instance, to a months rather than weeklong wait for learning disability testing, remain in the background. Calarco (2018), studying socioeconomic variation *within* one school ("Maplewood Elementary" in "Fair Hills School District") that has a mix of lower and middle-class students, holds factor two constant to isolate factor one. But what would happen if the state legislature where Fair Hills is located slashed school funding, and negotiations about extra teacher attention took place at a school struggling with larger class sizes and less paraprofessional support?

This Chapter aims to show how the unequal interactions studied in past research might produce unequal outcomes when districts face new budget pressure. Understanding this more complete set of pathways—how variation in monitoring of professionals leads to variation in rationing outcomes—requires measuring these social interactions on a large-enough scale to investigate how they moderate large-scale pressures on organizations. That involves measuring interactions in either a representative sample or census of organizations that pressure affects. The Chapter thus re-purposes data from a database of parental complaints to study these interactions on a large scale: all school districts in a state ($\sim$ 500,

observed over a period of ten years, with over 3000 parent complaints filed).[54]

Recently, Saatcioglu and Skrtic (2019) show *that* one district had discretion to change the status of different disability categories to accommodate court pressure to increase the number of Black students in a disability category. The present study, by leveraging variation in how intensively parents monitor school decisions regarding children with disabilities, highlights a specific mechanism–inequality in parent monitoring of district decisions that lies behind large-scale changes in categorization. This general mechanism–unequal surveillance *of* organizations causing unequal outcomes–can be applied to a range of organizational decisions.

Question / hypothesis: parent monitoring prior to budget pressure reduces districts' likelihood of rationing after budget pressure

As discussed in Section 3.2.2, the present Chapter exploits detailed administrative data on parent monitoring of two types of district decisions about disabilities—*whether* a child has a disability; if the child has a disability, what services the district will provide–to measure 1) whether the average causal impact of the shift to block grants shown in Chapter Two conceals heterogeneity in the impact and 2) whether variation in the monitoring that district professionals face explains this heterogeneity. In sum, ethnographers have documented stratified parent surveillance of district decisions–for instance, the analysis in Calarco (2018) of parent-teacher interactions where higher SES parents are "quick to challenge teachers and bring complaints to higher authorities if they believed that teachers were being insufficiently responsive to their children's needs"(p. 155). The Chapter explores whether this unequal monitoring produces stratified outcomes for students who potentially have disabilities.

[54]As Salganik (2017) notes, researchers can use this type of government "trace data" to study behaviors at scale. And while other research shows how organizations use large-scale data to engage in unequal surveillance *of* citizens (Brayne, 2017), the present article flips the data's use to study how *citizens engage in unequal monitoring of organizations.*

3.2 Data

3.2.1 Dependent variable

The dependent variable is a district's count of students categorized as having a disability (issued an IEP) over the total number of enrolled students. Since Common Core Data is missing this district-level information for important years, I use the New Jersey Department of Education's district-level classification data. Appendix Table 7.22 discusses data sources for the other predictor variables. The final analytic sample of 598 school districts excluded about 80 small districts that were not at risk for a change because they only existed as districts during either the pre-treatment period or the post-treatment period, but not both periods.[55]

3.2.2 Main predictor variable: parent monitoring of district disability decisions

What might affect the discretion of district professionals to ration resources in the wake of cost pressure? Figure 2.5 shows that the primary actors who curtail educators' discretion are parents. Parents can monitor and intervene in professional decisions at several steps (Caruso, 2004; Pasachoff, 2012; Ong-Dean, 2009; Baldwin Clark, 2018). Parents can request an evaluation to start the process of deciding whether a student has a disability (20 U.S.C. §1414(a)(1)). Parents can supplement the district's publicly-financed assessment of whether the child has a disability with a private evaluation from medical or psychological professionals they pay for themselves (IDEA 2004 §300.502(a)(3)(i)). Finally, if district professionals make a decision the parent disagrees with–which is usually a decision to *deny* the child an IEP/disability category–parents can use the formal "due process hearing" system that I discuss in greater detail in Chapter Four. This appeals system is free and technically

[55]Note that this is distinct from missing data during one of the periods, since Common Core Data tracks that. Instead, these are usually small charter-only districts that either existed at some point before the formula change (e.g., in 2004) but did not survive until the 2008-2009 school year (the first post-treatment year) or districts that existed at some point after the formula change (e.g., 2008-2009, 2009-2010) but did not exist in any of the pre-treatment years.

requires no attorney representation, but parents often bring an attorney. In the hearing, parents and districts each present evidence in favor of their arguments to an administrative law judge called an impartial hearing officer who issues a ruling (20 U.S.C. §1415(f)(3)(C)).

Past work suggests that parental socioeconomic status may be a useful *proxy* for how closely the parent monitors professionals who serve their child (Lareau, 2000, 2011; Calarco, 2018). I argue that we can improve this proxy by using direct data on this third step. This approach aligns with other studies that try to more directly measure professionals' exercise of discretion, like the analysis in Sattin-Bajaj et al. (2018) of counselor discretion in the type of guidance they provide to students on choosing schools.

Specifically, a key feature of the IDEA, and why many parents view IEPs as more desirable than other disability-focused contracts like Section 504 plans, is the robust system in place where parents can intervene to protest decisions that school professionals make. In particular, the statute establishes a state-level due process hearing system that is designed to make it easier for parents to intervene on their child's behalf than if the parents had to file a case in federal court (Melnick, 2010).[56] These due process requests, which can only be filed by a child's parents on behalf of *that particular child* as opposed to, for instance, public interest groups filing class action lawsuits on behalf of a group of children, are by definition challenges to the judgment of district professionals over which children to categorize as having a disability and what resources to promise (Mueller and Carranza, 2011). Most of these parent interventions never "go to trial." And thus, most are never heard by an impartial state hearing officer (IHO). Instead, many are settled or are used by the parent to gain leverage on districts in negotiations over resources. Furthermore, unlike litigation, parents can file a request for these hearings at no cost and without attorney representation.

The *filing* of these complaints, regardless of whether they progress to an actual hearing, represents a potent form of parental monitoring and intervention into district decisions. To link these filings to school districts, I submitted a request under the New Jersey Open

[56]In addition, parents must make use of this state-level due process hearing system before they progress to the federal district court level in disputes with districts, meaning that any intervention that eventually progresses to the district court level first passed through that state's due process hearing system.

Records Act (OPRA, N.J.S.A. 47:1A-1 et seq) with the Records Custodian of New Jersey's Office of Administrative Law (OAL). Appendix Figure 7.55 shows the language of the request. This request enabled the parental monitoring variable to capture *all formal attempts* at intervening in district decisions about disabilities, even if the attempt, like most, was withdrawn or settled.[57] These "administrative trace data" thus re-purpose data collected to help a state bureaucracy keep a log of complaints to study behavior across all school districts and years.

The request yielded metadata on all parent-district disputes about disability services in the time range of the 2000-2001 school year to 2012. I then applied two inclusion criteria: the filing occurred in the pre-treatment period since I am interested in the effect of *pre-treatment parent monitoring* on heterogeneity in district responses to cost pressure. Second, I excluded the small percentage of filings where the district filed a request against the parent (rather than the parent against the district) due to my interest in parental monitoring. This analytic sample of 3,821 interventions was then merged with Common Core and NJ DOE data on district characteristics and placement rates, with details of this name-based fuzzy matching described in Appendix Figure 7.56.

The result is what I call each district's *parent monitoring history* in the pre-treatment period. This intervention history ranged from zero interventions in the pre-treatment period to 61 interventions in the pre-treatment period (Newark, the state's largest district) with an average of 6.71 interventions per district in the pre-treatment period (an average of 0.84 interventions per district per school year). Yet to highlight that district demographics (and size) are not fully determinative of the presence of monitoring, we can compare two districts–Boonton Township and Cranbury Township–with similar enrollments and similarly high socioeconomic status (in each, fewer than 2% of students are eligible for Free or

[57]The reason for this request is that New Jersey, like most states, publishes decisions of due process requests that "go to trial" (more formally, are adjudicated by an Administrative Law Judge to result in a written decision). But these public decisions represent only a small fraction of all parental interventions in the form of protesting a disability-related decision, since most interventions result in a written, legally-binding settlement between districts and parents or are resolved more informally after the parent files a request. Therefore, the request yielded a comprehensive set of all *attempts* at formal intervention rather than the selected subset of attempts that progress all the way to a hearing and written decision.

Reduced Price Lunch). The different histories indicate that there is residual variation in monitoring even amongst districts with similar demographic profiles:

Parent monitoring during each school year (spring)

	2001	2002	2003	2004	2005	2006	2007	2008
Boonton	2	2	0	2	2	3	0	2
Cranbury	0	0	0	0	0	0	0	0

Chapter Four uses computational text analysis to delve more deeply into *what* this monitoring focuses on. Quotes from selected hearings highlight the *forms of discretion* that parents try to limit. For instance, in a dispute where the district argued the student (S.B.) did *not* have a disability, and where the mother argued that her daughter did, the mother used technical language–e.g., referencing her daughter's auditory processing disorder–to assert her claim to expertise:

> Petitioner[mother of student] testified that she feels, based on her knowledge and the evaluations, that S.B. should be classified as eligible for special education. She also testified that S.B. needs goals and objectives and a program that is designed to address her central auditory processing disorder (taught by a teacher with that certification). Petitioner also testified about S.B.'s need for additional modifications, such as additional examples, increasing the size of answer spaces and a specific FM unit.(A.J. o/b/o S.B., v. Berkley Township Board of Education, decided on May 16th, 2005)

The hearing officer, an administrative law judge, praised the mother's detailed testimony but ultimately sided with the district's judgment that S.B.'s problems did not cross the implicit threshold required to be categorized as a disability:

> Petitioner's testimony was detailed, passionate and intelligent. While I do find her testimony to be credible, I do not agree with her that her child should be classified for special education. The Petitioner's passion and desire to help S.B. is commendable, but the overwhelming weight of the evidence shows that the district made the proper determination in not classifying S.B. [as having a disability](A.J. o/b/o S.B., v. Berkley Township Board of Education, decided on May 16th, 2005)

This quote highlights that the results in the previous Chapter could come from threshold raising–districts agree with a parent that the child has problems that limit learning, but raise the threshold for how severe these problems must be to warrant a category.

The hearings also show how other parents seek to reduce district discretion over specific services after the district has already agreed to categorize a student. For instance, one mother of a child with autism argued that the district needed to increase the number of therapy hours from 45 minutes per day to at least 160 minutes:

> N.L.[student's mother] believed that the related services being offered both children were not enough. Greenspan therapy was being offered for 45 minutes per day whereas Greenspan recommends eight to ten 20 minutes sessions per day. She believed the Greenspan consultation being offered was not sufficient. (G.A.L. v. Saddle River Board of Education, decided on June 22nd, 1999).

In sum, the parent complaints serve as a tool in reducing district discretion over various decisions. The present section tests whether districts that face *more monitoring* are thus less likely to ration resources following the cost pressure.

The main results use a single measure–whether a district had any parent monitoring during the pre-block grant period–for three reasons. First, as the Newark case highlights, a district's sum of pre-treatment interventions is more sensitive to district size than whether or not the district had an intervention at all. Second, as the Boonton Township example highlights, there may be "contagion effects" within a district once the first parent files a complaint. That is, once other parents are able to see that parents can use this tool to shape resource allocations, we see a pattern where districts, after the first complaint, tend to have other complaints in future years; districts that have not yet had their first complaint tend to persist in having zero complaints. This interactive visualization shows these dynamics: `https://rjohnson.shinyapps.io/nj_dp_visualize/`. Third, the same parent may file complaints repeatedly as shown in Table 7.21. These are not clerical errors: each case has a unique ID in the database log system. Instead, they likely reflect parents who use a repeated request for a due process hearing to ensure the maintenance of a service for their child from school year to school year. This occurs since the IDEA contains a "stay-put" provision. If a district wants to discontinue providing a service to a child and the parent disputes that discontinuation and files a request, "stay-put" requires the district to continue providing the service until the dispute is resolved.

3.2.3 Control variables/competing explanations for variation in categorization

The models also include the following control variables, all from the pre-reform period, that might confound the relationship between the treatment—monitoring—and the outcome: a drop in IEPs in the first year post-reform relative to the pre-reform school year (Appendix Figure 7.60 shows the DAG). For the purposes of interpreting coefficients, all percentages are coded as 0 - 100. First, since the disproportionality literature largely focuses on and finds significant differences in placement for African-American students, I focus on a district's percentage of African-American students (or more precisely, the percentage of African-American students in public schools at the district) to control for differences in categorization that might be related to a district's racial/ethnic composition. Second, because districts may be differently sensitive to state budget changes depending on whether they have the ability to compensate for state budget shortfalls with higher local allocations, I use a district's percent reliance on non-local revenue sources in the pre-treatment school year (so 100 percent - percent revenue from local sources). Districts with higher reliance on non-local revenue sources have less local property and other tax wealth to compensate for changes in state aid, so are more fiscally vulnerable to changes in this state aid.

For parent socioeconomic status, I use a district's District Factor Group (DFG) rating. DFG's are eight letter-based categories that I convert to an integer, with the lowest integer representing the *lowest SES* districts and the highest integer representing the *highest SES* districts. Socioeconomic data is taken from the 2000 decennial census and thus is pre-treatment, and the DFG is a summary indicator of a district's SES relative to other districts in the state based on a principal components analysis of six variables: percent of adults with no high school diploma, percent of adults with some college education, occupational status of adults, unemployment rate of adults, percent of individuals in poverty, and median family income. The DFG then places each district in categories based on the first PC. I also control for the district's pre-treatment percentage of English Language Learners (ELL) in the most recent year in which this was measured, since ELL is a category that, like

the disability category, comes with extra state and federal resources that might be diverted to address funding shortfalls following the fiscal reform.

Different model specifications also controlled for a binary indicator of whether a district was an *Abbott* district–that is, whether the district was among the 31 districts targeted for supplemental funding under the *Abbott v. Burke* school finance legislation–but the high correlation between this variable and the lowest DFG (20 out of the 31 districts were DFG = 1; the remaining were DFG = 2 or DFG = 3) led to the inclusion of DFG in the final models but not the *Abbott* indicator. Similarly, a district's percentage of Free or Reduced Price Lunch (FRPL) eligible students was highly correlated with the DFG categories and is not included in the final model.

The presence of these control variables means that while past quantitative studies use socioeconomic status as a proxy for parents' degree of advocacy for their child, the present analysis compares this proxy to a more direct measure of parent advocacy. By comparing these two sets of variables, the analysis can explore whether variation in the surveillance that district professionals face can explain variation in outcomes beyond that explained by a district's socioeconomic composition.

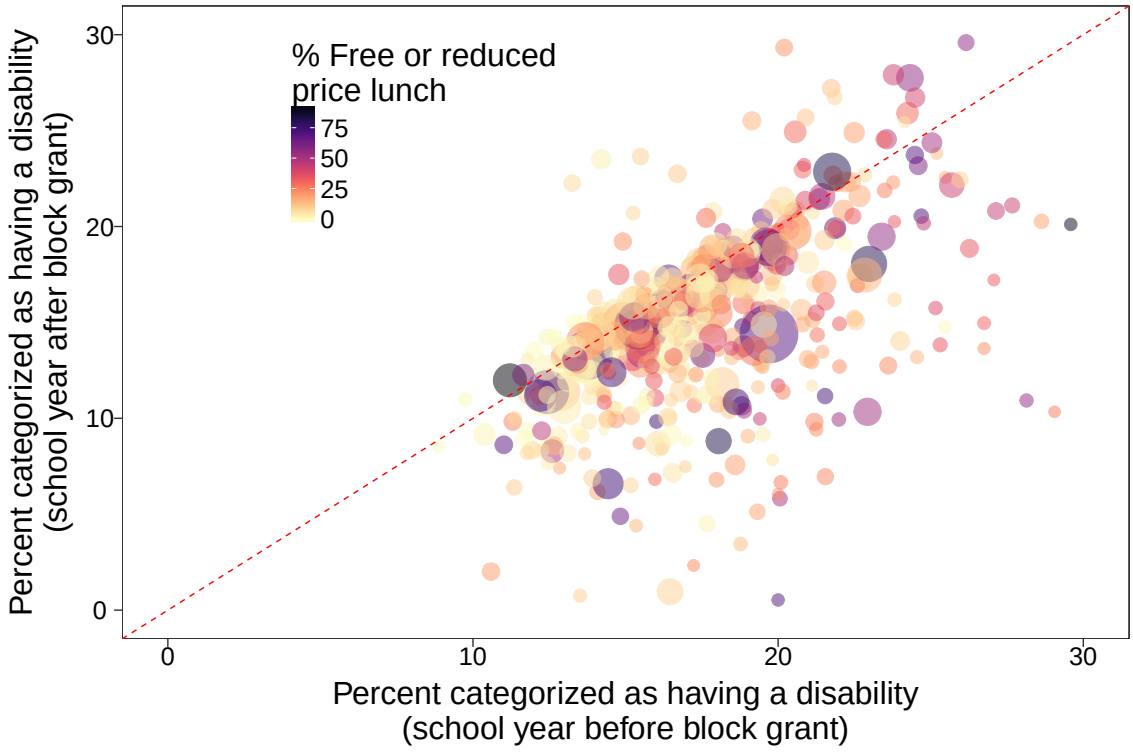
3.3 Results

3.3.1 Descriptive results

Overall shifts in categorization

Figure 7.57 in the Appendix shows the full count of New Jersey districts at each special education placement rate in the school year prior to the formula change (2007-2008) versus the school year after the formula change. A two-sample Kolmorogov-Smirnov test of equality of distributions confirms that, despite being composed of the same districts, the two distributions are not equal (D = 0.25549, p ¡ 0.001). In particular, we can see from the graph that following the policy change, there was a leftward shift in the distribution towards lower rates of categorizing students as having a disability.

Figure 3.9: **Descriptive relationship: rate at which district categorizes students as having a disability in school year before block grant versus school year after block grant** The Figure highlights that most districts categorized similar percentages of students (clustering around the 45-degree line), with the size of the dots scaled to total student enrollment. Falling further beneath the line does not seem to be well predicted by district SES (color of the dots).



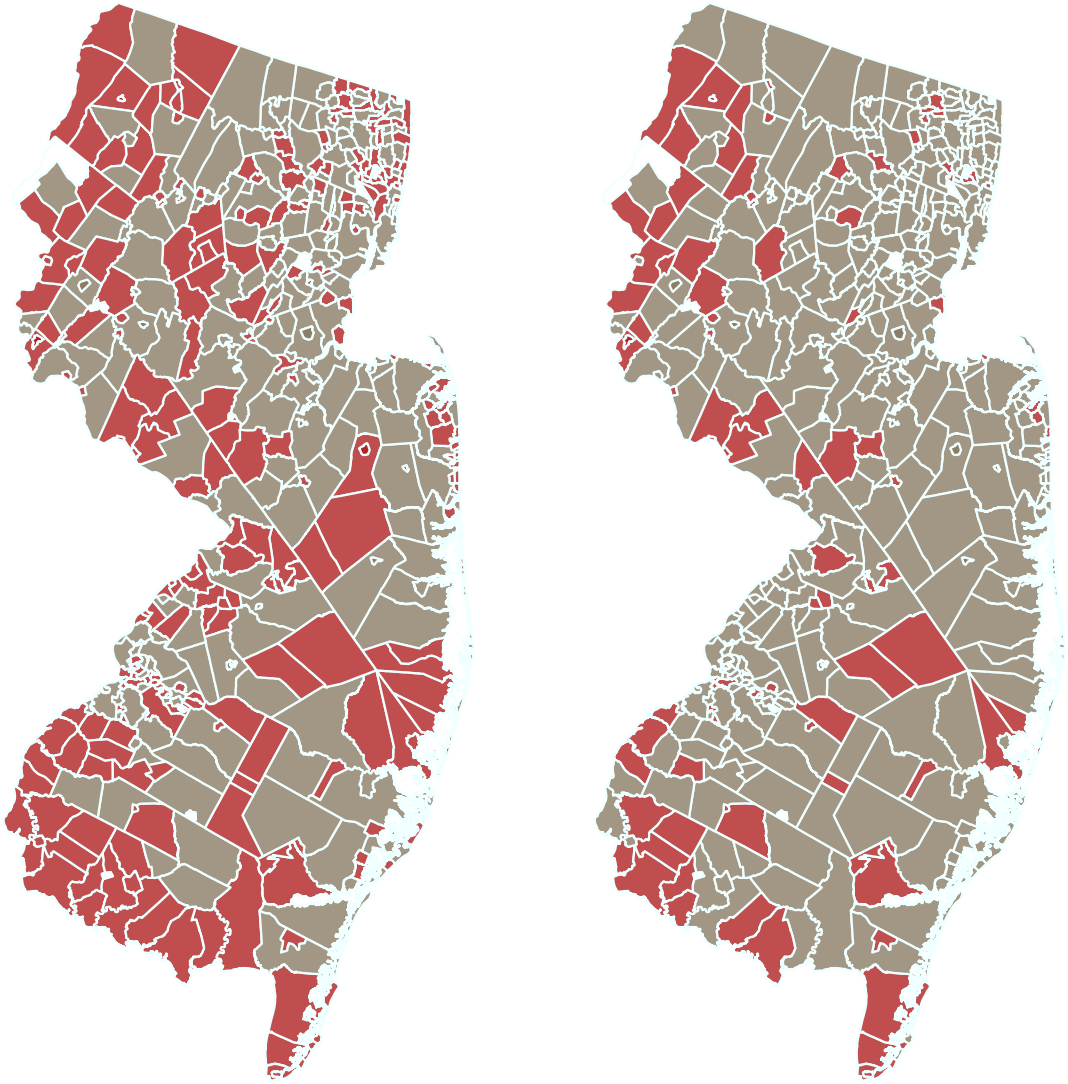
Between-district heterogeneity in rationing categories

Figure 7.57 reveals a shift in the distribution of districts towards lower rates of categorizing students. But it does not tell us whether *all districts* experience a shift downwards in categorization following the formula change or whether the downward shift is more concentrated in certain districts. Is the district's likelihood of categorizing fewer students correlated or uncorrelated with that district's characteristics? Figure 3.11 highlights that many districts have similar categorization in the post-reform school year as the pre-reform year (a clustering around a 45 degree line). Districts with lower parent SES appear slightly over-represented among those that categorize fewer students, but there are also many higher SES districts that ration the category. Appendix Figure 7.59, showing a district's summary factor group

rating on the x axis and the district's drop in categorization on the y axis, likewise shows a weak trend where higher SES districts have less of a drop in categorization, but also highlights significant variation *within* the same SES grouping.

While parent SES is a proxy measure for how likely the parents are to engage in monitoring and intervention of districts, we have direct data on one form of those interventions. The left panel of Figure 3.10 shows the parental monitoring measure across districts/counties at the beginning of the database; the right panel shows any monitoring *up until* the final school year prior to the block grant. The Figure shows that while monitoring spread across districts over time, there remain many that continue to have no formal parent monitoring.

Figure 3.10: **Distribution and diffusion of parent monitoring over time**: *Left panel*: shows the distribution of *any complaint* (in gray) during an initial year of the database tracking these complaints (2001-2002 school year); *Right panel*: shows the distribution of having *any complaint* up until the final school year prior to reform (2007-2008 school year; so capturing any complaint in the school years 2000-2001 up until that school year). The Figure highlights that while complaints spread over time, there are some districts that persisted in facing no formal monitoring by parents prior to the state's shift to block grants. An interactive visualization that juxtaposes cases against district demographic information is here: `https://rjohnson.shinyapps.io/nj_dp_visualize/`.



3.3.2 Analytic results

Figure 3.10 highlights variation across districts in whether there was *any formal parent monitoring of the district* prior to the shift to block grants, which we call monitoring for shorthand. In turn, the presence of this monitoring might have a causal effect on the district's response to the fiscal reform. This interpretation maps on to how a legal aid attorney who represents low-income parents in a large urban district described the importance of these parent filings, most of which are withdrawn or settled. As the attorney put it, "filing for a hearing definitely focuses the minds of the Department of Education [the district's administration] in some ways."[58] She went on to describe how districts try to avoid a hearing, and will settle with a parent by providing an "independent neuropsych"—an agreement to let a psychologist not employed by the district assess the child's disability—or "some form of comp."—compensatory education in the form of extra services that are meant to compensate for too-low levels of resource provision in the past. Parent monitoring in the form of requesting a third party to closely scrutinize the district's decisions can impact how a district allocates resources.[59]

To analyze the district's history of facing monitoring in this way, we rely on *selection on observables*: once we condition on characteristics of a district correlated with both 1) the district's likelihood of having any pre-treatment monitoring and 2) the district's likelihood of rationing access to the disability category following the cost pressure, we can identify the effect of parent monitoring. Figure 7.60 describes the causal process. Worth noting is that, by analyzing changes between the district's pre-reform categorization and

[58] Author Interview, Supervisory Attorney at public interest law firm, June 17th, 2019.

[59] Another attorney discussed more potent tools to reduce district discretion. She described her experiences working in two urban school districts with similar demographic characteristics and fiscal situations. One of the school districts had experienced litigation that led to a consent decree, which led to an extreme reduction in the discretion that professionals had in the district due to the strict legal control and supervision of the professionals' work.(Author Interview, Attorney at public interest law firm, November 18th, 2016.) The other had no consent decree. As she described, the two districts were like "night and day" when it came to deciding which students have a disability. The consent decree district conducted outreach in churches and low-income neighborhoods to satisfy their "child find" obligations to locate all children with disabilities residing in the district regardless of whether the student's parents proactively sought out help. The one without the decree, as she put it, "sort of sat around waiting for parents to repeatedly point out a problem." While a consent decree represents a much more dramatic reduction in the discretion of district professionals than a parent filing a complaint.

post-reform categorization, we can control for time-invariant factors that affect the *levels* of categorization across both pre-reform and post-reform years but that do not affect the *change* in categorization across the two school years. In addition, by analyzing the change from one school year to the school year immediately following, we minimize the risk of biases induced by differential parent migration across states and districts. This is because migration to school districts in pursuit of better disability services is more likely to occur when a child *first enrolls* in school than immediately in the year following a little-publicized formula change (Lareau and Goyette, 2014).

I estimate the following two models, where i indexes districts, t refers to the post-reform school year (2008-2009), $t-1$ refers to the pre-reform school year (2007-2008), Y refers to the disability categorization rate, and X contains a vector of pre-treatment covariates assumed to affect the likelihood of parent intervention and the potential response to the cost pressure. First is a linear regression of the categorization rate in the post-reform year controlling for the rate in the year immediately prior to reform:

$$Y_{it} = \alpha_i + \beta_1 \times \text{any intervention } (1 = \text{yes})_i + \beta_2 Y_{it-1} + \gamma X_{t-1} + \epsilon_i \tag{3.1}$$

Second is a logistic regression where the outcome is a binary indicator of whether there was *any* drop in categorization following reform:

$$\mathbf{1}(Y_{it-1} > Y_{it}) = \alpha_i + \beta_1 \times \text{any intervention } (1 = \text{yes})_i + \gamma X_{t-1} + \epsilon_i \tag{3.2}$$

The quantity of interest in the models is the effect of any monitoring in the pre-treatment period on either the district's post-reform rates (linear regression; controlling for pre-reform rate) or the district's predicted probability of a drop in categorization following the reform. In both models, X contains the controls summarized in the previous section.

The unit of analysis for all models is the district. This is due to the data available, but also due to the fact that it is more interesting to explore monitoring as an *organization-level* treatment. Although whether a student is categorized is an individual-level outcome, the main predictor variable of interest–parent monitoring of and intervention into a district's

decision-making–is a district-level treatment both legally and substantively. Legally, the IDEA only permits parents to file complaints against districts.[60] While a complaint may name specific teachers and school professionals, the defendant is the district as a whole. Substantively, we might care about the effect that a complaint filed by hypothetical student Bob's parents has on Bob's later categorization (a student-level analysis). But it is arguably more interesting to show that a complaint filed on behalf of student Bob changes decision-making for *students other than Bob* living in the same district (a district-level analysis). Thus, similar to the literature on deterrence effects of malpractice litigation on *all patients* a focal doctor treats (e.g. Mello and Brennan, 2001), the present analysis investigates whether parent monitoring has deterrence effects on *all students* amidst cost pressure.

I run each of the models on two samples. First is the full sample of 598 districts. Second is a sample pruned using coarsened exact matching (CEM) (Iacus et al., 2012). In particular, CEM prunes/re-weights districts to achieve better balance on covariates between treatment districts (districts with at least one pre-reform intervention) and control districts (districts with no pre-reform interventions). It does so by first coarsening each of the covariates into bins (e.g., districts with the same district factor group SES rating; districts that place between 5 and 10 percent of special education students), then performing exact matching of treatment and control districts within strata defined by those bins. While this matching still does not address *unobserved* confounders between these two groups, by restricting the sample to treatment and control districts with substantively similar values on observed covariates, we reduce the likelihood that our estimate of β_1 is sensitive to modeling choices (e.g., whether district socioeconomic status has a linear or quadratic effect on drops in placement). Figure 7.63 highlights the cutpoints used to coarsen the covariate values and the resulting pruning of the sample from 448 treatment districts and 150 control districts, to 205 treatment and 77 control districts occupying common strata. Figure 7.64 shows the reduction in imbalance between treatment and control groups on the means of the variables, while Figure 7.65 visually illustrates the reduction in imbalance on the distributions of those variables. We see in particular that before matching, treatment and control districts

[60] Or occasionally, against state educational agencies.

had imbalance on the percentage of students categorized as having a disability in the pre-treatment year–unsurprisingly, districts with a very low percentage of categorized students (e.g., some charter-only school districts that placed gave close to 0 percent of students tags) were less likely to have a case; likewise, districts with a very low district factor group rating (low SES) were slightly less likely to have a case.

Table 7.23 highlights the results of the model in equation 1, showing that the presence of some pre-reform monitoring has a positive and significant effect on a district categorizing a similar percentage of students as having a disability as prior to the cost pressure. Perhaps easier to interpret, Table 7.24 highlights the results of the model in equation 2, which shows that districts with some parent monitoring are significantly *less* likely to decide that fewer students have a disability than districts with no formal parent monitoring.

Does measuring parent monitoring more directly add anything beyond using socioeconomic status as a proxy?

Quantitative research on parent-school district interactions tends to use socioeconomic status as a useful proxy for parents' ability to secure resources that benefit their child (e.g., Saatcioglu and Skrtic, 2019). The regression results show that while wealthier districts have *fewer changes* in categorization *before* we add in information on parent monitoring, district socioeconomic status is only weakly significant (non-CEM sample) or not significant (CEM sample) when adding in the more direct measure of parent monitoring of districts (Appendix Tables 7.23 and 7.24). The analysis shows that using socioeconomic status as a proxy for the presence of discretion-reducing monitoring is useful, but that the more direct measure of parent monitoring of district decisions is a more consistently significant predictor of aggregate rationing outcomes.

Robustness checks

The results are robust to estimating these models on either the full sample or the CEM-pruned sample with better covariate balance. For the latter sample, since some treatment districts were removed if they occupied a strata without any control units, the meaning of

β_1 (any pre-reform parent intervention) shifts from the sample average treatment effect on the treated (SATT) to the feasible treatment effect on the treated; that is, the effect of any pre-reform monitoring on treatment districts with similar covariate values as control districts.

Figure 3.11 helps us assess the substantive significance of these results. Either setting other covariates to their mean values or keeping them at their observed values, we see that districts with some monitoring in the pre-reform period have a meaningfully lower probability of changing categorization following cost pressure. Put differently, the presence of parent monitoring of district decisions helps buffer the students in the district from rationing.

Figure 3.11: **Predicted probability that cost pressure causes a drop in categorization: comparing districts with and without parent monitoring**. The coefficients used in the model were from the estimates on the CEM sample; likewise, covariate means were calculated on this matched subsample. Means and 95% confidence intervals were generated using the method described in Tomz et al. (2003) of sampling from a multivariate normal distribution centered at $\hat{\beta}$ with $m = 10000$ draws, with the mean calculated as the mean across the draws, and 95% confidence intervals constructed from the 2.5 and 97.5% quantiles.

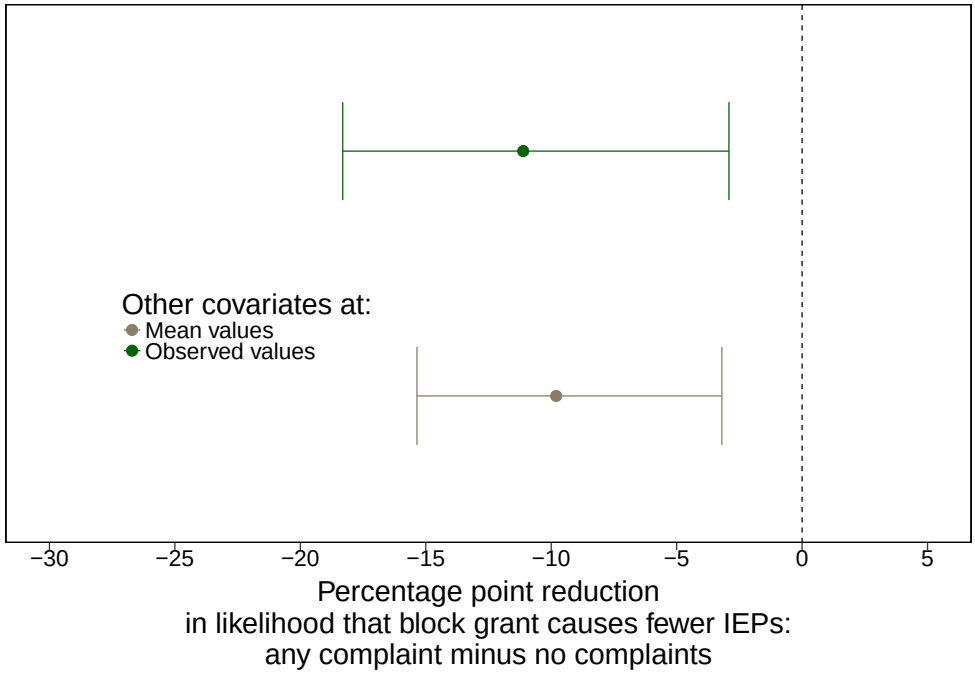
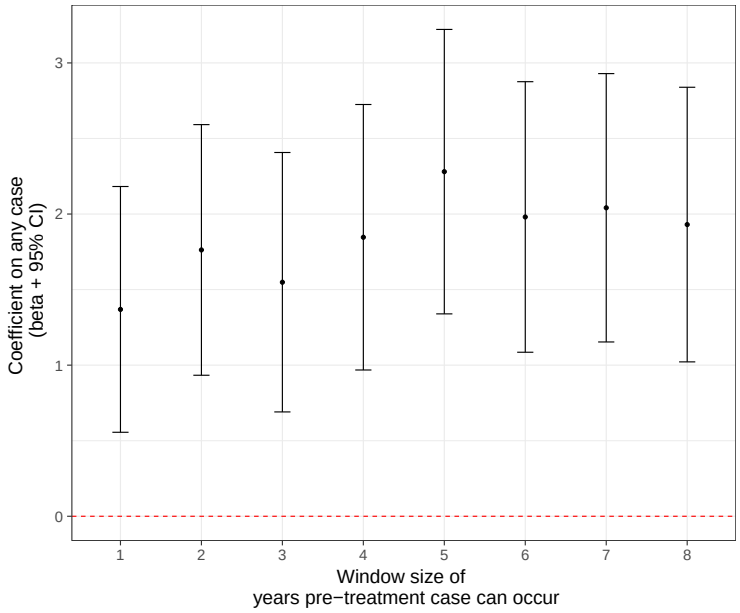


Figure 3.12, showing the coefficient on any intervention in different windows preceding

the reform, shows that across windows, the presence of *any parent intervention* led to less rationing (higher levels of categorization, controlling for their pre-reform rates) following the reform. Appendix B describes the results of other robustness checks. First, parent monitoring significantly reduces rationing when we change the window size from "any monitoring" in the pre-reform period to monitoring with varying degrees of temporal proximity to the reform for the logistic regression model (Appendix Figure 7.66). Second, using the approach to sensitivity analysis from Blackwell (2014), we see that an unobserved confounder would need to explain over 25 percent of the variation in parent monitoring in order to change the significance and main direction of the causal effect of these interventions on drops in categorization. This would be a very powerful confounder–by comparison, a district's poverty level only explains about 1.4 percent of the variation in whether a district had any parent intervention (Appendix Figure 7.67).

Figure 3.12: **Linear lagged DV results are robust to changing the size of a window for when monitoring can occur**. The graph presents the coefficient and 95% confidence interval around the "any intervention" variable, which has a significant positive effect on the percentage of students categorized as having a disability, controlling for a district's pre-reform levels. The results vary the window size from one (parent intervention had to occur in the year immediately preceding reform for a district to be coded as having any case) to a window size of eight (parent intervention could occur anytime between the 2000-2001 school year and the school year immediately preceding reform). The graph shows that the results are robust to any window size, and the table shows the significance of the coefficient on any case across these window sizes.



Window size for pre-tx case	β on any case	p-value
School year immediately before reform $(t-1)$	1.3690	0.0011
$t-2$	1.3690	0.0011
$t-3$	1.7624	0.0000
$t-4$	1.5488	0.0005
$t-5$	1.8464	< 0.0001
$t-6$	2.2804	< 0.0001
$t-7$	1.9806	< 0.0001
Any time between start of window and school year immediately before reform $(t-8)$	2.0414	< 0.0001
	1.9303	< 0.0001

3.4 Conclusion

Chapter Two showed that one way districts deal with the tension between increased budget pressure and legal prohibitions on changing which categories they prioritize is to engage in hidden rationing, or using discretion to decide that fewer students fall into a category. The present Chapter investigates whether different districts may have different amounts of discretion that depend on how closely parents monitor the decisions of district professionals. The Chapter complements recent qualitative work that shows how middle class parents interact with schools in ways that undermine teacher and administrator authority (Calarco, 2018, p.153-158) by showing how these interactions may moderate district responses to tightened budgets.

In addition, the findings highlight a potential perverse cycle of monitoring. Haskins and Jacobsen (2017) show how fathers with criminal justice contact feel more monitored *by* districts and interact less with school professionals. While Haskins and Jacobsen (2017) show how parents who face monitoring *by* districts engage in less monitoring *of* district decisions, the present study shows one potential consequence of these lower levels of parent scrutiny of district decision-making: districts having more discretion to ration resources in response to budget changes.

3.4.1 Broader contributions and future research

Unequal monitoring of organizations causing an unequal amount of discretion

The focuses on a particular black-box organization–schools–and a specific type of monitoring of school decisions: parent monitoring of teachers' and administrators' decisions regarding their child. Yet the case has three features that generalize. First, black-box organizations are given resources to allocate to vulnerable individuals. Second, these organizations have discretion when deciding how to allocate the resource. Third, inequalities in how closely third parties monitor the decisions can cause inequalities in the resources that individuals receive.

Organizations with this structure contain individuals who face difficulty self-advocating for resources. Instead, the individuals often benefit from third parties—parents in this case—to serve as their advocates. Future research can apply the framework of uneven monitoring causing unequal outcomes to other cases that share this structure. Here, I briefly highlight two examples: (1) correctional officers' discretion over important decisions that affect vulnerable inmates in jails and prisons and (2) administrators' discretion over important decisions that affect vulnerable residents of nursing homes.

For the first, Wildeman et al. (2018) highlight large variations in the conditions of confinement that individuals in state and federal prisons face. Prisoners are given rights to file complaints about the conditions of confinement (Calavita and Jenness, 2015). If a complaint is successful, the institution might face a consent decree that limits the number of inmates they can house or that challenges specific conditions like spoiled food or inappropriate medical care (e.g., Burkhardt and Jones, 2016). If there are inequalities in which prisoners file grievances that result in third-party monitoring, monitoring that reduces correctional officers' discretion over important decisions, this uneven distribution of discretion can mean individuals most vulnerable to abusive tactics are least likely to receive help (Jenness and Calavita, 2017).

For the second, just as inmates in black-box correctional facilities are vulnerable to abuse without third-party monitoring, long-term residents of assisted living facilities (nursing homes) are vulnerable without discretion-reducing monitoring (Aka et al., 2011). Facilities might save costs while endangering residents through neglect or through measures like inappropriate use of physical restraint or antipsychotic therapies (Williams, 2000; Alper, 2016; Foebel et al., 2016). In turn, since adult children of residents are the primary agents who monitor abuse and negligence (Stevenson and Studdert, 2003; Studdert et al., 2011), the same inequalities that emerge in *parents'* monitoring of their child's schooling might occur in *adult children's* monitoring of their parents' residential care, with similar impacts on discretion and inequality. Thus, the framework can be applied to other cases where inequality in monitoring of black-box institutions causes unequal outcomes.

Methodological: tools to more efficiently study individuals' monitoring of organizations

Sociological work on the impact of "big data" on inequality tends to focus on a specific form of monitoring: organizations like police departments, nursing homes, or courts engage in unequal monitoring *of* vulnerable individuals (Brayne, 2017; Berridge et al., 2019).

The present paper highlights a flipped use of large-scale data: data can also be used to study inequalities in vulnerable individuals' monitoring *of* powerful organizations. For example, Dokshin (2016) merges speaker names from local meetings concerning fracking with address records to show that those commenting on fracking were often large landowners rather than more vulnerable residents. A *USA Today* database aggregates data on police offices who were decertified following citizen complaints about misconduct and shows how police officer behavior can be monitored.[61] As Chapter Four discusses in greater detail, re-purposing these large-scale data on individuals' monitoring of organizations requires tools to efficiently extract information from unstructured text data–for instance, since no unique district identifier is attached to a filing record, using string distance measures to recognize, for instance, that these four districts are the same: *South Orange-Maplewood*; *South Orange Mapl*; *South Oarng-Maplewood*; *South Orange-Mpalewood*. Easy-to-use tools geared towards the types of complaints that social scientists study–citizens about police; consumers about corporate actions–can help facilitate further research.

3.4.2 Limitations

The present analysis has limitations. First is that analyzing the impact of cost pressure at the district level could fall prey to the ecological fallacy: districts with *more monitoring* were *less likely* to ration the disability category, but perhaps students in those districts with *more monitoring* by their individual parents were *more likely to lose* access to the category. Two considerations help ameliorate this concern. First, as discussed earlier, parent monitoring is directed at an entire district's administration–as a result, while it is filed on behalf of

[61] Source in Kelly and Nichols (2019).

a particular student, it is more interesting to examine the presence of district-level spillover effects. Second, New Jersey has one of the most fragmented education systems–that is, unlike states that have a limited number of large districts, New Jersey has many small districts with low enrollment counts and small district boundaries (Bischoff, 2008). Bischoff (2008) shows how this high degree of fragmentation creates highly-segregated school districts. This degree of segregation makes the district-level analysis less susceptible to ecological fallacy issues. Appendix Figure 7.68 highlights the full distribution of two variables for which we would like to have individual-level rather than district-level data, the measure of student poverty and the percentage African-American students, and that shows that most districts are: 1) low on each of these measures; and 2) there are not a large number of districts that are close to 50 percent. However, caution should still be exercised and we should interpret these variables as measures of district-level SES and race predicting district-level outcomes, rather than as evidence of what happens to Black and lower income students *within* a particular district.

Indeed, two recent studies show that a student's likelihood of being categorized is related not only to his or her own attributes but also the racial composition of the school/district. Fish (2019), focusing on Wisconsin, finds that as a school's proportion of white students *decreases*, white students in that school are *more likely* to receive a higher-status disability label; Elder et al. (2019), studying Florida, find that Black students are *under-represented* in the disability category relative to their measured need as a school's proportion of minority students increases. Each study focuses on states that used a static financing formula during the entire period under study, preventing them from analyzing how *changes* in the incentives affect changes in classification. Yet while not directly comparable, the present study offers a potential mechanism behind that research's findings; for instance, white parents in majority-minority districts might use their surveillance of district decisions to press for specific classifications (Fish, 2019; Saatcioglu and Skrtic, 2019); the under-identified Black students in Elder et al. (2019) may have achieved higher identification rates with more vigilant parent monitoring of district decisions. Future research should further explore these connections.

Second, I have often referred to parents' filing of a complaint as "parent monitoring" of districts. But qualitative work highlights that parents take many steps to monitor district decisions that may leave fewer traces in data (Lareau, 2000, 2011; Calarco, 2018). For instance, a parent might call a school principal to dispute the district's decision about a child's disability before they progress to filing an official complaint.[62] The complaint is recorded; the call may not be. Future work could take advantage of data like visitor logs in schools or parent's emails and text messages to teachers to measure large-scale inequalities in less formal forms of monitoring.

3.4.3 Concluding

Together, Chapter Two and this Chapter present a framework for linking two levels of analysis. First, pressure often has heterogeneous effects on organizations. Second, one mechanism behind those heterogeneous effects is the uneven exercise of discretion. Some professionals have large amounts of discretion to change behavior in the wake of pressure like tighter budgets. Others have little discretion. Concluding, I highlighted the value of the framework for studying how organizations that face different degrees of monitoring have different degrees of discretion over decisions that impact vulnerable individuals. This can be applied to a variety of new cases that can help extend the theory and highlight its scope conditions: discretion of immigration officials in categorizing individuals as refugees; discretion among university administrators facing different diversity mandates; discretion of corrections officers and nursing home administrators over decisions affecting residents.

[62] In this particular context, the emphasis on both parents and school districts putting things "in writing" helps mitigate some of this concern. School districts use extensive written documentation to be able to defend their decisions against parent complaints. Likewise, advocacy organizations advise parents to utilize formal routes: for instance, the Advocates for Children of New Jersey, in its handbook for parents of children with disabilities, advises parents that: "Every request a parent makes of the school district must be in writing to ensure their child's rights are protected."(KidLawResourceCenter, 2017, p. 6).

Chapter Four: Measuring Parent Monitoring of Disability-Related Decisions

4.1 Introduction

> *On August 14, 2015, Former Attorney gave DCPS [DC Public Schools] written notice that the parents were rejecting the "partially completed" August 10, 2015 IEP and would not send Student to school at DCPS and would instead enroll at Nonpublic School 2 and would expect DCPS to reimburse them for their enrollment costs. Former Attorney gave the following alleged reasons for the parents' decision....On or about August 16, 2015, DCPS mailed the parents Prior Written Notice (PWN) that Student's multidisciplinary team (MDT) determined that Student required special education in both the resource and inclusive settings and that Student's IEP could be implemented at in-boundary school.* (DC Hearing Officer Determination, April 2017)

> *Student and Student A got into a physical altercation near the school gate. The students punched at each other. ... The SRO [School Resource Officer, a police officer] physically restrained Student. Other police officers were summoned and Student was arrested....Student was suspended from PCS-3 on October 24, 2014. (Exhibit R-6). Following an investigation of the October 20, 2014 incident, Dean determined that Student had committed two Category III school code of conduct violations, fighting and violent behavior and threatening behavior; and Category II violations, disrespect to staff and insubordination. (Exhibit P-7). PCS-3 convened an MDR meeting on October 29, 2014. The purpose of the meeting was to determine whether Student's October 20, 2014 code of conduct violation was due to her disability or based on implementation of her IEP....The October 29, 2014 MDR team determined that Student's behavior on October 20, 2014 was not caused by and did not have a direct relationship to her*

> *disability, and that the conduct was not a direct result of DCPS' failure to implement Student's IEP (Exhibit R-2). The MDR team felt that what happened on October 20, 2014 was not symptomatic of Student's regular practices or her disability (Testimony of Dean). The Parents disagreed with the MDR determination (Testimony of Mother).* (DC Hearing Officer Determination, January 2015)

The previous Chapter studied how parent monitoring makes it less likely that schools will ration resources. In turn, inequalities in this monitoring across schools and districts can mean inequalities in which students continue to access a prioritized category when budgets tighten.

This Chapter expands the study of parent monitoring of disability-related decisions in three ways. First, it investigates the feasibility of monitoring parent monitoring: can we use data like that obtained from New Jersey to see where students are less protected by parent advocacy? Second, using data obtained for three jurisdictions—Texas; the District of Columbia and Ohio—the Chapter investigates whether there are systematic inequalities in disability-related monitoring occurs beyond New Jersey.

Finally, as the excerpts from the two DC hearings highlight, the same "yes monitoring" variable in a dataset can conceal qualitative differences in *which decisions* spur parents to use monitoring. In the first hearing, the parents used monitoring in ways similar to Drew's parents: to assert a right to resources. Just as Drew's parents felt that the in-school services were insufficient, the parents in the hearing argued that reimbursement for "Nonpublic School 2" was needed to correct for insufficient services at the student's in-boundary school. In the second hearing, the parents used monitoring in a very different way. The parents argued that the student, suspended after a fight that drew a police response, should have been protected from disciplinary action due to her disability. While each form of monitoring uses a legal right granted to the student to reduce school professionals' discretion, the two arguably have very different consequences for inequality in cash-strapped districts. If some parents are using monitoring to help their child get extra help, while other parents are using monitoring to protect their child from school discipline, inequalities in the *substance* of monitoring can mean that the same action—a due process complaint against a district—has very different implications for between-student inequality.

The remainder of the Chapter proceeds as follows. First, I discuss the historical origins of the rights granted to parents of students with disabilities to monitor district decisions. I show how this historical path laid the groundwork for present-day inequalities. Then, I highlight challenges in measuring these inequalities. Next, I discuss the three case studies and show how they fit in to the broader landscape of disability-related monitoring. Finally, I present results that show two forms of inequality in monitoring: inequality in *where* monitoring occurs and inequality in *which* decisions are monitored.

4.1.1 Pathways to present-day inequalities

Neal and Kirp (1985) and Pasachoff (2011) each give detailed accounts of how the IDEA (and its predecessor, the EAHCA) gave parents important roles in monitoring schools' and districts' compliance with the statutes' rules about what students are owed. Here, I briefly show how two features of this historical path laid the groundwork for present-day inequalities.

First, legislators and courts were each reluctant to establish a *substantive* standard for what districts owe students with disabilities—for instance, a minimal package of benefits that all students with autism would receive; a floor on the number of hours of speech therapy a student with a speech or language impairment would get (Neal and Kirp, 1985). Yet the lack of a "common floor" of benefits means that whether parents monitor district decisions, and whether that monitoring focuses on resource decisions like benefits or minutes of speech therapy, could produce wide variation in what students get.

Second, the administrative due process hearing system was meant to make monitoring inexpensive—rather than navigating federal court, parents could air their issues in a forum that was meant to both be less intimidating and less time and resource-intensive. Yet the structure of the hearings—the burden of proof rests on the party who alleges the harm has occurred, which usually means the parent—means that although the *actual filing* of a hearing request is free, marshalling the evidence required to prove that the child deserves something different than what the district has provided can be expensive. For instance, in order for Drew's parents to argue that Firefly Autism House was a better fit for Drew than

the neighborhood public school, they first needed to pay for the private school themselves. Then, they needed to pay expert witnesses to testify that the school's approach was necessary for Drew to receive an appropriate education. Only after paying for the school and paying for witnesses to testify to its benefits could they seek tuition reimbursement.

As a supervisory legal aid attorney in a large urban school district points out, low-income parents can neither afford the upfront costs of paying for the services themselves nor go into debt during years of litigation. She highlights that while many firms that wealthier parents pay for out of pocket specialize in tuition reimbursent cases, that is not a focus of legal aid:

> When there's a private attorney involved, it's almost always for private school tuition. And by definition they're usually dealing with parents who can pay upfront, and get reimbursed. And for most of our clients, it's not a really good option for them to get indebted to that extent, even if they need it. First of all, there's always a deposit they have to pay, and it's also if we don't think we can win ... you don't want to hook them into years of potential litigation and uncertainty for the kid, unless you have a really strong case (Author Interview, Supervisory Attorney at City Legal Aid, June 17th, 2019).

As a result, while the *filing* of a due process hearing is free, requirements that parents first prove that their child would benefit from something else in order to get the district to pay for it mean that it becomes prohibitively expensive for certain parents to use monitoring to ask for more.

In turn, this means that inequality in *whether* parents monitor might be compounded by inequality in what rightsparents use monitoring to enforce. We can distinguish between two sets of rights.[63] First are positive rights *to* some good: in the case of the disability

[63]Some philosophers challenge the distinction between "positive" and "negative" rights on various grounds. Two challenges stand out. First is that while some argue that negative rights are easier for states and other entities to fulfill than positive rights, positive rights can be equally costly to fulfill–for instance, the right to avoid physical harm can require an extensive system of public safety. This seems context-dependent. In the school district case, rights involving resource allocations are generally more costly to fulfill than rights to avoid outcomes like inappropriate school discipline. This cost disparity might be related to the issues discussed in Chapter One of the latter type of rights being easier for organizations to ignore or symbolically comply with than the former type of rights. Second, while some in favor of the distinction argue that individuals' negative rights should generally receive higher moral priority than positive rights, others argue that whatever moral principle grounds the fulfillment of negative rights–e.g., respect for autonomy–is also likely to ground the provision of positive rights. Since the argument in the dissertation focuses less on whether positive rights to resources *ought* to be fulfilled and more on what consequences districts fulfilling these rights has, this second objection does not seem to undermine using the distinction to classify cases.

category, these are resources meant to benefit a child. The resources may include a claim to the category itself (i.e., a child was denied a contract for services and the parents argue that this denial was inappropriate). Once a child is given that contract, the contention then might focus on changing the benefits the contract promises: services not currently provided to the child (e.g., a one-on-one aide), a claim to an increase in the intensity of services a child is already receiving (e.g., a switch from 20 minutes of speech therapy a week to 60 minutes), or a claim to reimbursement for a special needs private school placement.

Second are negative rights *to avoid* discipline or discrimination. In the case of the disability category, these largely focus on the right to avoid discrimination on account of one's disability status. For instance, the case might protest a disciplinary decision like suspension or expulsion on the ground that the behavior was caused by the child's disability.

The quote from the legal aid attorney suggests that we may see socioeconomic variation in whether parents use monitoring to enforce positive rights to resources or negative rights to avoid discipline. Going back to its historical origins, the due process rights given to parents of children with disabilities were modeled off of civil rights legislation that, rather than granting individuals rights *to* specific goods on the basis of a categorical status like race or gender, were focused on helping individuals avoid discrimination on the bases of these categories (a negative right). The Chapter investigates whether there is drift from this historical purpose, and socioeconomic variation in that drift.

4.1.2 Measuring inequalities in disability-related monitoring

What do we know about how representative the patterns we saw in Chapter Three are? Existing data on monitoring comes from two sources. First, as part of reporting requirements under the IDEA, states must submit yearly counts of the number of requests for due process hearings that parents file in a particular year. These filings are at the stage of the blue square of Figure 4.13. Yet as Chapter Three shows, there can be vast *within-state* inequalities in where monitoring occurs and these inequalities mean that two students residing in the same state—one that either has a high or low overall rate of monitoring—can have very different odds of protection via monitoring. As a result, while I use these data

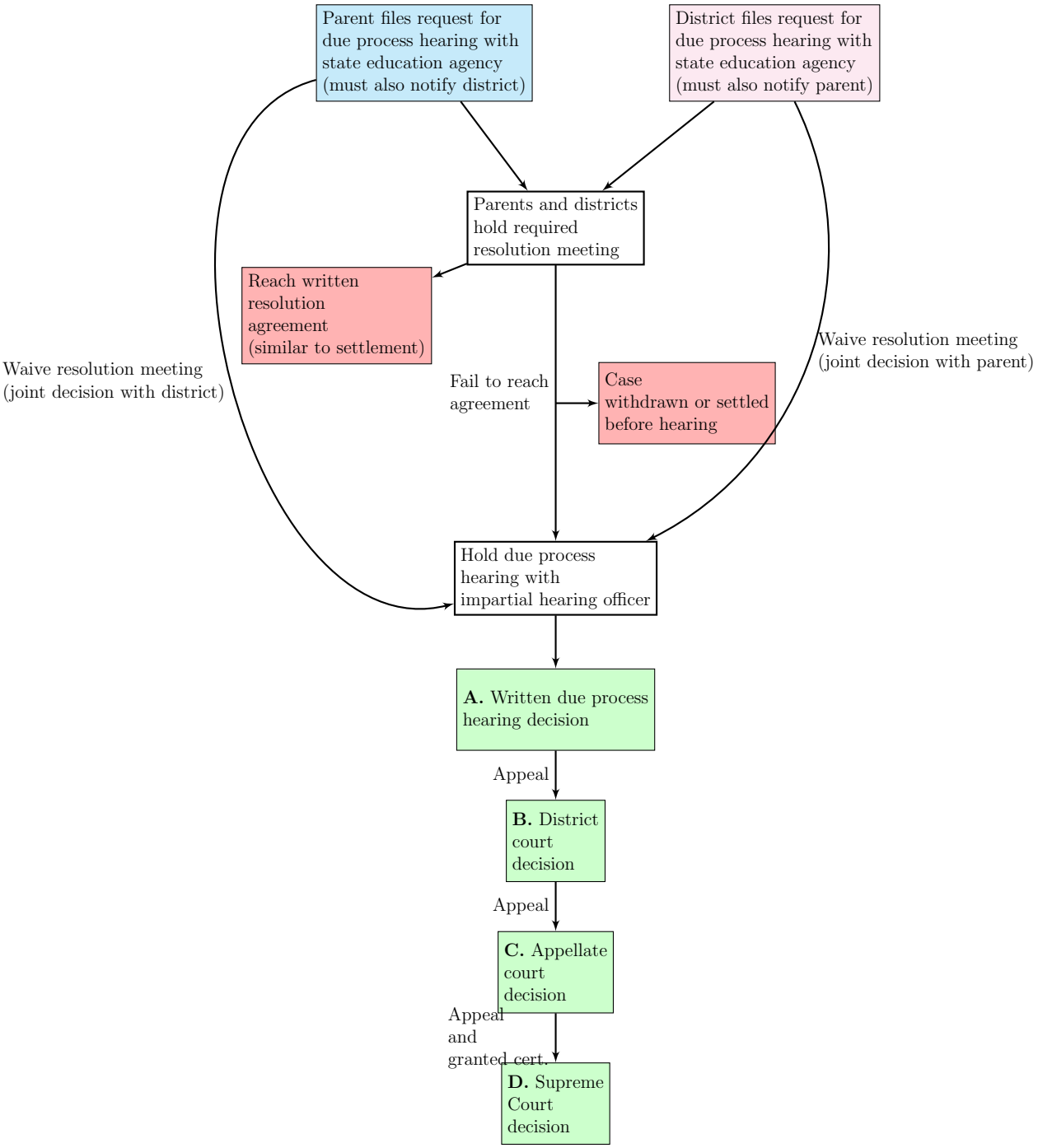
in Chapter Five to study the impact of federal resource boosts to states on disputes over resources, they are less useful for studying inequality.

Second are richer data from much further along in the case trajectories: data from complaints that are appealed out of the administrative hearing system into U.S. District and Courts of Appeals. Yet existing analyses, summarized in Table 4.4, highlight two limitations. First, cases appealed to federal courts represent only a small fraction of hearings heard at the state administrative hearing level (green box). As a result, we have no insight into the substance of decisions within state hearing systems. Second, the analyses rely upon hand coding of cases, which is challenging to scale and often requires researchers to sample from a broader corpus of cases. The first part of the Chapter, which examines district-level variation in *requests* for a hearing (blue box in Figure 4.13), is thus the first to (1) examine filings at the school or district level and (2) investigate patterns by student socioeconomic composition. The second part, which examines district-level variation in the *content* of requests that go to a hearing (Box A in 4.13), is the first to (1) inductively examine themes in cases rather than code pre-existing categories and (2) correlate these themes with measures of disadvantage both within the case itself and in the district it was filed against.

Table 4.4: **Past empirical analyses of disability-related monitoring**

Article	**Data**	**Unit**	**Dem. info. re: district**	**Other information extracted**	**Main conclusions**
(Zirkel and Gischlar, 2008)	Survey of state special education directors on number of hearings 1991-2005 adjudicated (Box A in diagram)	State	None		States like NY and NJ account for majority of due process hearings
(Zirkel, 2011)	206 decisions from the federal court system (1992-2008) (Box B or C in diagram)	None	None	Whether autism was a listed disability	Autism represents a disproportionate amount of court cases relative to its share of special education students
(Zirkel and Scala, 2010)	Survey of state special education directors on number of hearings 2008-2009 adjudicated (Box A in diagram)	State	None	Structure of hearing system; professional background of impartial hearing officers (IHOs)	DC and a small number of states account for majority of due process hearings
(Mueller and Carranza, 2011)	575 due process hearings from 41 U.S. states during 2005-2006 school year (Box A in diagram)	State	None	Hand coding of 11 dispute issues (e.g., placement versus IEP versus behavior), student's gender, and student's disability	Autism and learning disabilities are the most highly-represented disabilities; placement and IEP issues were the most common issues
(Zirkel and Skidmore, 2014)	Sampled 300 decisions from a database of 4300 hearings (Box A in diagram); note that database is not comprehensive as there were over 35,000 hearings during the period	State	None	Hand coding of topic of hearing and outcomes	More recently, hearing decisions have tended to favor districts over parents

Figure 4.13: The Trajectory of Disputes. Blue refers to actions parents take; pink refers to actions Districts take; green refers to actions that generate a qualitative record about the nature of contention, and red refers to actions that generate only metadata without discussing the nature of contention. White refers to general steps in the process.



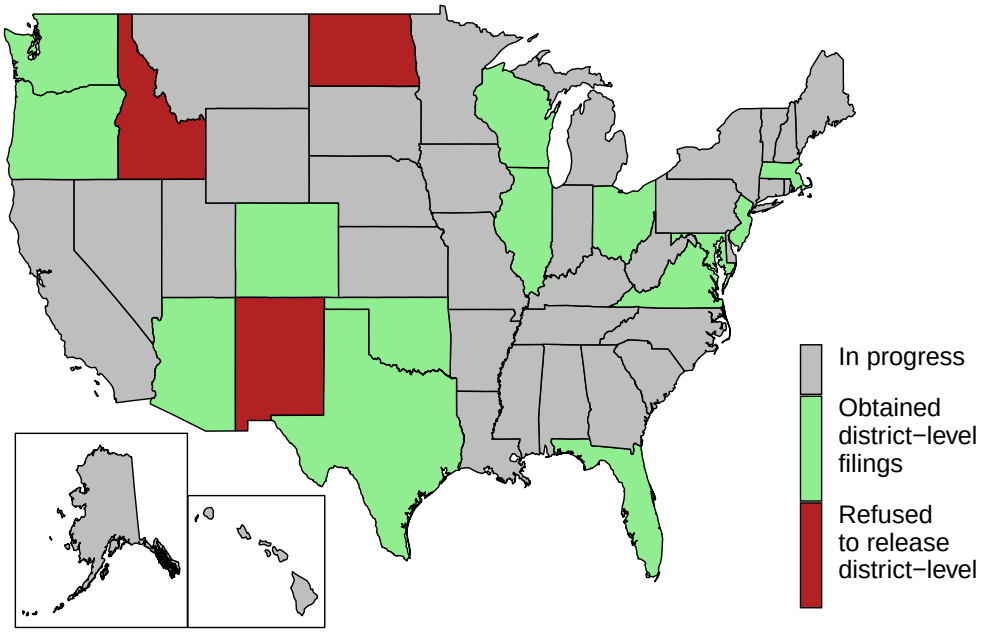
4.1.3 What contributes to the data gap?

What has impeded efforts to study parent monitoring of districts' disability decisions at the district rather than state level? Two issues stand out. First, while states are legally required to publish decisions from requests that go to a hearing (Box A), there is no legal requirement that they publish information about requests that do not reach a hearing. Therefore the many stages that precede a hearing remain a "black box," with little information at the district level on the many filings that are withdrawn or settled. The present Chapter explores the feasibility of obtaining this information via state-level open records act requests (Section 4.2). Second, hearings are generally stored as a PDF of a decision. These PDFs are more amenable to hand-coding than to quantitative analysis—in particular, and as Section 4.4 discusses in greater detail, they mention the district by name, which then requires merging to unique identifiers maintained by data systems like the Common Core of Data. While neither barrier is insurmountable, Table 4.4 shows how these barriers have led to there being no studies of which I am aware that examine demographic patterns in monitoring.

4.2 General method: open records requests to states for district-level filing information

Between May and September 2019, two paralegals assisted in filing open records requests to states to ask for (1) metadata on all *filings* of requests for a due process hearing, and (2) for this metadata to be stored in a usable form like a CSV file. Figure 4.14 summarizes the results at the time of this writing (April 2020). States either granted the request (green), explicitly denied the request citing privacy laws (red), or have neither fulfilled nor denied the request (gray). For the latter, two major states with a high prevalence of hearings—New York and California—have not yet fulfilled the request despite repeated follow-ups by the paralegals, and may require open records act litigation to fulfill. The results thus far highlight three challenges with systematic monitoring of parent monitoring. First, some states, perhaps those with more sparsely-populated rural districts, interpret

Figure 4.14: Progress on due process filings



Family Educational Rights and Privacy Act (FERPA) provisions as requiring not only the redaction of parent names in filings but also the redaction of district names. Second, states do not always comply with open records act laws mandating timely provision of records. Third, and as Section 4.4 shows, states provide the information on filings in a variety of formats, including PDFs composed of a series of images of tables with filing records that then require Optical Character Recognition (OCR) to extract information (Table 4.5).

Table 4.5: Years and format of the filings data

State	Years	Format
Arizona	2009-2019	Excel or CSV
Colorado	2000-2016	PDF (no OCR needed)
DC	2012-2019	PDF (OCR needed)
Florida	2015-2019	Excel or CSV
Illinois	2017-2019	Excel or CSV
Maryland	2014-2018	PDF (no OCR needed)
Massachusetts	2009-2019	Excel or CSV
New Jersey	2000-2012	Excel or CSV
Ohio	2014-2019	Excel or CSV
Oklahoma	2017-2019	Word doc
Oregon	2000-2007	PDF (OCR needed)
Texas	2000-2019	PDF (OCR needed)
Virginia	2014-2020	PDF (OCR needed)
Washington	2000-2019	Excel or CSV
Wisconsin	1974-2019	PDF (no OCR needed)

4.3 Case selection

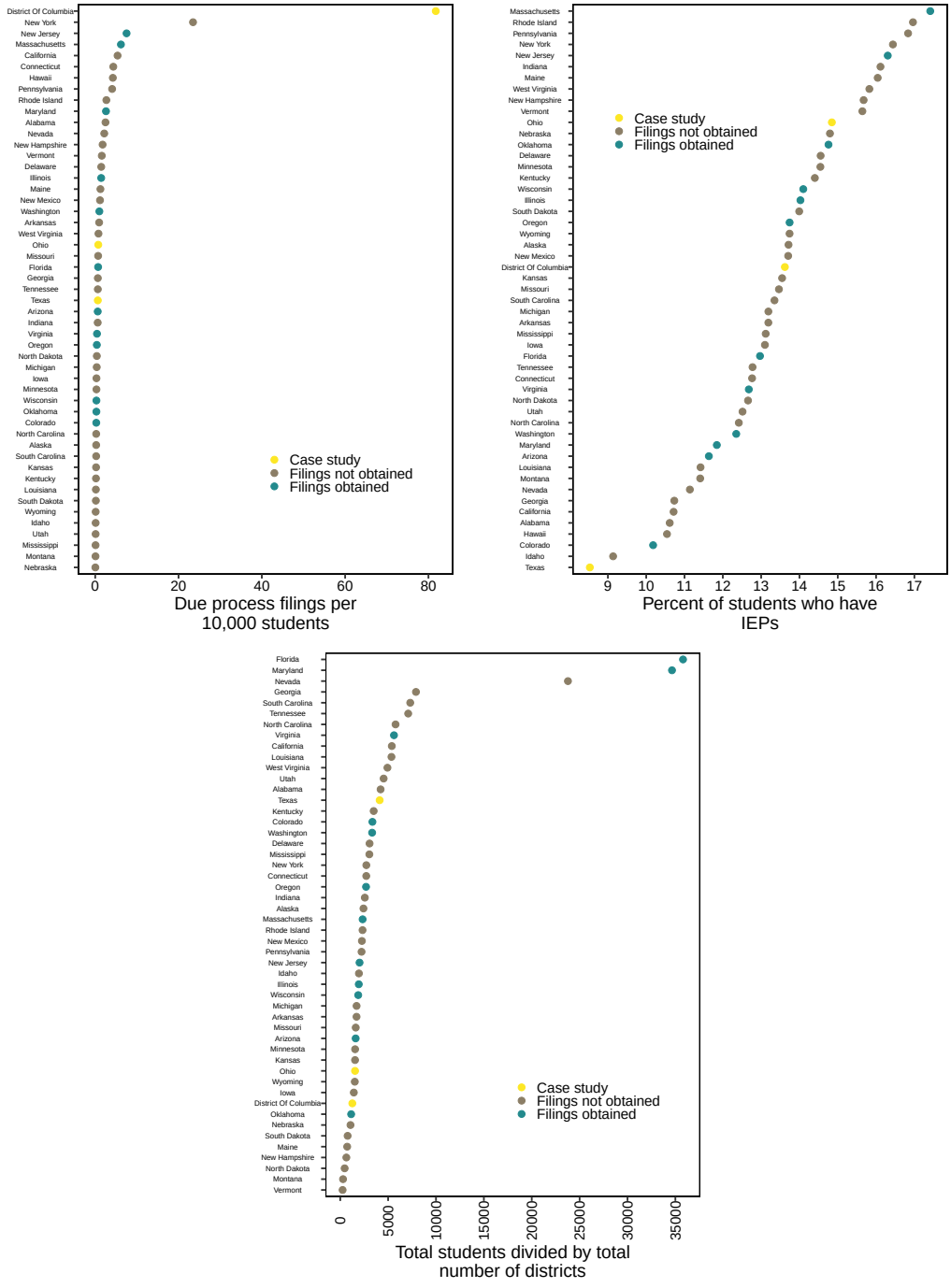
Within the states that gave usable data (Table 4.5), I chose three case studies—DC; Texas; and Ohio—to both (1) maximize variation along a few dimensions, and (2) choose settings where the administrative structure of schools and districts means that school (DC) or district (Texas and Ohio) demographic information is less vulnerable to ecological fallacy issues.

Figure 4.15 compares the three selected states with two other sets of states: those with filings information available (green) and those without (gray). Focusing on the top panels, we see that DC has the highest rate of due process filings per student, but is in the middle range of states/territories in terms of the percentage of students with an IEP. Ohio has a higher rate of IEPs, but is in the middle in terms of its due process filings rate. Texas, consistent with the Texas Education Agency scandal, has the lowest rate of IEPs—categorizing fewer than 9 percent of students as having a disability. The filings rate, however, is similar to Ohio's. As a result, when investigating inequalities in monitoring, the case studies focus on states with a non-zero number of filings, which creates room for some district-level variation, but that are different places in the overall distribution of filing rates.

For ecological fallacy issues, the filings data from DC is at the school rather than district

level. Texas and Ohio each are on the lower end for the number of students divided by the number of districts, and thus make better case studies than states like Maryland and Florida where many students are consolidated into a few large districts.

Figure 4.15: **How do the three case studies compare to other states?** All figures focus on the 2013-2014 school year. The top left panel shows the rate of due process filings per 10,000 students. It shows DC has an extremely high rate relative to other states, while Texas and Ohio are in the middle. The top right panel shows the percent of students in the state who receive an IEP, showing Texas at the very bottom. The bottom panel shows the total number of students divided by the total number of operational districts, with all on the lower end compared to states like Florida and Maryland that provided filings and would otherwise make good case studies.



4.4 Data and Methods: filings

The main data use school (DC) or district (Texas and Ohio) level filing information, which are drawn from databases that record all filings by parents, regardless of whether or not they progress to a hearing. These data help us investigate *whether* this form of monitoring occurred in a district. Since precise date information on the filings was inconsistently recorded (e.g., some databases record the date of filing; others record the date of closure; others both), the present analyses:

1. Focus on all states during *calendar* years 2014-2018, since school years are less reliably extracted than calendar years;

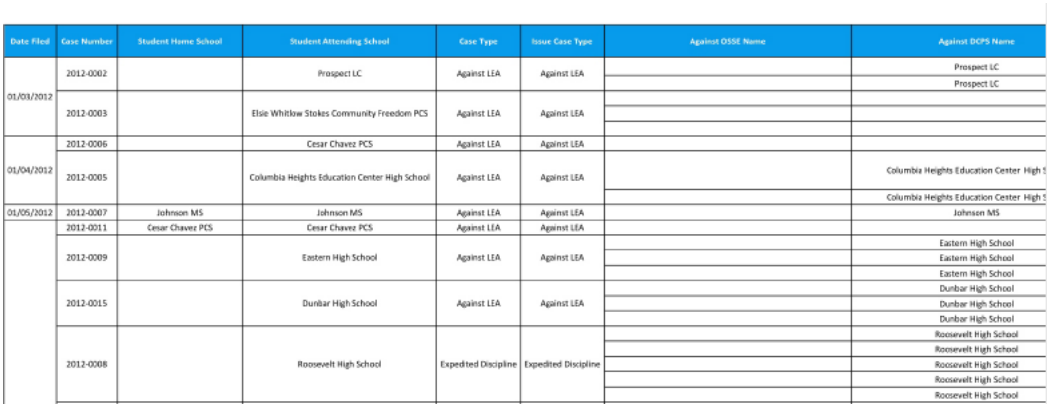
2. Use demographic information from the school for the 2013-2014 School Year, drawn mainly from the Common Core of Data (CCD) but supplemented with Civil Rights Data Collection data in certain cases. This means the analyses examine the relationship between demographic attributes from the baseline year (2013-2014 SY; 2014 calendar year) and the presence of cases from that year until the end of 2018.

The following sections give a broad overview of the process for merging the filings data with district demographics in each state. More details of and code for the implementation can be found at this Github repository: `https://github.com/rebeccajohnson88/rights_towhat_chapter`.

4.4.1 DC filings

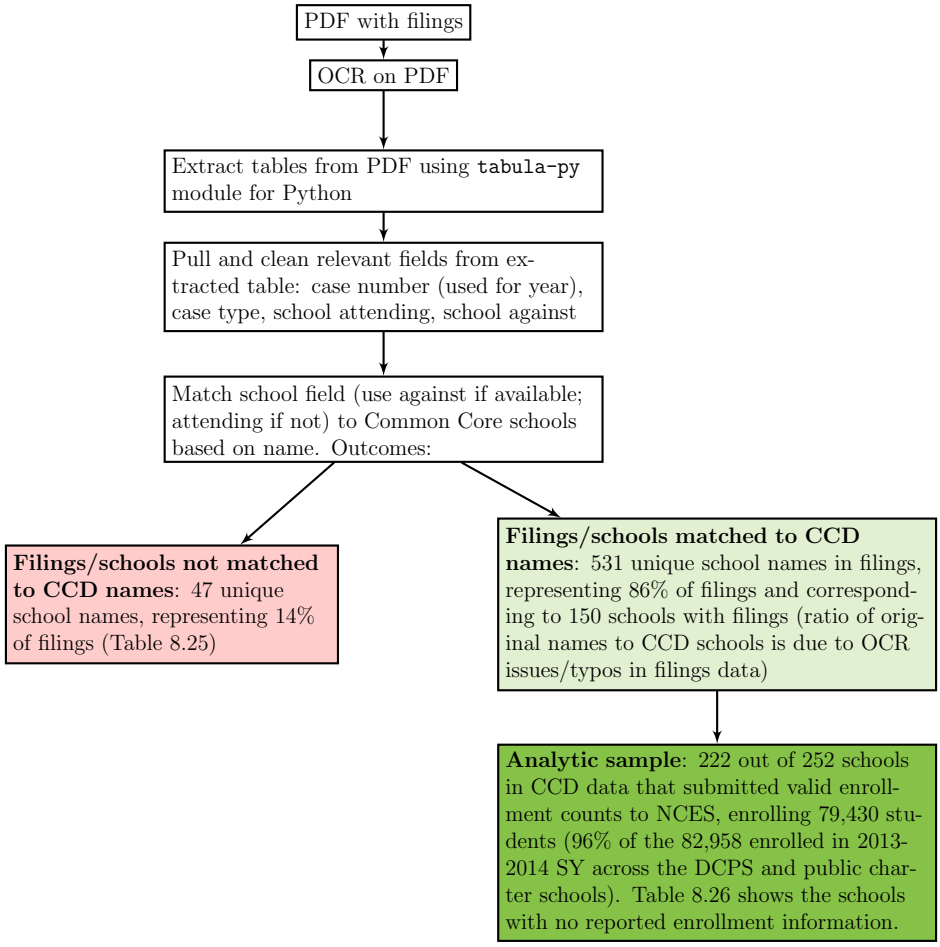
The data were obtained in September 2019 from an Open Records request filed in May 2019 and reproduced in Appendix Figure 8.69. Figure 4.16 shows the original form of the data, which was a 300-page PDF with embedded tables of cases beginning in 2012 and ending in 2019. Figure 4.17 shows the steps to extract the relevant information and merge with NCES demographics.

Figure 4.16: **DC filings:** original form of the data.



Date Filed	Case Number	Student Home School	Student Attending School	Case Type	Issue Case Type	Against OSSE Name	Against DCPS Name
01/03/2012	2012-0002		Prospect LC	Against LEA	Against LEA		Prospect LC
							Prospect LC
	2012-0003		Elsie Whitlow Stokes Community Freedom PCS	Against LEA	Against LEA		
	2012-0006		Cesar Chavez PCS	Against LEA	Against LEA		
01/04/2012	2012-0005		Columbia Heights Education Center High School	Against LEA	Against LEA		Columbia Heights Education Center High S
							Columbia Heights Education Center High S
01/05/2012	2012-0007	Johnson MS	Johnson MS	Against LEA	Against LEA		Johnson MS
	2012-0011	Cesar Chavez PCS	Cesar Chavez PCS	Against LEA	Against LEA		
	2012-0009		Eastern High School	Against LEA	Against LEA		Eastern High School
							Eastern High School
							Eastern High School
	2012-0015		Dunbar High School	Against LEA	Against LEA		Dunbar High School
							Dunbar High School
							Dunbar High School
	2012-0008		Roosevelt High School	Expedited Discipline	Expedited Discipline		Roosevelt High School
							Roosevelt High School
							Roosevelt High School
							Roosevelt High School
							Roosevelt High School

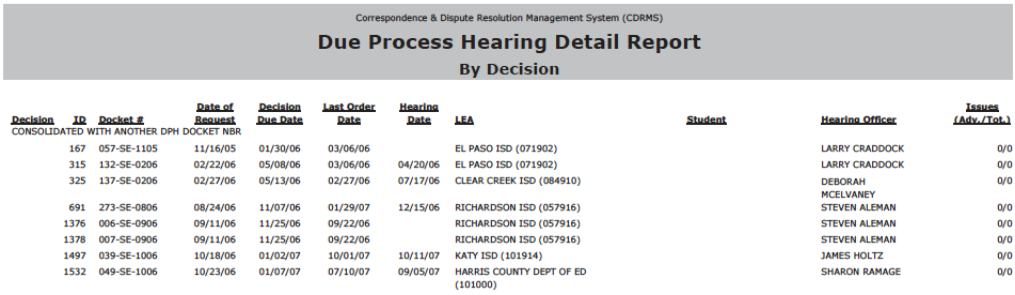
Figure 4.17: **DC filings:** steps in preprocessing and merging



4.4.2 Texas filings

The data were obtained in June 2019 from an Open Records request filed in May 2019 and reproduced in Appendix Figure 8.70. Figure 4.18 shows the original form of the data, which was a 128-page PDF with embedded tables of cases beginning in 2005 and ending in 2019. Figure 4.19 shows the steps to extract the relevant information and merge with NCES demographics.

Figure 4.18: **Texas filings:** original form of the data.



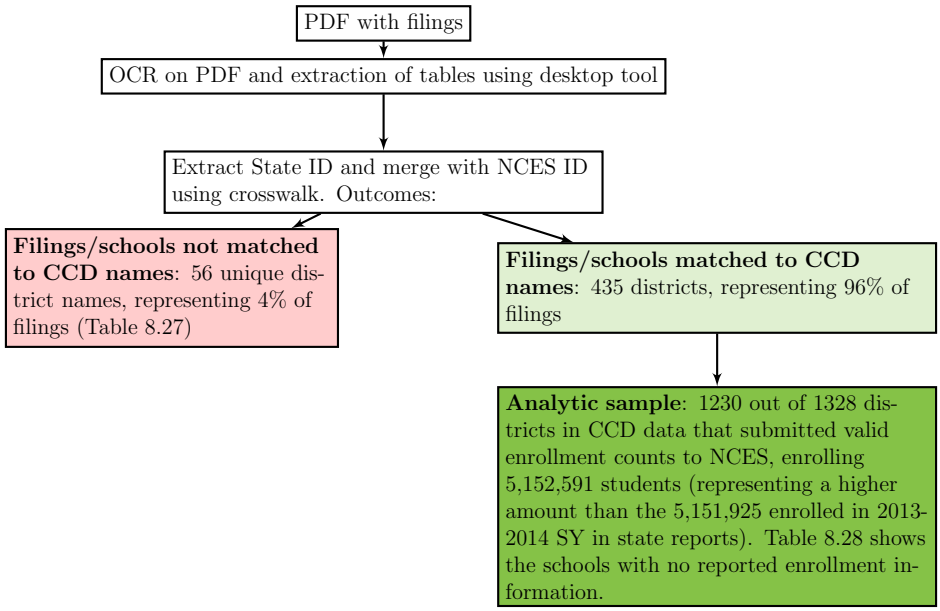
Correspondence & Dispute Resolution Management System (CDRMS)

Due Process Hearing Detail Report

By Decision

Decision	ID	Docket #	Date of Request	Decision Due Date	Last Order Date	Hearing Date	LEA	Student	Hearing Officer	Issues (Adv./Tot.)
CONSOLIDATED WITH ANOTHER DPH DOCKET NBR										
	167	057-SE-1105	11/16/05	01/30/06	03/06/06		EL PASO ISD (071902)		LARRY CRADDOCK	0/0
	315	132-SE-0206	02/22/06	05/08/06	03/06/06	04/20/06	EL PASO ISD (071902)		LARRY CRADDOCK	0/0
	325	137-SE-0206	02/27/06	05/13/06	02/27/06	07/17/06	CLEAR CREEK ISD (084910)		DEBORAH MCELVANEY	0/0
	691	273-SE-0806	08/24/06	11/07/06	01/29/07	12/15/06	RICHARDSON ISD (057916)		STEVEN ALEMAN	0/0
	1376	006-SE-0906	09/11/06	11/25/06	09/22/06		RICHARDSON ISD (057916)		STEVEN ALEMAN	0/0
	1378	007-SE-0906	09/11/06	11/25/06	09/22/06		RICHARDSON ISD (057916)		STEVEN ALEMAN	0/0
	1497	039-SE-1006	10/18/06	01/02/07	10/01/07	10/11/07	KATY ISD (101914)		JAMES HOLTZ	0/0
	1532	049-SE-1006	10/23/06	01/07/07	07/10/07	09/05/07	HARRIS COUNTY DEPT OF ED (101000)		SHARON RAMAGE	0/0

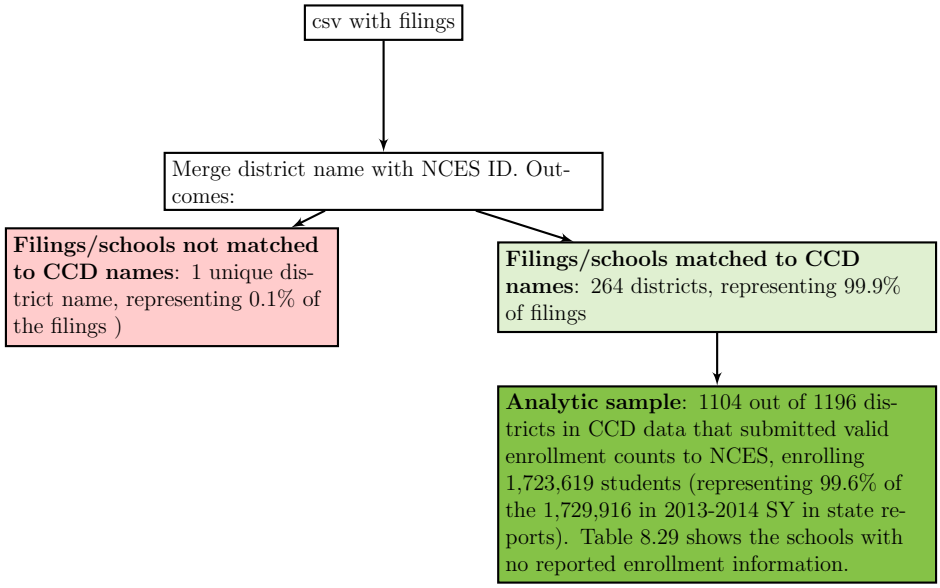
Figure 4.19: **Texas filings:** steps in preprocessing and merging



4.4.3 Ohio filings

The data were obtained in August 2019 from an Open Records request filed in July 2019 and reproduced in part in Appendix Figure ZZ. The original form of the data was a .csv file. Figure 4.20 shows the more limited number of steps needed to merge the data with district demographics.

Figure 4.20: **Ohio filings:** steps in preprocessing and merging



4.4.4 Methods for analyzing filings

For filings, I study the descriptive relationship between school (DC) or district (Texas and Ohio) demographics and (1) whether a school or district has any attempts at disability-related monitoring from a filing and (2) the count of attempts.

For comparability across the three settings, I examine the cumulative presence and count of filings from the 2014-2018 calendar year. To visualize the relationship compared to the socioeconomic status of parents in the school or district, I first plot the location of *any monitoring* at the latitude and longitude of a school district's centroid against tract-level demographics from the 2013 American Community Survey (ACS) 5-year estimates. This comparison is most valid for Texas and Ohio, since in Texas, fewer than 6 percent of students attend an open-enrollment charter school that may be located far from their census

tract and Ohio similarly lacks a robust school choice system. In contrast, in DC, over 70 percent of students attend a non in-boundary public or public charter school, and in some wealthy areas, over 40 percent of students are enrolled in private schools. While this makes area-level demographics a weaker measure of school demographics, we still see patterns of less monitoring in high poverty areas in DC's Southeast.

After examining the presence of monitoring compared to local demographics, I investigate the bivariate relationship between school or district demographics and monitoring. I use a district's share of students eligible for free lunch. As I discuss in greater detail in Section 4.6.1, this is a more valid measure for Texas and Ohio than DC.

4.5 Data and methods: hearings

4.5.1 Data

For hearings, I focus on Texas and DC, the two states that show the most sharply different patterns of socioeconomic variation in filings. In contrast to filings, which are not posted publicly, the federal government requires states to post all hearing decisions publicly. The PDFs from Texas and DC hearings were scraped from their respective state pages, outlined in scripts in the `dc_decisions` and `texas_decisions` directories in this Github repository: `https://github.com/rebeccajohnson88/rights_towhat_chapter`.

4.5.2 Methods for analyzing hearings

After converting the PDFs to text strings, I performed the following preprocessing steps implemented via `nltk` in Python, with details of the PDF conversion and preprocessing found in the code:

1. Remove stopwords contained in nltk's standard stopwords dictionary plus 4 custom words for each state (decision, office, petitioner, [state name])

2. Restrict to words rather than digits, and filter out words shorter than 3 characters

3. Use the porter stemmer

After this preprocessing, I then estimate three sets of structural topic models (Roberts et al., 2014, 2016) to estimate how the prevalence of themes in text (operationalized as word co-occurrence) varies by attributes of the hearing (for further discussions of their role in sociology, see, e.g. DiMaggio et al., 2013; Chakrabarti and Frye, 2017). First, I combine the hearings from DC and Texas and estimate a model that looks at how the prevalence of different themes varies across the two states. Then, I fit a Texas-specific model that examines how themes vary as a function of district poverty share. Finally, since the DC hearings redact the name of the school, and since DC only has two "districts"—DC Public Schools and Public Charter Schools that are redacted from the hearings—I fit a topic model that uses a proxy measure of socioeconomic status that the Texas data show is highly correlated with poverty share.

Appendix Figure 8.72 shows two metrics—exclusivity and semantic coherence—for the two-state pooled model across $k = 5$ to $k = 20$ topics.[64] Models with fewer topics score high on semantic coherence for the few topics they have but low on exclusivity—the few topics are less likely to feature distinct words as the top words. The plot shows that $k = 17$ balances higher exclusivity with high semantic coherence; the models use that k.[65]

4.6 Results

4.6.1 Correlated disadvantage in school districts

One question when examining inequalities in parent monitoring is: how do we operationalize inequality? In school districts, there are three primary forms of disadvantage. First is disadvantage across race/ethnicity. Applied to disability categories, while past research worried about the *overallocation* of IEPs to Black and other minority students, financial incentives might instead cause the *misallocation*, or false negatives when there is budget

[64] These use the default metrics from `STM`

[65] While these metrics were assessed on the model that pools hearings from DC and Texas together, rather than separately for each of the three models, I use $k = 17$ for all three to have similar levels of granularity in the topics.

pressure, but false positives when there are financial incentives to classify. Parents can use monitoring to reduce both types of errors—while parents usually protest not receiving an IEP (false negatives), they can also dispute receiving an IEP. Therefore, if there is less monitoring in districts with higher minority shares, that monitoring can have consequences for inequality.

A second dimension of disadvantage is socioeconomic status. While we lack detailed data on the socioeconomic status of a district's students, one imperfect proxy is the share who are eligible for Free lunch, which enrolls families earning 125% of below of the federal poverty line (Domina et al., 2018).[66] As Domina et al. (2018) and others note, there are several reasons why free lunch eligibility status is an imperfect proxy for school or district-level poverty. First is its coarseness—there is wide variation in levels of poverty among families who qualify for the measure. Second, the measure is based on program participation, which is subject to two types of errors—false positives (families misreporting income and qualifying when they should not) and false negatives (the district failing to enroll some families who meet the income guidelines). Third, and most relevant for DC, is the Community Eligibility Provision (CEP) measure in the Healthy, Hunger-Free Kids Act of 2010. CEP allows districts where over 40 percent of students meet the income eligibility guidelines according to Direct Certification (DC) to offer free meals to all students. Direct Certification involves assessing eligibility based on family participation in other safety net programs—most notably, SNAP and TANF. In DC, many public and public charter schools have opted in to Community Eligibility Provision (CEP) status that provides free meals to all students. This means that there is a cluster of schools recorded as having close to 100 percent of students eligible for free lunch, and a smaller group of schools below that share.

Despite these drawbacks, it is the only measure of student poverty in districts that does not draw on state or district-level administrative data, so the present analysis uses this measure. In turn, the relevance of class for parent advocacy leads us to predict that districts and schools with lower shares of students in poverty will have less active parent

[66]The present Chapter uses Free lunch eligible rather than Free or reduced price lunch eligible to capture a lower threshold.

monitoring.

The final dimension, and one most relevant in Texas, is language status. Just as socioeconomic status can be a barrier in parents' ability to successfully advocate for their child, students who are English Language Learners often have parents who face more barriers to advocacy (Tarasawa and Waggoner, 2015). As a result, districts and schools with higher shares of ELL students might have less active parent monitoring.

While each dimension likely matters, disentangling their relative contribution is made more difficult by their correlation at the district and school level. As Owens et al. (2016) show, districts are highly segregated along both racial and socioeconomic lines, with most of the patterns attributable to residential segregation. Figure 4.21 shows how this plays out in Texas, Figure 4.22 in DC, Figure 4.23 in Ohio. The axes compare the racial shares of different groups and the points are shaded by the poverty level of the students. The figures highlight that race and class cannot be disentangled—namely, there are many districts that have either 100 percent White students or 100 percent Black or Hispanic students; the former tend to have very low levels of poverty; the latter, very high. As a result, the analyses largely present bivariate correlations between poverty share and monitoring of disability decisions; one should interpret the results as also showing that the same districts with high poverty shares also have high Black and Hispanic minority shares.

Figure 4.21: **Texas: racial and socioeconomic segregation across districts (2013-2014 SY)**. The figures use a GAM smoother to show how the share of one race/ethnic group tends to decrease as the share of another increases, with the patterns sharpest for districts with high percentages of Hispanic students and very few White students. The sizes of the dots are scaled to the district's total student population, with the colors shaded by poverty status. Compared to DC, where over 70% of schools eligible for CEP had opted in, in Texas, only 25% of eligible districts opted in. Therefore, we see fewer schools clustered at "100% free lunch eligible."

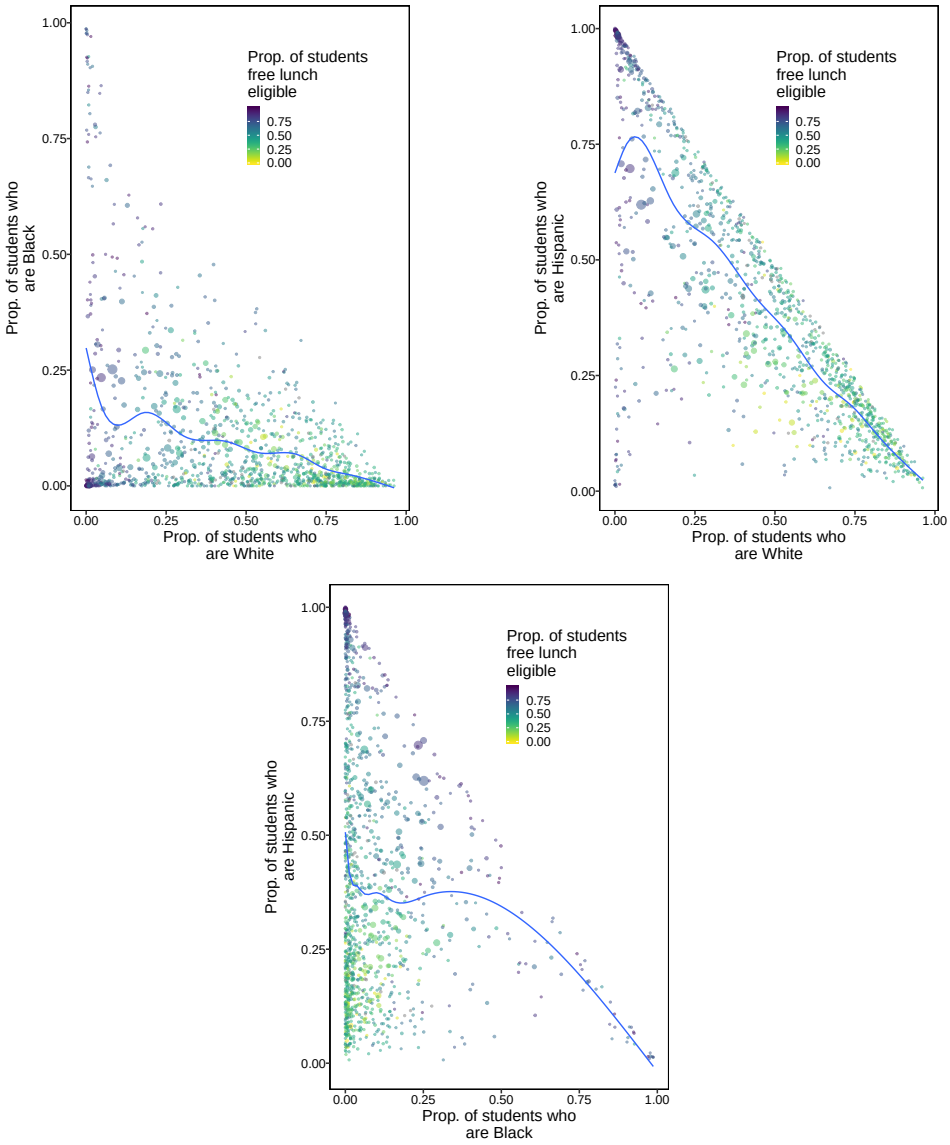


Figure 4.22: **District of Columbia: racial and socioeconomic segregation across schools (2013-2014 SY)**. The figures use a GAM smoother to show how the share of one race/ethnic group tends to decrease as the share of another increases, with the patterns sharpest for districts with high percentages of Hispanic students and very few White students. The size of the dots are scaled to the district's total student population, with the colors shaded by poverty status. Compared to Texas, we see very low percentages of white students in schools (e.g., the schools with the highest White shares are around 50-60% white rather than 100% white), and are elementary schools. We also see much higher levels of student poverty–e.g., there are no schools with less than 65% of students in poverty, and many schools have opted in to CEP and thus record 100% of students as free lunch eligible.

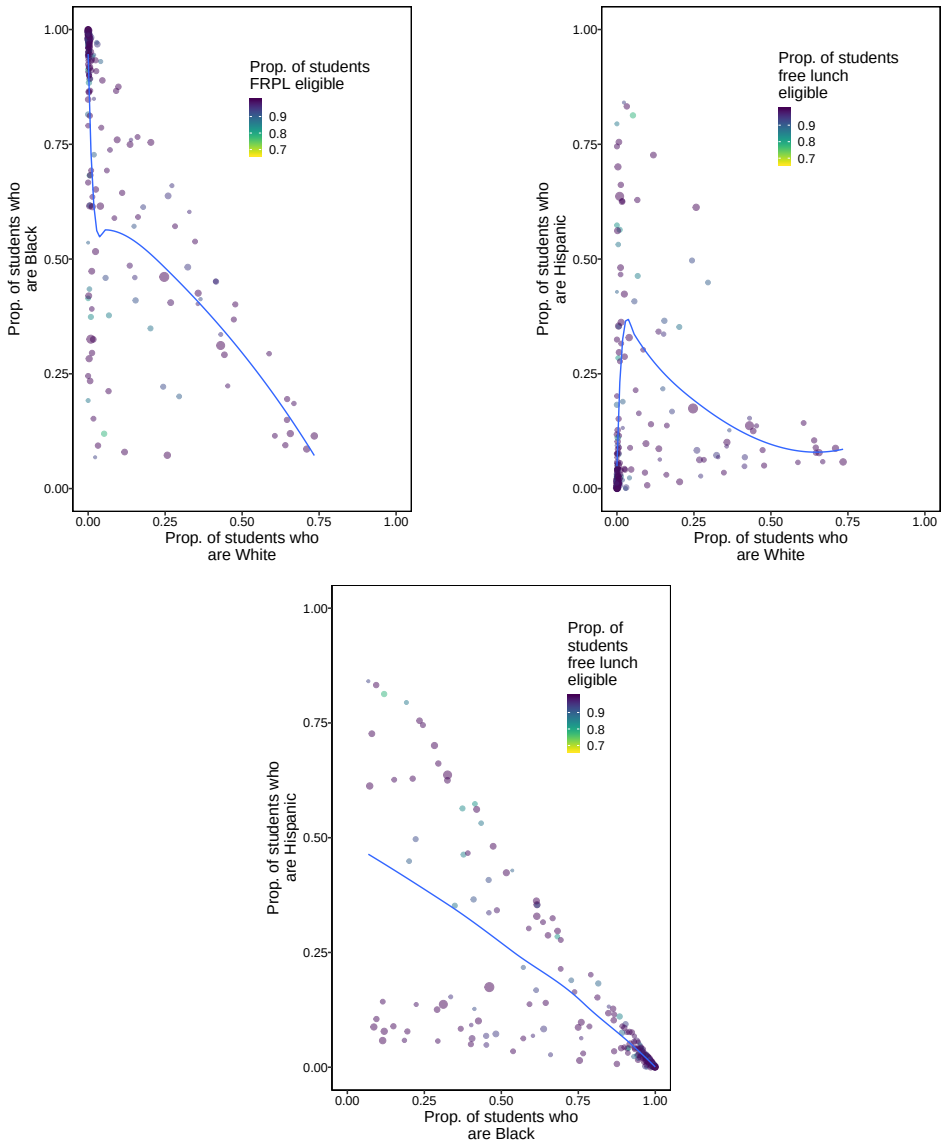
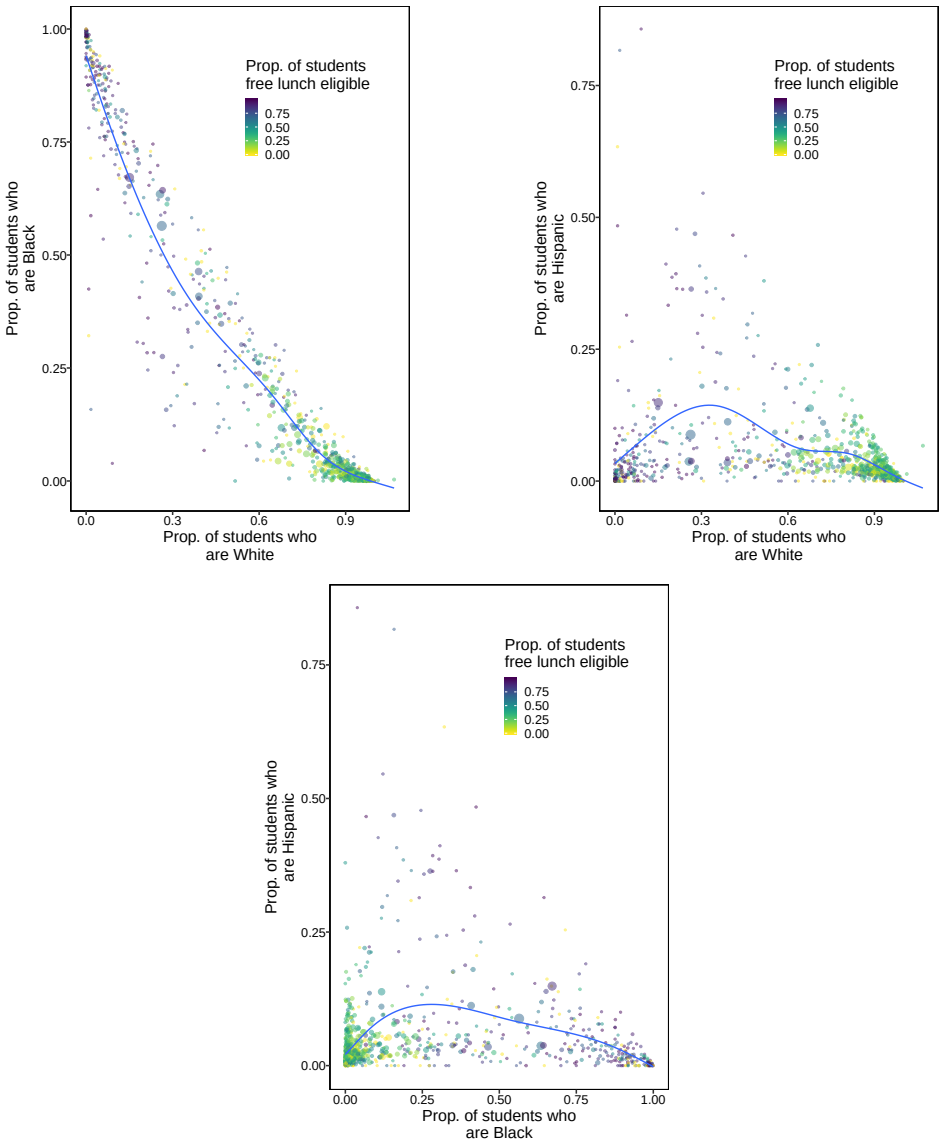


Figure 4.23: **Ohio: racial and socioeconomic segregation across schools (2013-2014 SY)**. The figures use a GAM smoother to show how the share of one race/ethnic group changes as the share of another decreases. In contrast to Texas and DC, where relatively large Hispanic student populations mean that we see decreases in the White share with increases in either Black or Hispanic student shares, in Ohio, the share of Hispanic students is relatively constant across different shares of White students. Similar to Texas, in Ohio, there are districts with poverty shares close to zero; and similar to Texas and DC, districts with large shares of Black students have much higher poverty levels than districts with large shares of White students.



4.6.2 Inequalities in whether monitoring occurs

Texas

Figure 4.24 shows the locations of filings against districts between 2014 and 2018, with the tracts shaded by household income from the 2013 ACS 5-year estimates. Figure 4.25 zooms in on the Dallas metro region. The latter figure highlights that (1) there are several wealthy census tracts with few public school districts located nearby and (2) in the highest-poverty area towards the south of the city, there are many districts with no monitoring.

Figure 4.26 shows the distribution of cases: 79 percent of districts had no filings between 2014 and 2018. Figure 4.27 shows the results from a Generalized Additive Model (GAM) where the total number of filings varies smoothly as a function of the district poverty share, also controlling for the total number of students in the district (Wood and Wood, 2015). The figure shows a largely linear relationship: as a Texas district's share of free lunch eligible students goes up, the predicted number of filings decreases. Appendix Table 8.30 show the results from the GAM regression of either total filings or any filing, while Appendix Table 8.31 shows the results from a negative binomial model of total filings and a logistic regression model of any filing.

In sum, we should be careful *not* to interpret this as parents in poverty doing less of monitoring school decisions, since it could be the case that poorer parents in wealthier districts are more likely to monitor than wealthier parents in that district. However, the sharp socioeconomic segregation between Texas districts bolsters the interpretation that students in poorer districts are less likely to be protected by parent monitoring than students in wealthier districts.

Figure 4.24: **Variation in parent monitoring of disability decisions: Texas.** The maps show Census tracts shaded by median household income, with the dots showing the location of school districts (centroids). The *top panel* shows large variation in where monitoring occurs, with monitoring appearing to cluster in urban areas (*bottom panel* shows the location of major cities. However, there are also pockets of monitoring near the Southern border.

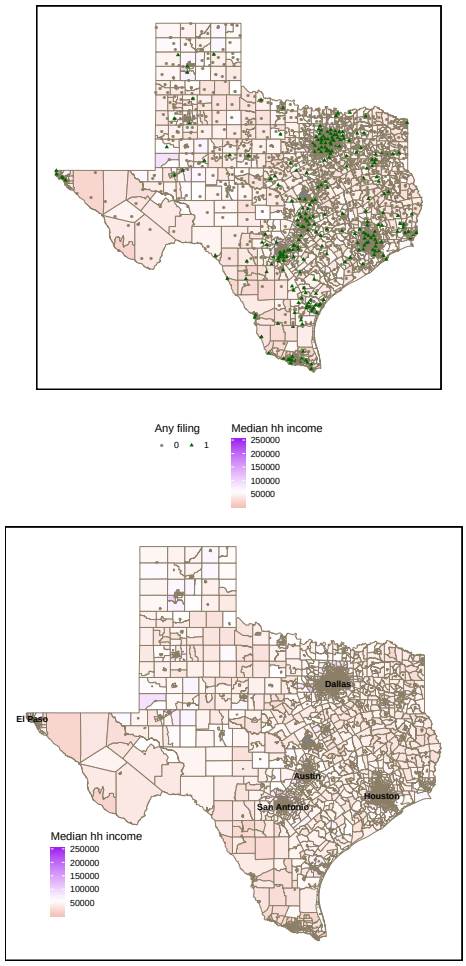


Figure 4.25: **Variation in parent monitoring of disability decisions: zooming in on Dallas area**

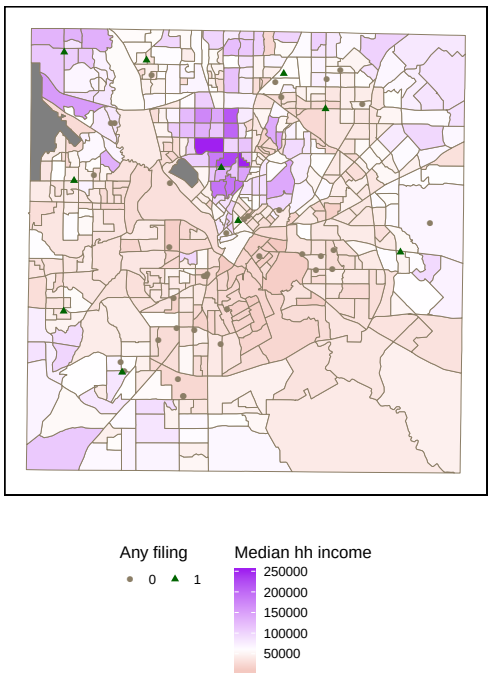


Figure 4.26: **Distribution of filings: Texas**

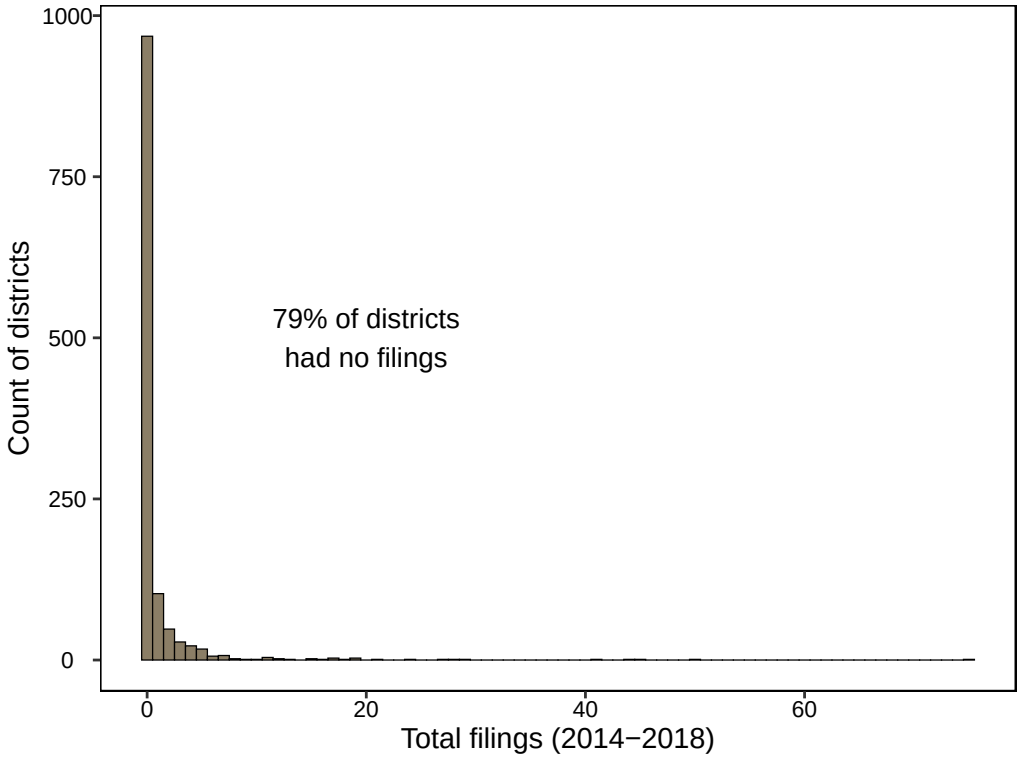
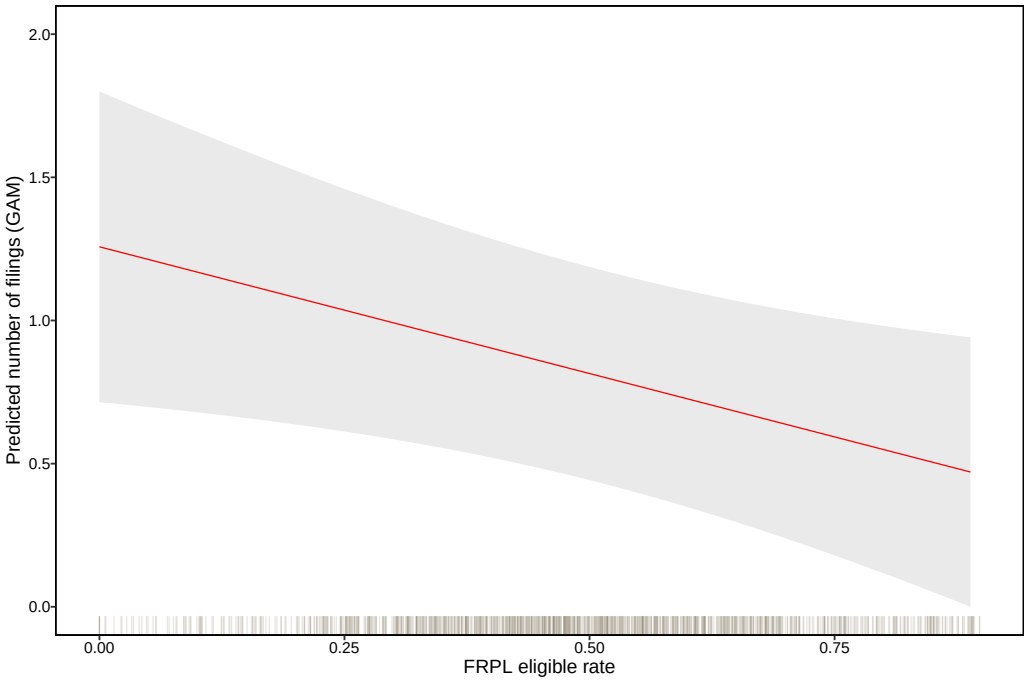


Figure 4.27: **Relationship between district poverty share and parent monitoring (predicted values): Texas.** The line in the plot shows predicted number of filings at varying levels of district poverty share but with the district size held at the state-wide mean, with the rug plot along the x-axis showing the observed poverty share. The plot shows that as the poverty share increases, the number of filings tends to decrease.



District of Columbia

Figure 4.28 through Figure 4.31 show the same relationships for DC. While wealthier areas in DC's Northwest have schools that consistently have *some monitoring*, Figure 4.31 shows that there is a relatively flat relationship between school poverty share and total filings across most of the poverty share, with a slope upwards driven by the CEP schools that classify nearly 100 percent of their students as free lunch eligible. Appendix Table 8.32 shows the results from the GAM regression of either total filings or any filing, while Appendix Table 8.33 shows the results from a logistic regression model of any filing.

What might drive the counterintuitive pattern in DC, where there is no relationship between school poverty and filings (if one excludes CEP schools) and a sharp concentration of filings in CEP schools?

While it is beyond the scope of the Chapter to identify mechanisms for this difference

with Texas, the Conclusion discusses differences that further research could explore. These include less policy-relevant reasons like DC's highly truncated distribution of socioeconomic status in public schools—namely, in even the lowest-poverty schools, over 60 percent of students are eligible for free lunch—due to factors like enrollment in private schools and residential patterns where more affluent families reside in DC-adjacent Maryland and Virginia suburbs. They also include more modifiable reasons such as DC's more robust "Educational Surrogate Parent (ESP)" program that pairs IEP students with volunteer advocates and a federal class action lawsuit, *D.L. et al. v. DC*, that may have heightened awareness among advocates about the need for monitoring.

Figure 4.28: **Variation in parent monitoring of disability decisions: DC.** The map shows that (1) schools located in the wealthier Northwest area of the city all have at least some parent monitoring, but (2) we also see monitoring in schools located in the higher-poverty areas east of the Anacostia river.

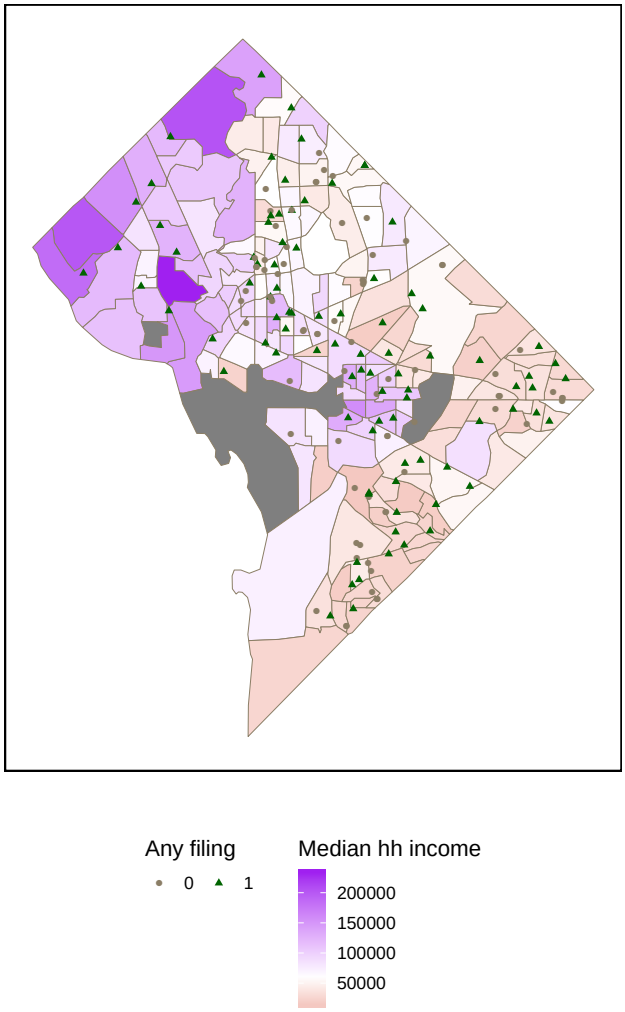


Figure 4.29: **Distribution of filings: DC**

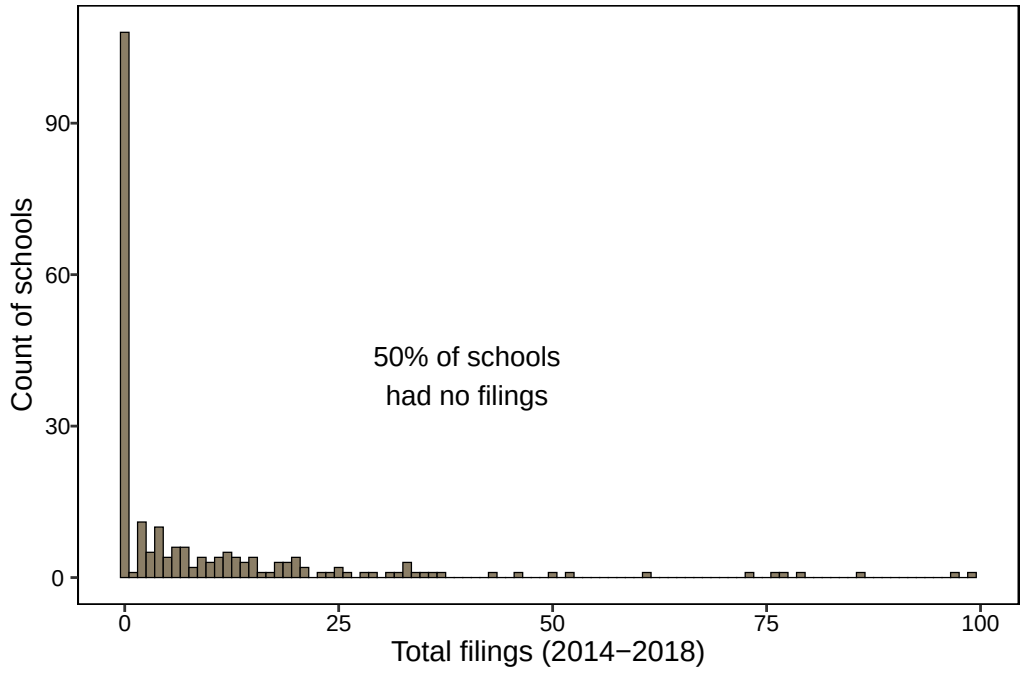


Figure 4.30: **Relationship between district poverty share and parent monitoring (predicted values): DC.** The figure shows schools with 80% or higher free lunch eligible students (or that opted in to CEP). 98% of schools are in this region of the distribution.

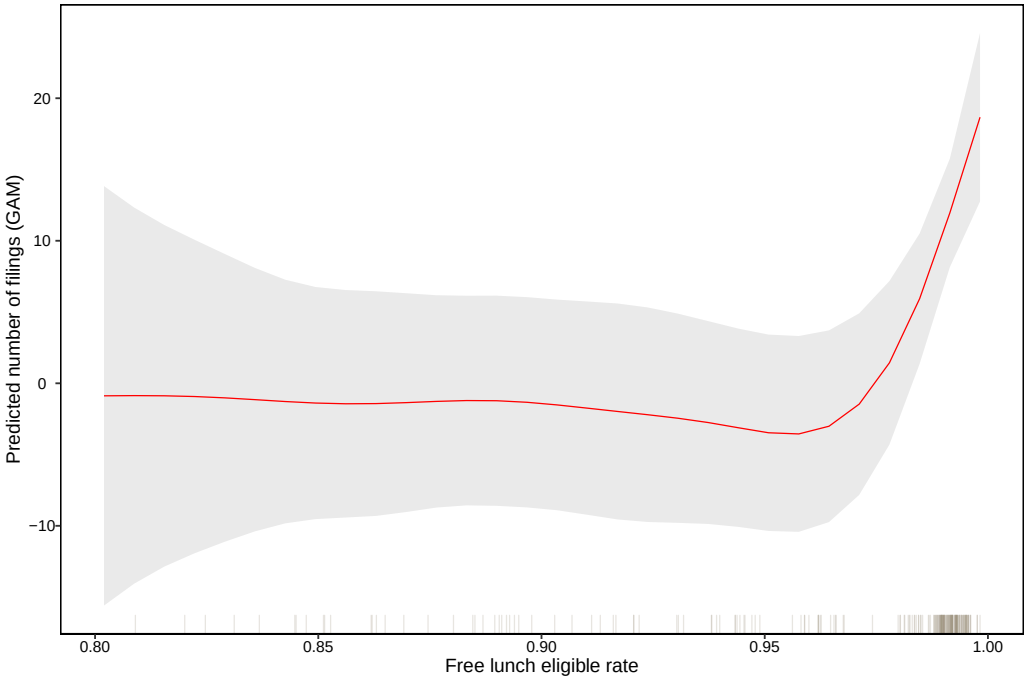
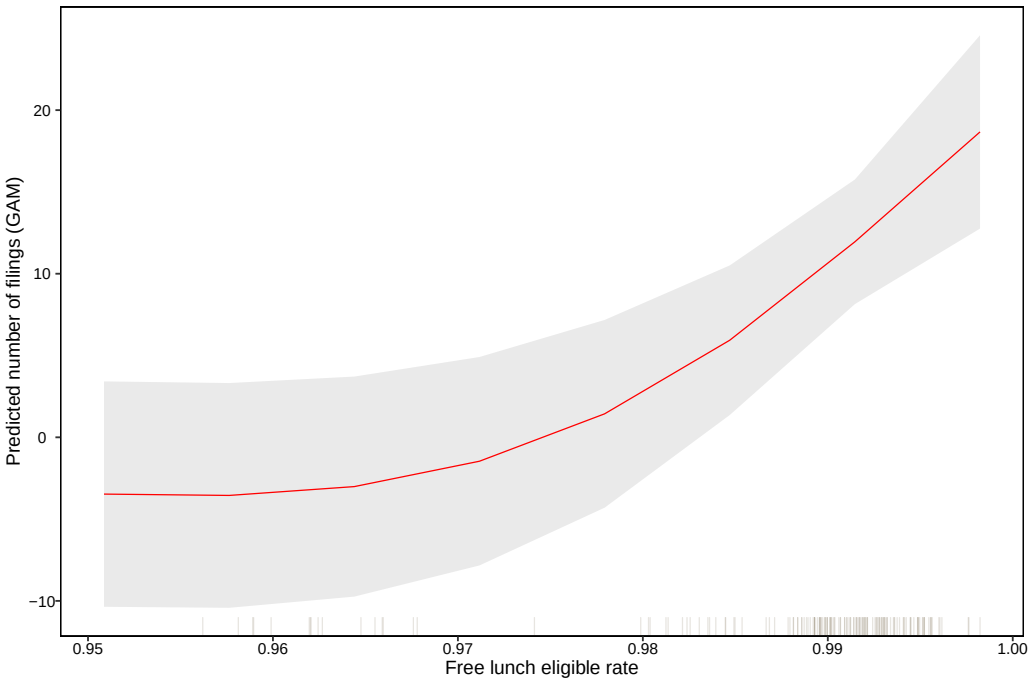


Figure 4.31: **Relationship between district poverty share and parent monitoring (predicted values, zooming in on highest-poverty region): DC.** The figure shows schools with 95% or higher free lunch eligible students (or that opted in to CEP). 73% of schools are in this region of the distribution.



Ohio

Figure 4.32 shows the locations of filings against districts between 2014 and 2018, with the tracts shaded by household income from the 2013 ACS 5-year estimates. Figure 4.33 zooms in on the Cleveland metro region. Similar to the patterns near Dallas, where monitoring was more heavily concentrated in affluent outer-ring tracts, we see that monitoring appears less prevalent in the high-poverty inner core of the city.

Figure 4.34 shows the distribution of cases, with a large peak at zero among the approximately 75 percent of districts with no monitoring. Table 8.34 shows the results of the GAM that allows the number of filings to vary smoothly as a function of the share of a student's district in poverty, also controlling for the total student population. The table shows that while student poverty has a significant relationship with *how much* monitoring occurs, it does not appear to predict whether or not there is *any* monitoring.

Figure 4.35 visualizes the predicted count of filings across poverty shares. While there are regions of the poverty share distribution with limited support, thus preventing us from drawing strong conclusions about the shape of the relationship, we see a different pattern than in Texas. Appendix Table 8.34 shows the results from GAM models of the total count of filings and any filing, with Appendix Table 8.35 showing the results from a negative binomial model of total filings and a logistic regression model of any filing.[67]

[67]The table shows that the GAM helps pick up the bi-modal peak at low and high poverty shares better than the other models.

Figure 4.32: **Variation in parent monitoring of disability decisions: Ohio.** The maps show Census tracts shaded by median household income, with the dots showing the location of school districts (centroids). The *top panel* shows large variation in where monitoring occurs, with monitoring appearing to cluster in urban areas (*bottom panel* shows the location of major cities.

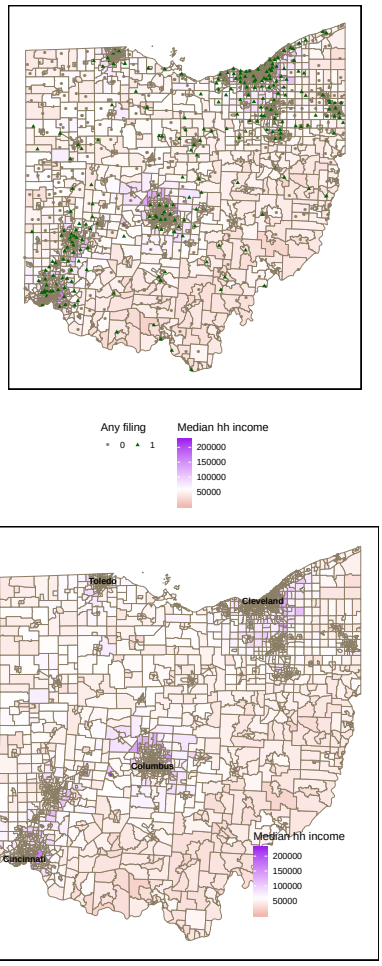


Figure 4.33: **Variation in parent monitoring of disability decisions: zooming in on Cleveland area.** The figure shows the tracts located within Cleveland's primary county (Cuyahoga). The dots outside the map boundaries are districts in neighboring suburbs.

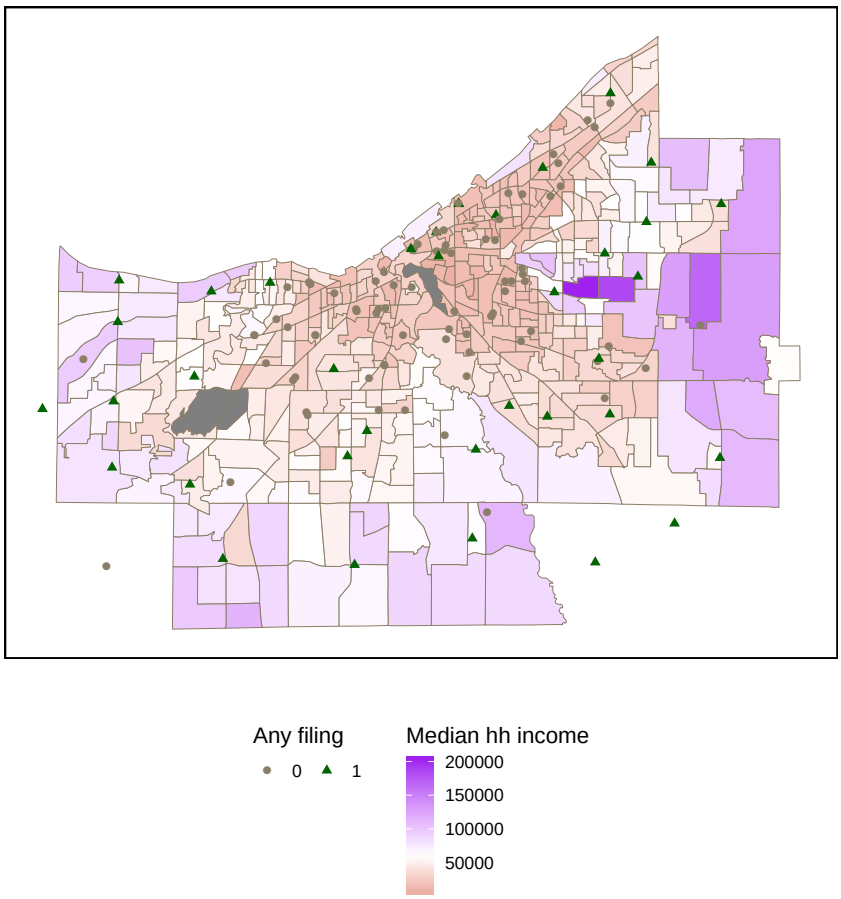


Figure 4.34: **Distribution of filings: Ohio**

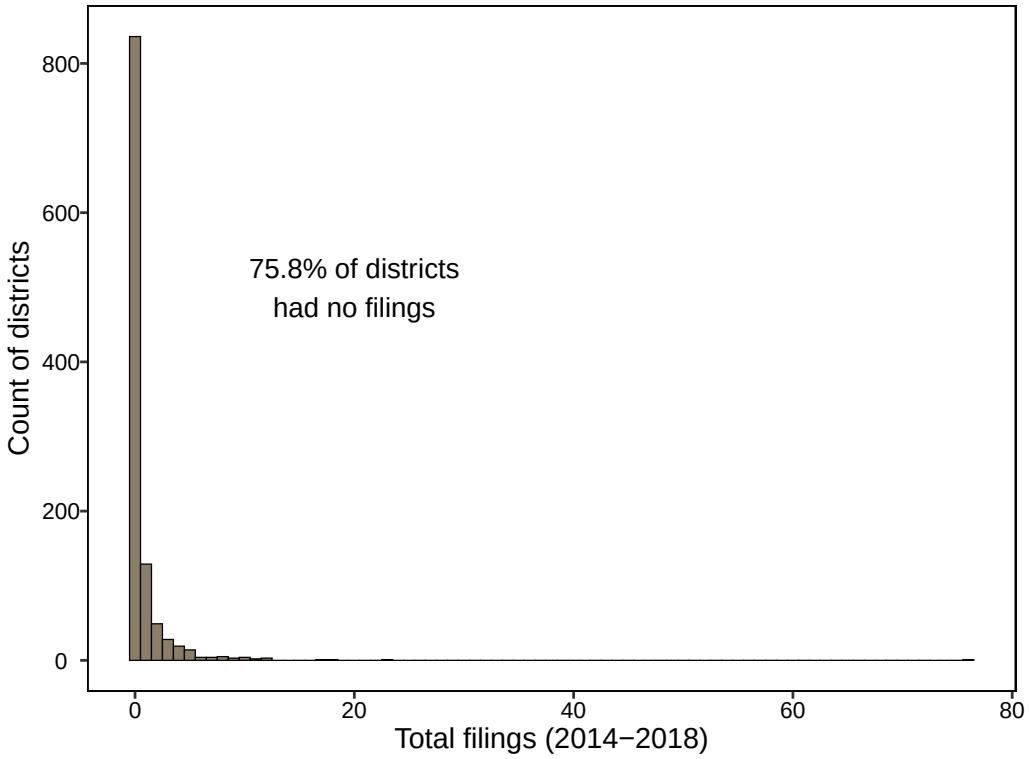
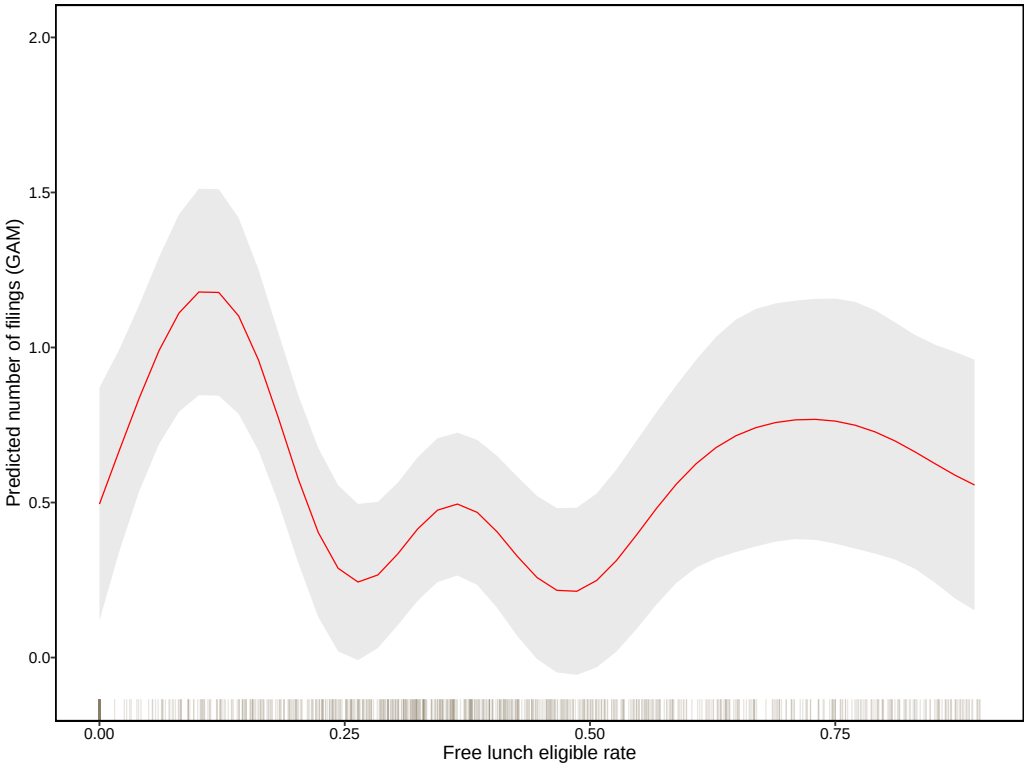


Figure 4.35: **Relationship between district poverty share and parent monitoring (predicted values): Ohio**



4.6.3 Inequalities in the substance of monitoring

The previous section shows patterns of inequality in *whether* parents monitor disability-related decisions in a district as well as the extent of this monitoring. Yet as the quotes at the beginning of the Chapter show, the same "yes monitoring" indicator for a school or district can reflect very different uses of monitoring. Some parents use monitoring to reduce discretion over rationing, filing a complaint to ask for a larger share of resources. Other parents use monitoring to reduce discretion over other decisions, like decisions to discipline a student with disabilities. Thus, inequality in the presence of monitoring may be compounded by inequality in whether monitoring gives a student a leg up in competition over finite resources or whether monitoring shields a student from school discipline.

Returning to the process that disputes go through, depicted in Figure 4.13, we see attrition in which disputes between parents and districts generate a written record for us to analyze. Most legal scholars studying the IDEA focus on a limited set of Court of Appeals and Supreme Court cases (green boxes C and D). The previous section expanded the lens to focus on the blue box—all filings by parents, regardless of whether they progress to Box A: a hearing that leaves a written record of the substance of the dispute.

The present section progresses down the process in Figure 4.13 to investigate whether potential inequalities in *whether* there is monitoring are accompanied by inequalities in whether the monitoring reflects parents asserting their rights to school resources, or parents using monitoring for other aims like protecting their child from inappropriate school discipline.

One important limitation is that as Figure 4.13 shows, there is substantial selection into the corpus. In DC, 673 of the 2105 total filings against districts during 2014-2018 resulted in a hearing, or 32 percent.[68] In Texas, 119 of the 1213 total filings against districts resulted in a hearing, or 10 percent. Therefore, and especially in Texas, the filings that progress to a hearing may concern issues where either the district or the parent is particularly unwilling or unable to arrive at a settlement. Keeping this selection in mind, we can nevertheless

[68]For each, I exclude filings or hearings that the district files against a parent, which are fewer than 5 percent in each state.

examine variation *within* those that go to a hearing by socioeconomic attributes.

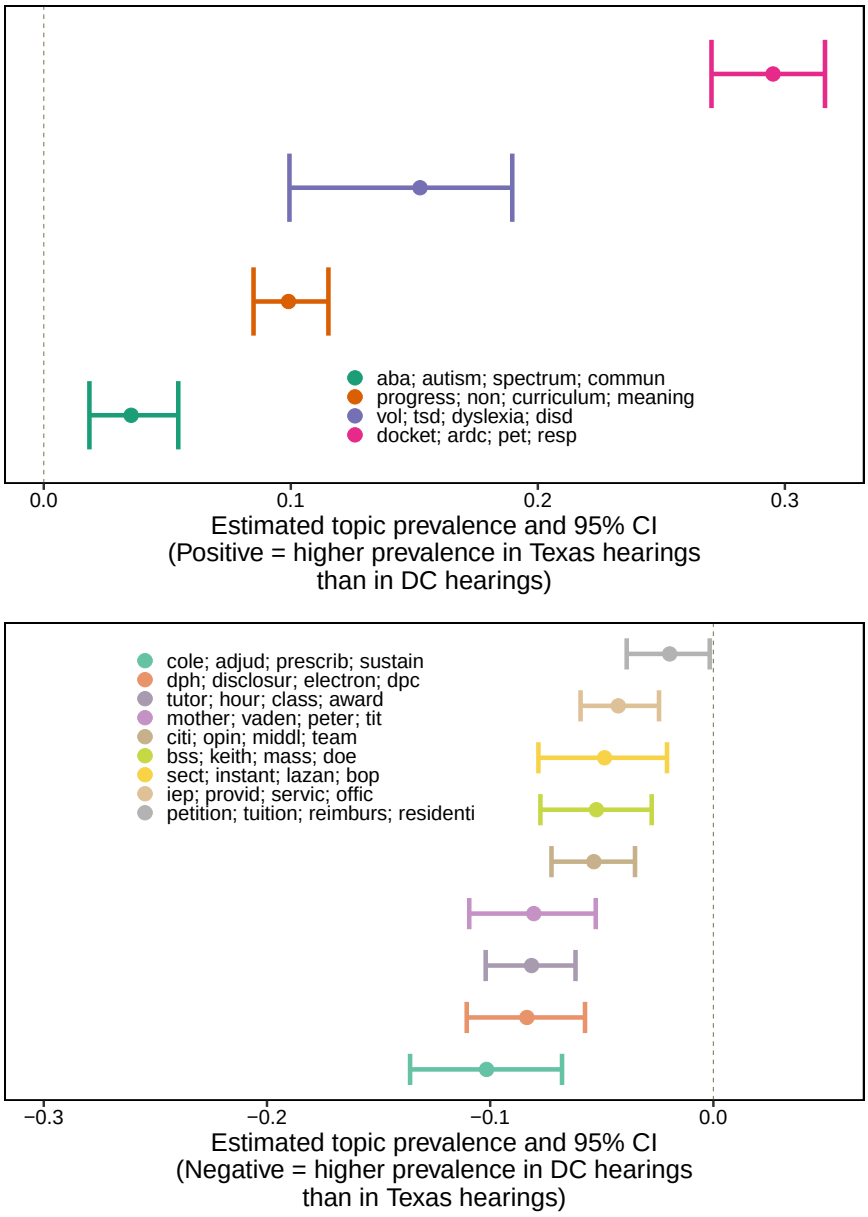
4.6.4 Between-state variation in which decisions parents monitor

Figure 4.36 shows differences in what parents monitor between Texas and DC, depicting top words from each of the $k = 17$ topics using the `FREX` metric, which balances a word's frequency within a topic with its exclusivity to that topic (Roberts et al., 2016). In our case, this metric is more meaningful than the highest-probability words for each topic, which tend to be words like "educ", "meet", "appropri" (for appropriate), and "assess" (for assessment).

The top panel of Figure 4.36 shows topics more prevalent in Texas hearings, which include those related to specific autism services like expensive ABA services (*aba; autism; spectrum; commun*), one related to reading issues/dyslexia (*vol*; *tsd*; *dyslexia*; *disd*), one related to general progress in the curriculum, and a topic that reflects the different structure of decision making around IEPs than content (Texas calls the team responsible for making decisions about IEPs the Admission, Review and Dismissal Committee (ARDC)).[69] The bottom panel shows topics more prevalent in DC, where hearings might also exhibit more variation in substance than Texas due to the much higher volume. While some topics appear more related to the hearing structure than the substance, there are more hearings that focus on issues like *whether* a child receives an IEP (*iep; provid; servic; offer*) and also slightly higher prevalence of hearings related to private school tuition reimbursement (*petition*; *tuition*; *reimburs*; *residential*). Appendix Figure 8.73 shows topics that do not significantly differ in prevalence between the two states, which include those related to schools' treatment of students with disruptive behavioral difficulties.

[69] In future work, I will explore refining the state-specific preprocessing to include more stop words related to the terminology in a state's hearing system.

Figure 4.36: **Comparing themes in hearings: Texas versus DC** The *top panel* shows themes more prevalent in the Texas hearings. The *bottom panel* shows themes more prevalent in the DC hearings. Appendix Figure 8.73 shows themes with no significant differences in prevalence.



4.6.5 Within-state variation in which decisions parents monitor: Texas

For Texas, we link the district a complaint was filed against to its share of free lunch eligible students. The model then estimates how the prevalence of a topic varies as a function of

the district poverty share. Because there are very few filings in Texas that go to a hearing, resulting in a small corpus of 119 hearings, the patterns are imprecisely estimated and none are statistically significant. Future work pooling more years will confirm these patterns.

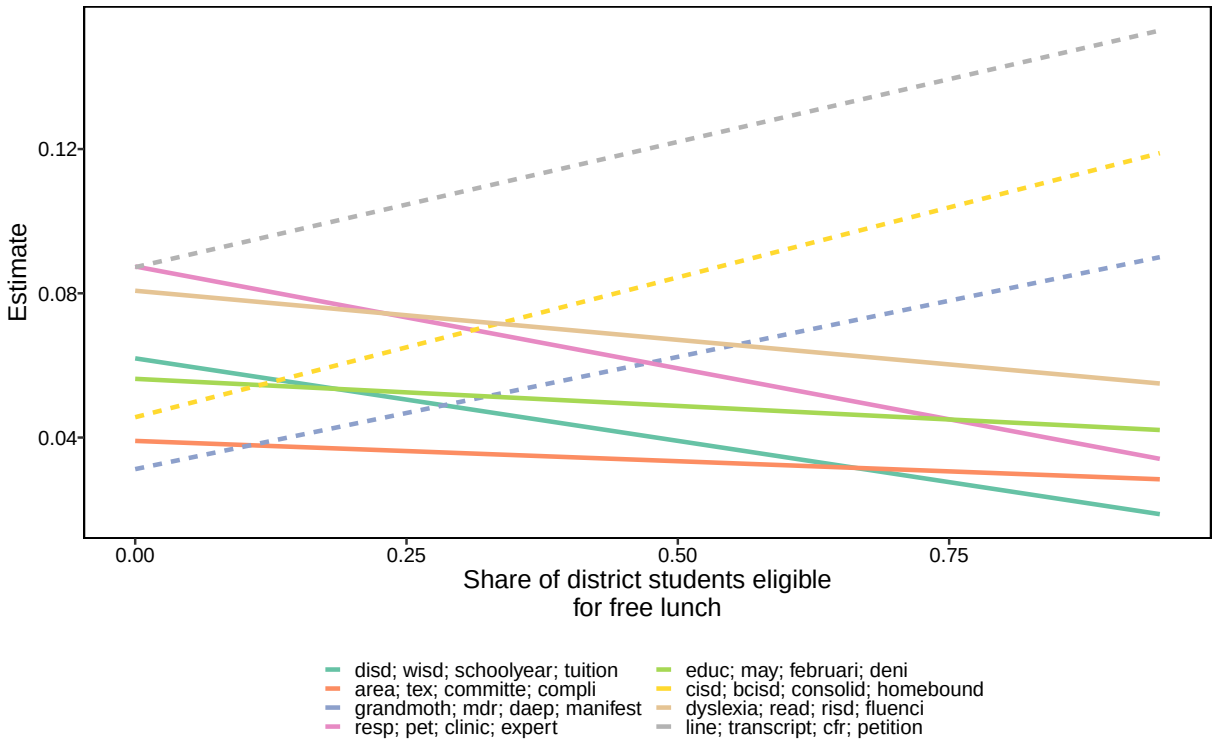
Figure 4.37 shows topics that either increase in prevalence as the share of students in poverty increases (dashed lines; positive slope) or decrease in prevalence as the share of students in poverty increases (solid lines; negative slope). We see patterns like hearings concerning school disciplinary matters (*grandmoth*; *mdr*; *daep*; *manifest*) increasing with poverty share.[70] MDR stands for Manifestation Determination Review meetings that the IDEA requires takes place within 10 days of a district's decision to change the placement (e.g., moving to a segregated classroom; expulsion) of a student with disabilities due to code of conduct evaluations. DAEP stands for a Disciplinary Alternative Education Program, a provision in the Texas Education Code that allows districts to remove students from regular classes for disciplinary reasons and place them in a separate DAEP learning environment. The higher prevalence of this discipline-related topic in districts with higher poverty shares suggests that, in these districts, monitoring may be more focused on reducing discretion over discipline than on asserting rights to resources.

For higher-income districts, we see topics related to expert testimony that a student's disability warrants additional services (*resp*; *pet*; *clinic*; *expert*). We also see a topic loosely related to private school tuition reimbursement (*wisd*; *disd*; *schoolyear*; *tuition*).

Appendix Figure 8.74 shows topics with a flat slope across poverty levels.

[70]The word grandmother in the topic could reflect grandmothers playing a larger role in child-rearing in low-income districts.

Figure 4.37: **Themes that vary across poverty levels in Texas**



4.6.6 Within-state variation in which decisions parents monitor: DC

Addressing redacted school names

While the Texas hearings contain the name of the district, allowing us to investigate how the topics vary by socioeconomic status, DC's status as a large urban school district means that school names are important for measuring socioeconomic status. However, unlike the filings that retain these names, the names are redacted from the hearings, with no unique identifier to link. As a result, we need to use some measure of socioeconomic variation that is not redacted from the hearing text.

Figure 4.38 shows one measure contained in both the Texas hearings and the DC hearings: which parents or guardians are mentioned in the filing? The Figure shows that while the majority of filings mention only the child's mother, there are also many filings where both the child's mother and father are mentioned as being involved in either the decision to file a complaint or the IEP meetings leading up to the complaint. Texas hearings contain both this *within-text* measure of advantage and district poverty share. Figure 4.39 shows the predicted probabilities from three logistic regressions: one that models the likelihood of both parents being mentioned (relative to the other three categories); another that models the likelihood of neither parent being mentioned; a third that models the likelihood of the mother only being mentioned. The Figure shows a meaningful relationship where, as a district's poverty share decreases, the likelihood of the hearing mentioning the joint involvement of the mother and father increases. Assuming that these patterns generalize to DC, I use the mention of both parents in the hearing as a marker of higher socioeconomic status.

Figure 4.38: **Which parents or guardians are mentioned in a hearing?**

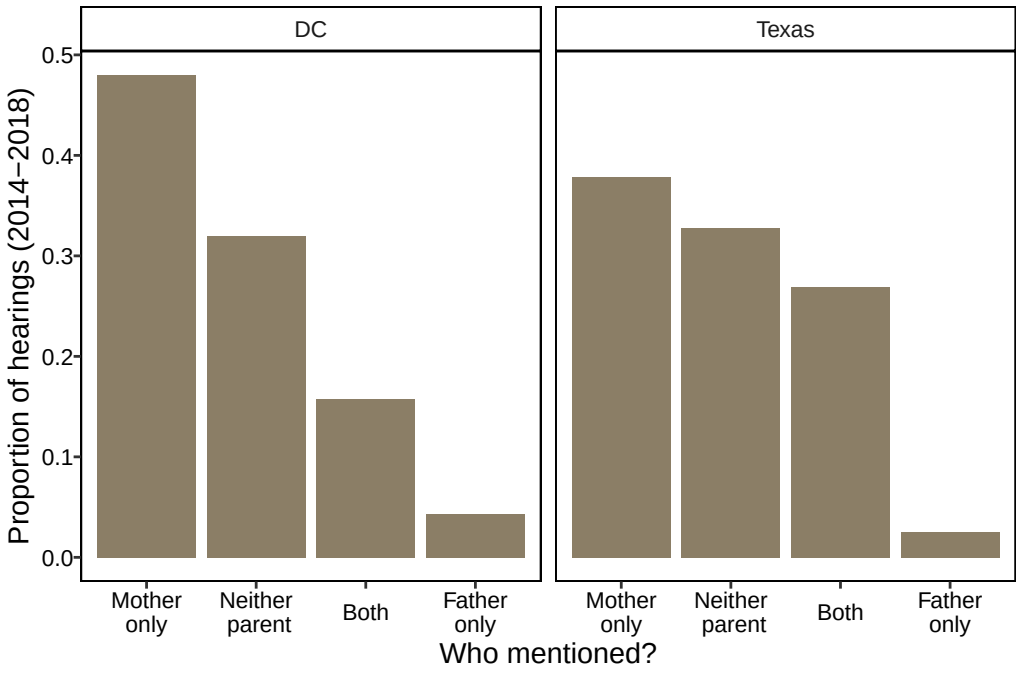
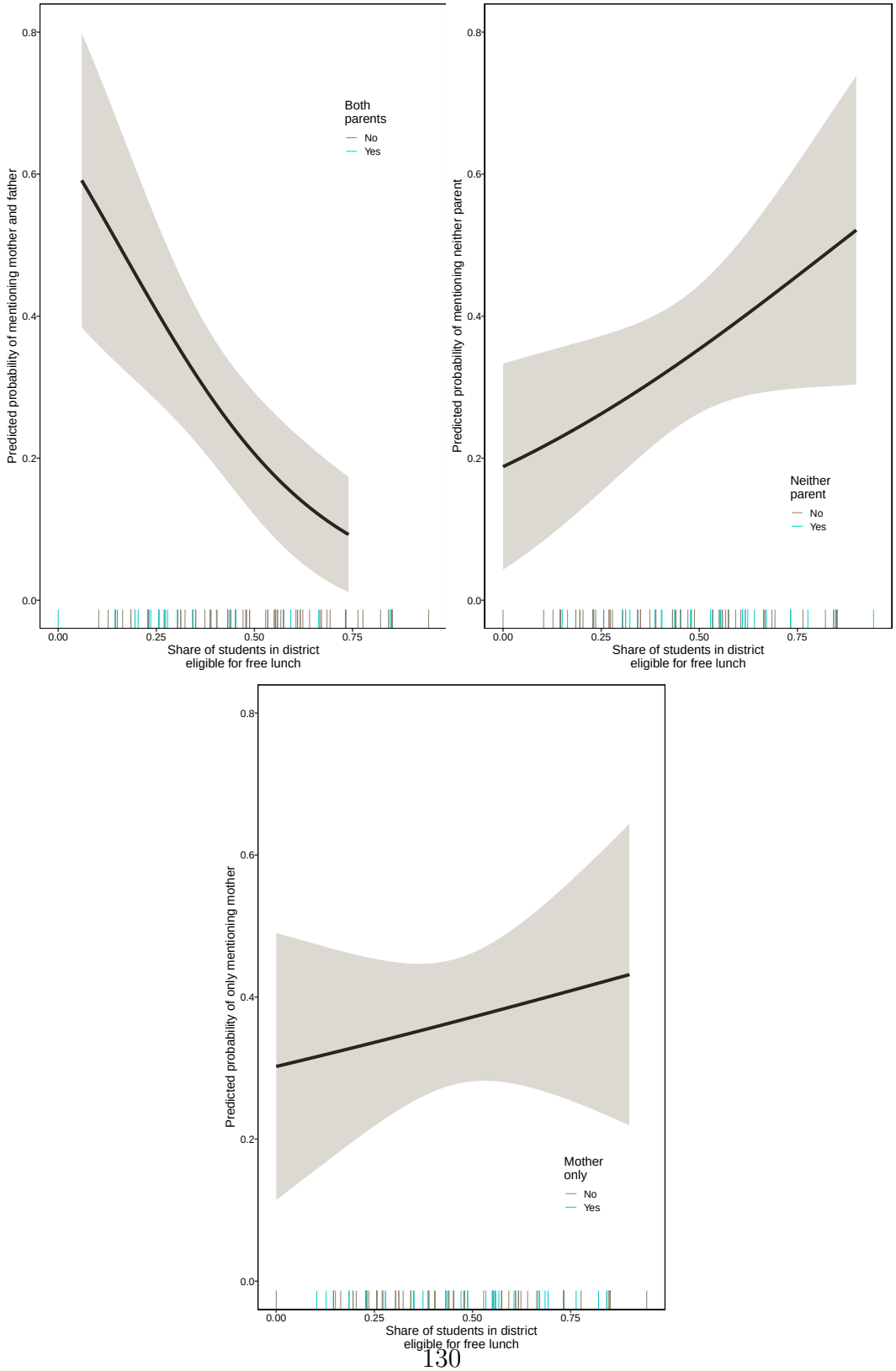


Figure 4.39: **Relationship between district poverty share and predicted probability of different parent mentions.** Each figure presents results from a different logistic regression of the relationship between the poverty share of the district the complaint was filed against and the parents mentioned in the hearing.

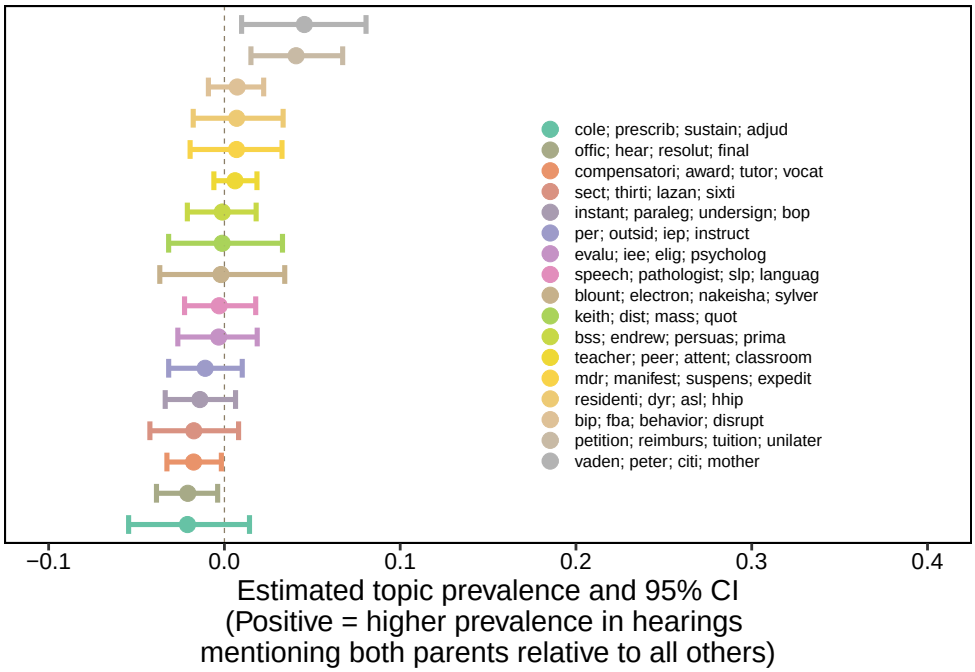


Variation

Figure 4.40 shows how themes vary across hearings using this proxy measure of socioeconomic status. While one topic more prevalent in hearings mentioning both parents relates to administrative features of a hearing (*vaden* refers to Peter Vaden, a hearing officer who once represented parents as a private attorney),[71] the topic with the second-largest increase in prevalence is one related to private school tuition reimbursement (*petition*; *reimburs*; *tuition*; *unilater*), with *unilater* referring to parents unilaterally placing their child in a private school and then seeking reimbursement. Interestingly, while we see a similar topic related to school discipline as in Texas—(*mdr*; *manifest*; *suspens*; *expedit*)—there are no differences in the prevalence of this topic using our proxy measure of SES. Instead, one topic that appears to have higher prevalence in hearings where the mother and/or father is not involved is one having to do with compensatory education (*compensatori*; *award*; *tutor*; *vocab*). In contrast to private school tuition reimbursement cases, where the parent gives extra services to the child and then asks the district for reimbursement, compensatory education involves the child having been deprived of services and the hearing officer awarding extra hours to them later to compensate. Thus, while monitoring focused on compensatory hours helps the student receive resources, it is resources to "restore the balance" back to normal after an inappropriate deficiency rather than resources aimed at higher priority.

[71] Throughout, I use the terminology "private attorney" to refer to attorneys who parents pay for out of pocket to retain. The other set of attorneys are legal aid attorneys who represent parents pro bono.

Figure 4.40: **Themes that vary across parent involvement in DC**



4.7 Conclusion

Chapter Three, using data from New Jersey, showed that parent monitoring of districts' disability-related decisions may help protect students from rationing. The present Chapter investigated three further questions. What is the feasibility of gathering systematic, district-level data on IDEA-related monitoring? The Chapter showed that open records requests can yield usable data but that the time span taken to fulfill the requests, and the variety of formats the data arrive in, would make it difficult for policymakers to try to continuously measure monitoring—e.g., a legal aid firm receiving an auto-alert each time there is a filing in a low-income district they may be able to aid with. Then, focusing on three case studies, I investigated inequality in *whether* and *where* monitoring occurs. Finally, focusing on the two jurisdictions with the most dramatic differences in filing patterns—DC and Texas—I use filings that progress to a hearing to show differences between and within states in monitoring to enforce positive rights to resources versus other rights. The Chapter focused on describing these patterns. In the Conclusion, I now focus on future research that can explore possible mechanisms behind the patterns.

4.7.1 Future research on inequality in whether monitoring occurs

Table 4.4 reflects that no research of which I am aware examines the descriptive relationship between district or school demographics and parent attempts at monitoring disability-related decisions, with Section 4.1.3 outlining reasons for the data gap. The descriptive analysis in the previous section shows two patterns. First, the three locations vary sharply in the presence of monitoring. While DC has monitoring in over 50 percent of *schools*, meaning that its district-level rate nears 100 percent if one treats DCPS as one district and charter schools as another district, Texas and Ohio have monitoring in approximately 21 and 24 percent of districts respectively. Second, the three locations vary in the relationship between school or district poverty shares and monitoring. In Texas, the number of filings increases linearly as a district's poverty share decreases; in DC, schools' nearly uniformly high levels of poverty mean there is a flat relationship and then a spike at schools that opt in to CEP assistance; in Ohio, we see a spike in the predicted number of filings at both districts with close to zero students in poverty and districts with higher shares of students in poverty.

The goal of these analyses is to show descriptive patterns that can spark future research. Here, I outline three avenues to explore.

Avenue one: residential and school enrollment decisions of middle and upper-class parents

Parents face interrelated decisions about their children's schooling. First is where to live, which affects the educational opportunities their child has via neighborhood schools. Second is whether to send their child to a private or to a public school. Finally, for districts with some degree of public school choice, there are decisions about which public or public charter school in which to enroll their child.

The first and second choices may produce patterns we observe in DC, where we see a truncated distribution of very few, low-poverty schools partly as the result of higher-

SES parents having choice sets that include higher-performing districts in nearby Maryland and Virginia suburbs. In contrast, in Texas and Ohio, there remain districts with close to 0 percent of students free lunch eligible that are composed nearly exclusively of White students. While there is no research that examines residential choices of parents of students with disabilities, future research could examine how having a child with a disability affects parents' choices in settings where large urban districts are surrounded by affluent suburban districts. Future work could also examine "metro area" patterns of inequality, where data from DC would be pooled with city-adjacent suburbs and compared to similar metro areas like Dallas, Cleveland, and others.

Second, the structure of the IDEA may constrain parents' access to either private schools or selective public charter schools. The IDEA does not require private schools to provide IEPs or services to students (Waitoller and Lubienski, 2019).[72] Therefore, higher-SES parents who may choose private schools for their children without disabilities may continue to enroll their children with disabilities in public school. Similarly, although selective public charter schools *are* required to provide IEPs and are barred from discriminating against students with disabilities in their admissions process, an audit study shows that charter schools appear to avoid taking IEP students (Bergman and McFarlin Jr, 2018). Applied to the present findings, these constraints may mean that the socioeconomic inequalities we observe in Ohio and Texas are driven in part by higher-SES parents of students with disabilities simultaneously remaining in traditional public schools while asking for these schools to provide more than the school feels is appropriate.

Avenue two: class action lawsuits and the legal landscape

While this Chapter focuses on monitoring by individual parents, class action lawsuits filed by advocacy groups on behalf of groups of children form the background against which individual attempts take place. The two settings I focus on in the next section—DC and Texas—have very different legal landscapes.

[72]This is different than special needs private schools and tuition reimbursement cases where the parent argues the special needs school is the "least restrictive appropriate" setting for a student.

In DC in 2005, advocates for students with disabilities filed a lawsuit, *D.L. v. District of Columbia*, arguing that the district had neglected its responsibilities under the "child find" mandate. Focused on children aged 3-5, the plaintiffs argued that the disability rate—about 2.5 percent of children categorized—was well below the rate of closer to 12.5 percent that would be expected based on the prevalence of trauma and other risk factors. The Court's ruling against the district cited budget pressures as one culprit behind this rationing, noting:

> The District of Columbia's special education policies are hampered by budget cuts and funding concerns....Budget cuts and shortages have led to a District-wide hold on hiring, causing extended vacancies in key positions, such as Part B Child Find coordinators, responsible for providing LEAs with training and technical assistance to ensure compliance with Child Find requirements (*D.L. v. District of Columbia, 2011*).

Both in an initial 2011 ruling, and a follow-on ruling in 2016, the district court placed strict requirements on DC for how to improve access to the disability category for students in low-income schools. The ruling required that DC identify at least 8.5 percent of children aged 3-5 as having a disability, and mandated measures like "regular screenings of preschool-age children in each ward of the District, and especially in wards in which children experience multiple risk factors."

As one legal aid attorney representing parents who practiced in DC following the suit and then moved to Chicago argued, the ruling had reverberations beyond the age range the suit focused on. As she described, the two districts—DC Public Schools and Chicago Public Schools—were like "night and day" when it came to finding students with disabilities.[73] DC conducted outreach in churches and low-income neighborhoods to satisfy their "child find" mandate; Chicago Public Schools, as she put it,"sort of sat around waiting for parents to repeatedly point out a problem."

DC's high *levels* and lack of socioeconomic gradient in parent monitoring could stem from factors like the court-ordered floor on how many students receive services, and the legal aid community's vigilance in making sure the district complied with the court's terms for low-income students.

[73]Author interview with attorney at public interest law firm, November 18th, 2016.

In contrast to DC, which set an 8.5 percent floor on the percentage of children who should be initially identified for IDEA services beginning in 2011,[74] as we heard earlier, Texas imposed a quota that penalized districts identifying over 8.5 percent of students. While this could have *increased* parent monitoring—the quota led districts to say "no" more often to parent requests to have their child evaluated—empirically, we see both a *lower level* of monitoring than in DC and a sharp socioeconomic gradient where the districts with the least monitoring are likely the ones with students most vulnerable to the quota's impact. While future research is needed, the cases suggest that class-action advocacy might serve as an important "initial spark" for parent monitoring to follow up on identified issues. In Texas, a state engaged in rationing that public interest groups did not successfully bring to light until 2016 to 2017, there was little parent monitoring to protect the students who may have faced the most harm.

Avenue three: surrogate parents

The 2004 amendments to the IDEA required districts to appoint "surrogate parents" for students with IEPs whose own legal guardians cannot serve as effective advocates, either because the student is in foster care, the foster parent is unwilling to serve as an advocate, the student is an "unaccompanied homeless youth," or the student's own parents want to cede control over IEP decisions to a surrogate. Yet reviews of states' programs showed that states varied widely in whether they had set up or funded a program to do so (Muller, 2009; Choe, 2012).[75] To the extent that the programs are robust, these may produce findings more similar to the ones we see in DC of a peak of filings in high-poverty schools with populations eligible for surrogate advocates, or in Ohio that has a peak for both very low poverty and very high poverty districts.

[74]More specifically, the court order focused on children aged 3-5 since that is when children transition from early intervention services to IDEA Part B services.

[75]Neither report provides information on the programs in DC, Texas, or Ohio.

4.7.2 Future research on inequalities in the substance of monitoring

The same three mechanisms that might affect whether monitoring takes place—the enrollment decisions of higher-SES parents; class action lawsuits; surrogate patterns—may also affect what monitoring focuses on. Topic modeling that linked the themes in hearings to demographic measures showed some patterns where monitoring in higher-SES districts was more likely to focus on resource issues like tuition reimbursement; monitoring in lower-SES districts on school discipline. Yet we also see substantial overlap across both types of districts focusing on topics like dealing with students with disruptive behavior issues and help for speech-language impairments.

Focusing on the contrast between monitoring focused on reducing school discipline versus monitoring focused on increasing a student's share of resources, the Texas results show over-representation of monitoring focused on school discipline in lower-income districts. A wealth of research finds that Black and Hispanic students face disproportionate rates of school discipline (Okonofua and Eberhardt, 2015; Fenning and Rose, 2007; Mittleman, 2018), and policymakers are concerned about the overrepresentation of minority students with disabilities (Morgan et al., 2019). Future research could find exogenous variation in the likelihood of monitoring—for instance, income thresholds for legal aid assistance—to see whether monitoring protects students from suspension and expulsion.

Chapter Five: Diversion from Categories with Less Monitoring

5.1 Introduction

The previous Chapter highlights a particular pattern of rights enforcement. The children with disabilities most in need of help from monitoring—for instance, children in Texas potentially harmed by the state legislature's quota—might be the least likely to receive it.

One solution is to empower parents from a broader range of socioeconomic backgrounds to increase their monitoring of disability-related decisions. As Pasachoff (2014) describes, the "general consensus is that the law's [IDEA's] heavy reliance on private enforcement has led to underenforcement, especially for poor or otherwise marginalized groups"(p. 461-462). Pasachoff (2014) goes on to argue that efforts to improve the ability of low-income parents to engage in the monitoring I describe in the previous Chapter should be complemented by advocates pressing federal agencies like the Office of Special Education Programs (OSEP) within the Department of Education to take a more active role.

Amidst finite school budgets, however, attempts to improve monitoring of the rights of students in one category might come at the expense of students in other categories. As school administrators concerned with the outcomes of Drew's case argued, school districts struggling with budget pressures cannot afford to give all students everything they ask for; the priority given to students with disabilities whose parents assert their rights can come at the expense of students in other categories like English Language Learners and Free or

Reduced Price Lunch students.

In this Chapter, I zoom out from the focus on one form of hidden rationing—rationing of disability categories or services amidst budget pressure—to focus on a second form of hidden rationing. Do resources meant for students in categories other than disability end up getting diverted to cover the costs of satisfying parent requests for disability-related services? Put differently, do district professionals not only have discretion over who falls into a category and what to give category member, but also over what happens with resources earmarked for students in certain categories?

I build upon Chapter One's discussion to highlight two features of the disability category that may mean that resources are illegally diverted from other students to help cover disability services. First is variation between categories in the *perceived beneficiary* of the extra funding: the student or the school/district. Is the category framed in policy discussions as an *individual-level claim* to a larger share of resources or is the category meant as a *school or district-level* marker of disadvantage? Second is variation in the rights that parents can exercise to monitor whether students in the category are receiving a fair share of resources.

This framework suggests that when policymakers try to prioritize students in categories *other than* disability, resources may be diverted to the disability category. Yet studying this diversion is complicated; since the diversion is illegal, it may be difficult to track in school expenditure data. Therefore, the next part of the Chapter argues that one measure of *revealed* expenditures on students with disabilities is the number of parent complaints about disability services. Examining a one-time influx of federal funding to students with disabilities as part of the American Recovery and Reinvestment Act (ARRA), I show that extra resources cause fewer complaints. Then, using this revealed measure of expenditures on students with disabilities, I use a regression discontinuity design (RDD) with a new grant in California to study whether districts receiving extra money for categories *other than* disability diverted some of this extra funding to students with disabilities.

5.1.1 First difference between categories: who is the envisioned beneficiary?

Chapter One discussed the distribution of prioritized categories in state funding formulas. Disability is the most widely prioritized, with students who are English Language Learners (ELL) and Free or Reduced Price Lunch Eligible (FRPL) the next most prevalent categories in terms of giving districts with a larger share a resource boost from the state budget.

Yet despite their prevalence in increasing a district's share of the state budget, ELL and FRPL as categories have a more ambiguous envisioned beneficiary than the disability category. ELL students, after being identified through a combination of a home language survey and English proficiency test or teacher judgment, are entitled to services that enable them to "meaningfully participate in school programs and activities." Yet unlike an IEP, which provides each categorized student with an individualized contract for services, federal statutes and case law define language assistance as a form of schoolwide support. While the Department of Education guidance to districts for students with disabilities emphasizes appropriate, individualized IEPs, its guidance on ELL students instead emphasizes evidence-based curricula:

> LEAs should apply the same standards that OCR [Department of Education's Office for Civil Rights] and DOJ [Department of Justice] apply when evaluating whether their chosen EL services and programs meet civil rights requirements. These standards, established in *Castañeda v. Pickard*, include a three-pronged test: First, is the program based on an educational theory recognized as sound by some experts in the field or considered a legitimate experimental strategy? Second, are the programs and practices (including resources and personnel) reasonably calculated to implement this theory effectively? Third, does the program succeed in producing results indicating that students' language barriers are being overcome within a reasonable period of time? (Department of Education, 2016)

Thus, while individual students are placed in the ELL category, the envisioned beneficiary is less a specific student with an individualized right to extra resources; instead, it is a group of English Learners in the district who participate in a curriculum like English as a Second Language or Dual Language Immersion classes. Within the category, there is less

differentiation of what different students within the same category are owed.

The category of FRPL-eligible students lies even further in the direction of being framed as a group rather than individual-level beneficiary. Extra funding for students in poverty comes first from federal allocations to school districts under Title I, which is based on Census poverty data. Then, districts allocate money to specific schools on the basis of their FRPL-eligible student share, or another metric if the school has opted in to CEP and no longer assesses each student's FRPL eligibility individually. In addition to federal funds, state legislatures often give supplemental funding from the state budget to districts with higher poverty shares.

Focused on Title I funds, Gordon and Reber (2015) summarize the gap between the statute's goals and the reality of its implementation: "Congress intended for local districts to target their grants to their highest poverty schools and, within those schools, to direct services to the most educationally deprived children. From the start, it has proved challenging for the federal government to ensure that districts direct their Title I money solely to the program's intended beneficiaries"(p. 129).

As Gordon and Reber (2015) argue, the statute has fluctuated between two visions of the intended beneficiaries of a school's extra funding for higher shares of students in poverty. One vision is of a beneficiary similar to IEP students, or "categorical aid," where schools are supposed to spend money they receive for Title I on those students alone, and might do so through methods like "pull-out services" that give extra help to specific FRPL-eligible students.[76] Another vision is that the funds are meant to compensate schools for needier student populations, and that schools can use the additional funding for services that benefit both FRPL and non-FRPL students (Gordon and Reber, 2015).

These two visions of the intended beneficiaries of Title I funds are reflected in two "tracks" within Title I that schools can choose. Schools where at least 40 percent of the students are living in poverty can opt for "Schoolwide Program" of Title I services (SWP)—they have increased flexibility to use the money for services that benefit all stu-

[76]As they argue, this vision is expressed through provisions like the "supplement but not supplant" requirements where districts cannot use federal Title I money for expenditures that should have been covered by state and local funding sources.

dents regardless of their poverty status (Le Floch et al., 2018). About 75 percent of Title I schools use this option. The remaining use the more traditional "Targeted Assistance Program" (TAP) approach, where services are designed more directly for specific students in poverty (Le Floch et al., 2018). The presence of two programs—one that envisions students in poverty as direct beneficiaries of targeted resources; another that envisions *schools* with high poverty shares as needing to spend more on all students—may mean that state-level policies that try to promote more direct targeting falter.

5.1.2 Second difference between categories: do parents of beneficiaries have monitoring rights for their children?

The first difference between categories—the disability category's framing as a direct entitlement to resources; the framing of other categories blurring the line between individual students and entire schools as beneficiaries of extra help—paves the way for the second difference. Can a parent of a student in the category monitor whether extra funding is helping their specific child?

The previous Chapter highlighted the robust, if unequally utilized, monitoring system for parents of students with disabilities. Parents can argue that what their child was promised was insufficient. Hearing officers can remedy those wrongs by promising specific services to that child. The result is extra help for one student; any spillover effects on other students in the category, like district administrators providing more generous services to avoid other complaints, are inadvertent.

The ELL category comes with some rights for parents to monitor the services their children are owed. Yet those rights are largely limited to parents submitting complaints to the Department of Education's (DOE) Office for Civil Rights (OCR) or the Department of Justice's (DOJ) Educational Opportunities Section of the Civil Rights Division, asking either department to investigate a district for noncompliance via inadequate service provision or accommodations for ELLs. The burden of proof is much higher for these complaints than for complaints parents can file on behalf of children with disabilities–the investiga-

tion must conclude that there is a *district-wide* pattern of non-compliance as opposed to non-compliance for a particular student (Oyeleye, 2013)–and potentially as a result, these complaints are rare. Systematic data on the number of complaints are not available, but one article reports 475 complaints submitted nationwide regarding ELL issues between 2011 and January of 2015 (Brown, 2015), or an average of about 120 per year. In contrast, there are over 20,000 disability-related due process complaints yearly.[77] This stronger monitoring system is not a historical accident. Instead, it results from greater political successes of parents with children with disabilities than parents of children with needs like ELL to strengthen legal tools through measures like 1986's fee-shifting provision.[78]

While individual parents of ELL students can file complaints to federal agencies, with these complaints needing to show district-wide patterns of harm, individual parents of FRPL-eligible students have even weaker monitoring rights. As Gordon and Pasachoff (2018) outline, federal government audits play the primary role in ensuring that districts are using Title I funds appropriately. A parent who feels, for instance, that the school should have spend the funds on extended school day services rather than on teacher professional development (Dynarski and Kainz, 2015), has few formal channels to voice these concerns by virtue of their child's category.[79]

[77]About 9 percent of students nationwide are ELL, while about 14 percent of students nationwide receive an IEP. This difference is not enough to account for the nearly 150-fold higher count of IEP-related complaints.

[78]However, we see some retrenchment of this private enforcement regime with the 2004 IDEA amendments. Most notably, the amendments added a provision where parent's attorneys could be held liable for the district's attorney fees if the case is deemed "frivolous, unreasonable, or without foundation" or filed "for any improper purpose, such as to harass, to cause unnecessary delay, or to needlessly increase the cost of litigation"(*IDEA Sec. 300.517 Attorneys' Fees*. Though a detailed account of the political history behind these revisions remains to be written, reviewing the Congressional Record discussions around the provisions shows that some legislators were motivated by concerns from constituents about inappropriately high levels of litigation—e.g, Senator Charles Grassley, "I have heard from many Iowa educators that the Federal IDEA law is too litigious." Senator Edward Kennedy, a notable disability rights advocate, supported the fee provision, saying that "no one wants to see our courts abused by frivolous cases and everyone wants to see less IDEA litigation," but also argued that he could not "stand by and listen to a debate that unfairly characterizes the majority of parents and the majority of attorneys as eager to sue schools." Congressional Record Online, May 12, 2004, Pages S5349-S5351.

[79]Especially for schools that use direct certification rather than having parents individually certify free lunch eligibility, parents might have little awareness of the supplemental funding tied to the category and its allowable uses.

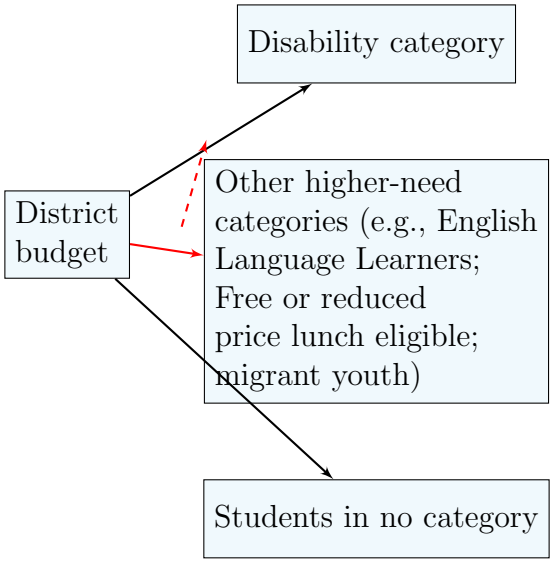
5.1.3 The potential for diversion

Chapter One showed how different categories in schools each correspond with ideas of humane justice (Jencks, 1988), or the idea that certain students need extra help to achieve similar outcomes. The previous sections showed how the categories, despite their common moral grounding, vary in two ways that create the potential for resources intended for non-disability categories to be diverted to cover the costs of providing extra help to students with disabilities. First, while IEPs have a clear beneficiary—the particular student whose IEP it is—students in other categories have no individualized contract for services. In addition, for FRPL students, the federal statute allows schools to spend the funds in ways that benefit the whole school. As a result, even when state-level policies encourage districts to target resources to non-disability categories, districts may struggle to say "no" to the potential beneficiaries in the disability category.

Second, when district administrators say "no" to parents of students with disabilities, parents have the ability to challenge the district's decisions. In contrast, when district administrators make choices that end up benefiting students with disabilities at the expense of students in other categories, the parents of those students have few rights to complain.

These two features may produce a "leaky pipeline" where resources intended for categories like ELL or FRPL-eligible students are diverted to students with disabilities (Figure 5.41).

Figure 5.41: A potential leaky pipeline of resource allocations



5.1.4 Measuring diversion

Diversion, like other forms of hidden rationing, is illegal. In the case I study below, districts that receive extra money for students in non-disability categories are meant to spend it on those students. Yet as others have noted (Gordon and Reber, 2015; Dynarski and Kainz, 2015), tracking how districts spend targeted funds is difficult for multiple reasons. First, line items in budgets are often insufficiently precise to tell what the money was used for. Second, in environments where districts and states fear audits finding evidence of misappropriated funds, districts may engage in "creative accounting" with their budget. For instance, many IEP disputes center on the gap between the minutes of service a student is promised in the IEP and what the student receives; the former is recorded in the school budget, while the latter is not.

These challenges have led to a limited body of academic research on diversion.[80] In one of the only studies of which I am aware, Conlin and Jalilevand (2015) study how revenue intended for general education students may get diverted to students with disabilities. They

[80]There is a larger literature on the broader topic of how grants meant to help certain categories of students get spent. This includes research on how federal, state, and local funding interactions, such as the finding in Gordon (2004) that local and state governments reduce their contributions to schools receiving federal Title I funds, which means that supplemental funding from one level of government can lead other levels of government to lower their financial support.

measure diversion by (1) using Michigan's monetary translation of IEP services into dollars (special education full time equivalent students—students with more intensive IEPs are closer to 1; students with less intensive IEPs are a fraction), and (2) comparing that amount to the amount of revenue specifically allocated for special education. The main drawback of this strategy is that it measures *formal promises* of services to students with disabilities; if IEPs overstate what students with disabilities are actually receiving, then the results are biased towards finding diversion.

The present Chapter thus expands the study of diversion in two ways. First, I use a measure of revealed expenditures that is less susceptible to districts' creative accounting of expenditures. Second, rather than focusing on diversion from "general education" students to students in the disability category, I study diversion from students in other categories that policymakers try to prioritize—in this case, categories reflecting poverty, language status, and foster care students—to students in the disability category.

5.2 Using complaints to study expenditures on students with disabilities

The previous Chapter showed that, among disability-related complaints that go to a hearing, some themes focus on resource decisions like reimbursing a special needs private school, providing ABA therapy for autism, or providing compensatory hours of education. Yet as I noted, complaints that go to a hearing are a selected subset of all that are filed, and they may be biased towards more resource-heavy issues if those are complaints that districts are least willing to settle. Another way to establish that complaints focus on resources, and thus that a drop in complaints likely illustrates that resources are reaching students with disabilities, is to show that the *quantity* of complaints drops when there is an exogenous increase to school resources for children with disabilities.

One such exogenous increase came as part of the stimulus package following the 2008 financial crisis. The American Recovery and Reinvestment Act (ARRA), signed into law

on February 17th, 2009, not only provided money to states to correct for state budget shortfalls that would affect education financing (the "state fiscal stablization funds"), but also resulted in a one-time doubling of the federal allocation to states for special education services. In particular, the previous year's federal allocation for disability services was $11 billion dollars, while ARRA allocated an additional $11.7 billion dollars to that existing funding.[81] Half of the funds were disbursed on April 1st, 2009; the other half of the ARRA funds were disbursed in September of 2009.

We can use this large exogenous increase in the money districts had available for disability services to investigate whether this sharp increase in resources led to decreases in parents of students with disabilities filing complaints against districts, with the data measuring filings and not just hearings. If we *do* observe decreases, it helps establish that increases in resources spent on students with disabilities cause decreases in complaints, which I use in the next section to study diversion.

All states and districts were treated by the ARRA funds, meaning I cannot use a difference-in-differences design to examine pre-ARRA versus post-ARRA trends in complaints. Instead, I use an interrupted time series design with state fixed effects to investigate whether there was a drop in complaints during the ARRA grant years (the 2008-2009 school year; the 2009-2010 school year) relative to non-ARRA years. Because time-varying confounders could cause this drop–for instance, a general drop in litigation during the ARRA years due to families struggling financially during the 2008 Recession–I test the robustness of these findings using the placebo outcome of trends in child-focused malpractice litigation.

5.2.1 Data

Dependent variable

The dependent variable is the count of disputes per 10,000 students receiving an IEP. There are two reasons why I measure disputes over *special education students* rather than *all students*. First is that there is significant variation between states in rates of special education

[81] More precisely, ARRA allocated $11.7 billion for IDEA Part B, which serves students aged 3-21. Additional funding was allocated to IDEA Part C, which serves younger children.

placement, so the variable as constructed is designed to pick up variations in disputes *net* of these placement differences. Second is that if we think of a rate as events over a count of those at risk of generating an event, most of the cases are generated by disputes among students *with* IEPs–with the dispute then focused on the content of those IEPs–making a count of those with IEPs the relevant risk pool for generating a case. However, I also test the robustness of the results to examining the rate of disputes over *all students* rather than students with an IEP.

Data for the numerator (count of disputes) are from the Department of Education's (DOE) Office of Special Education Programs (OSEP), available at this link: IDEA data products. Title 1, Part A, Subsection 618 of the IDEA mandates that states submit data on their count of disputes each year, and the present paper uses data from the IDEA Part B reporting, which covers children ages 3 to 21 in special education.[82] The variable is constructed as the sum of three counts: due process complaints, requests for mediation, and written signed complaints. There were no missing data for dispute counts. The denominator–the count of IEPs–comes from the Common Core of Data (CCD) count of all students having an IEP under Part B. Table 9.36 provides more details on data sources. Observations missing from the CCD data were filled in using the IDEA Section 618 child counts or by contacting state departments of education.

Break in complaints

The temporary change in the trend in complaints corresponds to the school years where ARRA grants were disbursed: the 2008/2009 school year (affecting complaints filed later in the academic year) and the 2009/2010 school year (affecting complaints that arise during the fall renewals/re-negotiations of IEPs).

[82]IDEA Part C, which covers early intervention services from birth to age 2, generates close to zero disputes.

Main covariate: financing formulas

The ARRA grants may have larger effects on complaints in some states than in others. And the main covariate is a state's special education financing formula. As discussed in Chapter Two, states fall into two categories: more generous weighting financing that gives extra money for each additional student with an IEP versus more restrictive block grant financing. In turn, we would predict larger drops in complaints during the ARRA stimulus years for states that employ block grant financing than weighting financing, since the former are more likely to have persistent shortfalls in *state* allocations to districts that prompt parent complaints about resource denials.

5.2.2 Results

Descriptive trends

Figure 5.42 shows the large resource boost during the ARRA funding.

Figure 5.42: **Increase in IDEA Part B funding from ARRA stimulus grant**

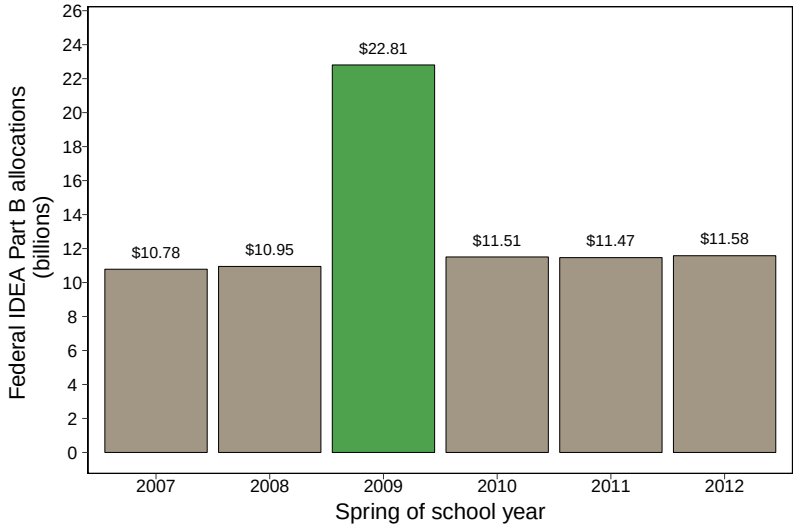
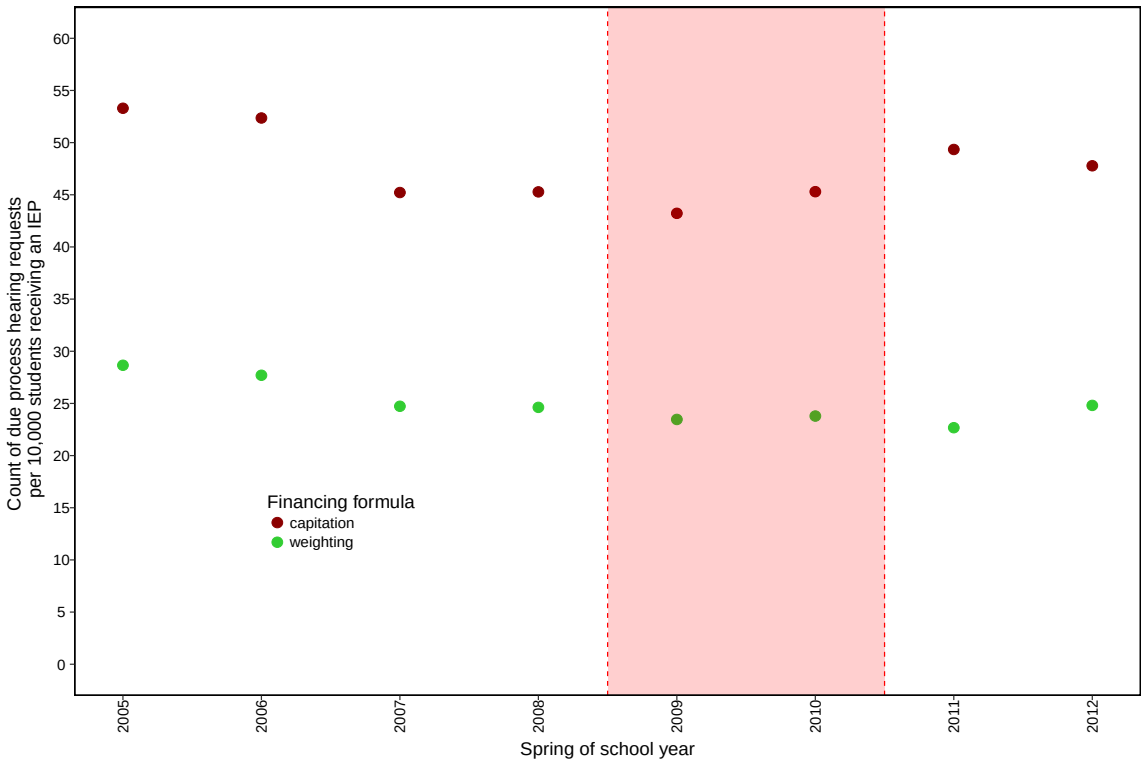


Figure 5.43 presents the trends in due process rates per 10,000 students receiving an IEP, presenting the mean rates by school year for the two types of states.[83] Two pat-

[83]The Figure restricts the sample to the 44 states with no changes in financing formulas during this period. The states that do change *are* included in the analytic models that follow.

terns stand out. First, states with the more restrictive block grant (capitation) financing for special education services tend to have higher rates of disputes throughout the entire period than states with the less restrictive weighting financing. However, there could be unobserved differences between the two types of states that cause both adoption of more restrictive financing of special education services and more disputes between parents and districts. Second, both sets of states appear to experience a drop in disputes during the two ARRA grant years (the 2008-2009 and 2009-2010 school years), with this drop potentially more pronounced in states with more restrictive capitation financing. Appendix Figure 9.76 and Figure 9.77 present the results separately by state, and show that much of the variation in dispute rates is between-state rather than within-state over time, highlighting the importance of state fixed effects in the subsequent section.

Figure 5.43: Trends in disputes associated with disability services



Analytic results

I estimate the following model. y_{it} represents the rate of disputes in state i in year t, α_i represents a state fixed effect that controls for time-invariant unobserved differences between states that affect disputes, and X_{it} contains a vector of controls by state and year that are plausibly correlated with how much the state benefits from the ARRA grant and dispute rates. In terms of which controls to include, the size of the ARRA stimulus grant to state i for special education followed the same formula that the federal government typically uses to allocate funds to states for special education:[84] the government allocates an amount equal to what the state received in fiscal year 1999, with any extra funds allocated based on the state's number of children in the age range for IDEA Part B (3-21), with a slight upward adjustment for the percentage of those children living in poverty. Therefore, I control for the percentage of a state's children living in poverty and also for the annual unemployment rate, which may reflect poverty not yet captured in the Census definition. The second set of controls is for factors that might lead to variation in the quality of services a school district provides and subsequent disputes. One variable examines, for each state, the share of overall education-directed revenue that comes from federal sources rather than state and local forces, since for states that rely on more federal revenue, the ARRA grant might have had a smaller effect on disputes. Another variable captures the expense-revenue ratio in the state's budget, which might affect a state's ability to continue to allocate towards education expenses during the recession.[85] Table 9.36 outlines data sources for this analysis and that of placebo outcomes.

$$\begin{aligned} y_{it} =& \beta_1 \times \text{ARRA year } (1 = \text{yes})_{it} + \beta_2 \times \text{weighting finance } (1 = \text{yes})_{it} + \\ & \beta_3 \times \text{ARRA year}_{it} \times \text{weighting finance}_{it} + \psi X_{it} + \alpha_i + \epsilon_{it} \end{aligned} \tag{5.3}$$

[84] More formally, IDEA Part B.

[85] For variables measured using calendar years rather than school years, the variable is matched to the fall of the school year. For instance, the unemployment rate in year 2004 is linked to disputes in the 2004-2005 school year.

The main coefficient of interest is β_1 (the effect of the ARRA grant on disputes between parents and districts), with the effect allowed to vary across financing regimes.

Table 5.6 presents the results. The results, which control for time-invariant unobserved features of states associated with disputes, suggest that the ARRA grant years were associated with statistically and substantively meaningful drops in disputes between parents and districts about IEPs. In particular, a move from a non-ARRA grant year (0) to an ARRA grant year (1) is associated with an average drop in disputes of 3.77 per 10,000 children with an IEP, which is roughly 12 percent of the average dispute rate of 30.4 disputes per 10,000 children with an IEP. The results also show an association between more generous state financing and lower levels of disputes, identified off of states that shift between financing regimes. Finally, the results are suggestive (but not statistically significant) of a positive interaction effect where states with more generous existing financing experienced a smaller drop in disputes during the ARRA years than states that use block grants to allocate to school districts.

Table 5.6: Effect of ARRA grant on disputes over special education

	β	
	(SE)	
	p	
ARRA grant year	-3.769	-3.08
(1 = yes)	(1.58)	(1.22)
	0.02	0.01
Weighting	-7.259	-7.846
financing	(2.68)	(2.85)
(1 = yes)	0.009	0.008
ARRA grant year (1 = yes) ×	2.005	1.998
weighting financing	(1.68)	(1.51)
(1 = yes)	0.23	0.19
Observations	400	400
(50 states × 8 years)		
State	Yes	Yes
fixed effects?		
Clustered	Yes	Yes
SE by		
state?		
Other controls?	No	Yes

Robustness check: defining disputes over all students rather than over students with an IEP

The results in Table 5.6 define the rate of disputes as the count of complaints over the count of students receiving IEPs:

$$\frac{\text{count disputes}_{it}}{\text{count IEP students}_{it}}$$

But districts that have extra resources as a result of the ARRA stimulus might use these funds in two ways.

First, and in line with Chapter Two's investigation, is to allocate more IEPs to students–in effect, giving more students the category of disability and associated rights. Second is that, conditional upon the same count of IEPs, districts may offer more generous services in those IEPs and face fewer disputes from parents.

We can capture these dynamics by looking at the count of disputes over *all students*, which is a function of both the disputes per IEP students and changes in the number of IEPs. We can then analyze this second type of dispute rate–disputes over all students–to make sure that the results above are not fully driven by the *same* count of disputes in the numerator but a higher *number* of IEPs in the denominator (leading to a lower rate).

$$\frac{\text{count disputes}_{it}}{\text{all students}_{it}} = \frac{\text{count disputes}_{it}}{\text{count IEP students}_{it}} \times \frac{\text{IEP students}_{it}}{\text{all students}_{it}}$$

Appendix Table 9.37 presents the results of the same model in Equation 1 applied to the different rate of the count of disputes over all students, which reflects both drops in disputes in the numerator and any increases in IEPs in the denominator. It shows that the ARRA grant led to significant decreases in disputes defined this way, though the weaker results suggest that some of the extra funding's impact came through its role in increasing the count of IEPs in addition to increasing the resources (and thus decreasing complaints) attached to each IEP.

Placebo test: patterns in child-focused malpractice claims

Since the federal government distributed ARRA funds to all states and distributed these funds at the same time, there is no control group of states untreated (or treated at a different time) by the ARRA grant. This lack of control group leads to concerns about time-varying confounding. In particular, there could be unobserved factors occurring during the stimulus years that result in fewer disputes between parents and districts independent of the stimulus funds. If so, this weakens the claim that the drop in cases we observe in the ARRA grant years is caused by the grant itself and weakens our ability to use these patterns to show that disputes tied to the tag of disability status are often about school resources.

One type of time-varying confounder are dynamics during the Great Recession that cause fewer disputes in general between families and professionals who serve their children. For instance, families facing negative income shocks and unemployment during the Recession may have had fewer monetary and time resources to devote to litigation in general. I investigate whether this form of confounding might be present by re-estimating the model depicted in Equation 1 with a placebo outcome of rates of child-focused malpractice litigation.

I constructed this rate as follows. First, using data from the National Practitioner's Database (NPDB) of malpractice claims, we filtered the claims to those filed on behalf of children (all claims where the patient age is 19 or under) and estimated the count per state and year.[86] Then, I constructed a rate of child-focused claims per 10,000 children using ACS data on the child population size under 18 in each state.

We hope to see two patterns in this placebo outcomes analysis. First, Figure 5.43 showed the descriptive pattern of more disputes in states where financing for special education from state sources is more scarce (capitation states). These differences could be related to unobserved features of a state or its parents associated with both the adoption of more restrictive financing regimes and the likelihood that parents dispute decisions by professionals. If child-focused malpractice claims show few patterns by special education financing regime, this supports this interpretation. Appendix Figure 9.78 presents the trends in child-focused malpractice claims by state and year. It shows no clear pattern where states with more restrictive financing for *special education services* have different malpractice claims rates.

Second, the figure also suggests that the ARRA stimulus years that *were* marked by drops in disputes over special education services *were not* marked by drops in child-focused malpractice disputes. Examining this more formally, Appendix Table 9.38 presents the results of the same model depicted in Equation 1 and Table 5.6, but where the outcome variable is the placebo outcome of the rate of child-focused malpractice claims. The re-

[86]Rather than giving a continuous value for age, NPDB classifies age in buckets and the final bucket is those aged 10-19.

sults show no significant effect of the ARRA grant in decreasing malpractice claims against professionals. This begins to help rule out the possibility that one form of confounding–a general drop in legal claims during the Recession years coinciding with the ARRA stimulus funds–biases the results from the previous section.

5.3 Is there diversion of funds meant for other categories to students in the disability category?

The previous section showed that increases in resources for students with disabilities prompt fewer complaints from parents; this suggests that, rather than using school expenditure data, we can study drops in complaints as a revealed measure of resource allocations. The present analysis uses this measure to investigate potential diversion of resources for students in other categories to students with disabilities.

5.3.1 Data and methods

Dependent variable

The data for district-level counts of disputes comes from California's Office of Administrative Hearings (OAH)'s Special Education Division. California was chosen for two reasons. First, the state experienced a reform to school financing that involved a sharp administrative threshold that allows us to disentangle the effect of district resources from the effect of district demographics. Second, similar to the filings data used in Chapter Four, California publishes counts of all *requests* for hearings by district regardless of whether they go to trial, which overcomes selection issues in which requests go to trial versus end in settlements.[87]

The analysis draws upon a count of all due process hearing requests by district, which were extracted using macros from Attachment B of the Special Education Quarterly Re-

[87]Unfortunately, these data are not available for most recent years so Chapter Four still uses an open records request to try to obtain for California.

ports.[88] These counts are the primary dependent variable. For shorthand, I refer to this outcome as a "case" even though it represents a filing ratehr than a hearing.

Predictor variables

The main predictor variable—whether a district was eligible for an extra boost in state resources, and how far a district was from the eligibility threshold–is described below. Other district-level predictor variables, used for controls and sensitivity checks, are outlined in Appendix Table 9.39.

5.3.2 Analytic strategy

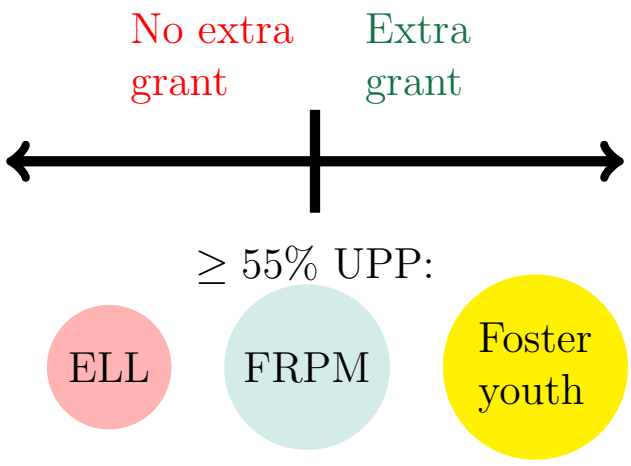
To isolate the effect of a resource boost intended for students *in categories other than* special education, I take advantage of a reform of the financing system in California that introduced an administrative threshold for allocating additional resources to districts. In particular, I use a sharp regression discontinuity design (RDD) where the running variable is a district's *unduplicated pupil percentage* (UPP). The UPP is composed of the percentage of a district's students falling into at least one of the following categories of need, categories that *do not* include special education students: 1) English Language Learner (ELL); 2) *eligible* for Free or Reduced Price Meals (FRPM) based on family income; or 3) in the foster care system (confirmed via administrative database).[89]

The UPP is used by the state of California to determine whether a district receives or does not receive an extra boost of state aid called a *concentration grant*. This extra boost of state aid was delivered in the context of a broader overhaul of the way that California distributes money to school districts, the Local Control Funding Formula (LCFF), which went into effect beginning in the 2013-2014 school year. LCFF created three grants for the

[88]http://www.dgs.ca.gov/oah/SpecialEducation/Resources/SEReportArchive.aspx. California's hearing system is constructed so that when parents file a request for a due process hearing, the parents also must agree to mediation before a scheduled hearing; if a settlement is not reached at the mediation, the case proceeds directly to the hearing stage.

[89]The unduplicated refers to the fact that students who qualify under multiple categories–e.g., an English Language Learner who also qualifies for free or reduced price lunch-only counts once towards a district's UPP, such that the UPP is constrained to fall between 0 and 1.

Figure 5.44: **Unduplicated pupil percentages and LCFF concentration grant funding**



distribution of state aid to districts, and the last grant involves a discontinuity in the UPP (**?**):

1. Base grant: all districts receive based on Average Daily Attendance (ADA), with some adjustment based on grades served by district

2. Supplemental grant: all districts with non-zero UPP receive base grant x 0.20 x ADA x district's UPP

3. **Concentration grant**: at or above a threshold of 55 percent UPP, district receives grant equal to base grant x 0.50 x ADA x district's UPP

The last category of grants, *concentration grants*, are disbursed according to a sharp threshold at 55 percent UPP for which districts receive versus do not receive this grant. For instance, a district with a UPP of 58 percent receives a concentration grant where a district with a UPP of 52 percent does not. Around this threshold is a subset of districts with similar observed characteristics that might affect the likelihood of a case. Districts to the right of the threshold receive a grant that explicitly earmarks resources for students other than those in special education, while districts to the left of the threshold do not receive a grant. Figure **??** is a stylized diagram of the relationship between district UPP and the concentration grants.

In the present context, we are interested in the following, where Y is the rate of litigation, X is the unduplicated pupil percentage, i indexes a district, $Y(1)$ indicates the outcome under receipt of the treatment (a concentration grant), while $Y(0)$ indicates the outcome under no receipt (no concentration grant):

$$Y_i = \begin{cases} Y_i(0) & \text{if } X_i < 55\% \\ Y_i(1) & \text{if } X_i \geq 55\% \end{cases} \tag{5.4}$$

Since the average treatment effect of the grant for districts around the threshold is identified by examining the difference in enforcement rates for districts in this subset around the threshold, a major decision in the RDD analysis is how large that subset of districts should be (the bandwidth around the threshold). Rather than choosing a bandwidth *a priori*, I use the optimal bandwidth selector proposed by Calonico et al. (2014) (CCT for short), implemented in R using *rdrobust*. More specifically, the bandwidth selector fits separate local linear regressions on either side of the threshold ($<$ 55% UPP for no grant; $\geq$ 55% UPP for grant) that assign smaller weights to districts further from the threshold but still within the bandwidth. CCT use a triangular kernel estimator for this local linear regression, that takes the following form, where $|u| \leq 1$ indicates that a district falls within the bandwidth around the threshold:

$$K(u) = \begin{cases} 1 - |u| & \text{if } |u| \leq 1 \\ 0 & \text{if } |u| > 1 \end{cases} \tag{5.5}$$

The bandwidth is then selected via iterating through different bandwidth choices and then selecting a bandwidth that minimizes the approximated mean squared error around the threshold. The standard error adjusts for bias created by this smoothing (CCT's robust bias-corrected confidence intervals).

Two features of a district are important for fitting the sharp RDD: its unduplicated pupil percentage, which influences whether a district is above or below the concentration grant threshold, as well as its distance from the threshold, and whether the district *did*

indeed receive a concentration grant, which affects whether we can analyze receipt of the concentration grant as a deterministic function of a district's UPP or whether the UPP only increases the probability that a district will receive the concentration grant treatment. The data source used for this analysis–California's LCFF funding snapshot data for fiscal year 2013-2014–reports the precise unduplicated pupil percentage and concentration grant status/amount for all districts. All analyses focus on the 2013-2014 school year, the first year of the concentration grant's implementation, using data on the same districts from the 2012-2013 to control for pre=concentration grant trends.

Finally, concentration grants are important because state aid is an important source for per-pupil expenditures in California districts. Though data on the percentage of per-pupil expenditures financed by state revenue sources *during* the concentration grant year are not available, data from the previous school year show that the mean state contribution to per-pupil expenditures is 48.4 percent of expenditures, while the local contribution averaged 42.4 percent and the federal contribution averaged 9.2 percent. This highlights that state aid, and by extension concentration grants, are an important component of how districts allocate resources between students.

5.3.3 Results

Sample used for regression discontinuity

For the analytic sample, we first exclude 81 districts with zero IEPs in the 2013-2014 school year (all of which had zero cases). The RDD makes two further restrictions on the sample of districts used for the analysis. First, California has a non-negligible number of administrative units classified as school districts that are only composed of charter schools. These charter districts are present in the case data, but there is not systematic data available on those districts' count of students with an IEP. Since this variable is important for ruling out the possibility that a drop in cases after concentration grant receipt stems from a drop in IEPs that might generate a case rather than a drop in cases, these charter districts were excluded, as were any districts that were missing a count of IEPs for the 2012-2013 school

year (the year before the concentration grant) or the 2013-2014 school year. Second, the RDD design does not generally use covariates, and a district's likelihood of having any case and its count of cases is heavily influenced by the count of IEPs (a count controlled for in the random effects model). In addition, even after excluding districts with zero IEPs, there is significant heterogeneity in what counts as a school district within California, its size, and the resulting count of IEPs. Appendix Figure 9.79 highlights the count of districts associated with each IEP. The range once districts with zero IEPs are excluded includes nine districts with one student with an IEP (e.g., Coffee Creek Elementary District, a district with average daily attendance of 58 students located in a rural northern county close to the Oregon border) to Los Angeles Unified School District, which had over 81,000 students with an IEP in the 2013-2014 school year. Third, there are many districts with zero cases, which creates difficulty in creating this rate since it means something different for a district with 400 students with an IEP to have zero cases than for a district with 4 students with an IEP to have zero cases.

The significant heterogeneity between districts in size and IEP counts generates a relationship where. above a certain count of IEPs, a district always has at least one case. More formally, we can fit the following logistic regression:

$$log(\frac{P(case)}{1-P(case)}) = \alpha + \beta * IEP\ count_i \tag{5.6}$$

Appendix Figure 9.80 shows that districts above a certain IEP count always have a case, while if we restrict districts to those below a certain IEP count, the curve better resembles a logistic distribution. This would not pose problems for the RDD if the count of IEPs was equivalent for districts above versus below the threshold within a range, but the fact that the unduplicated pupil percentage is based on categories like ELL or being in foster care that are rarer among students means that larger districts are at higher risk of being above the threshold and of also having a higher count of IEPs that generate the cases. Therefore, the second restriction limits the analytic sample to districts whose IEPs are in the range of a medium to high probability of generating any case ($0.4 \leq Prob < 0.9999$), which results

in the exclusion of 403 districts. In sensitivity checks, we iterate through different sample restrictions to highlight the range of windows for which the results are valid, and these iterations will include some of the 403 districts excluded based on the IEP threshold.

In sum, these exclusions result in an analytic sample of 221 districts in this middle range of predicted case probabilities based on size that are listed in Appendix Table 9.81. These include a mix of elementary school districts and unified school districts.

Sharp or fuzzy RDD?

The following table shows the percentage of districts receiving a concentration grant in the full sample of districts with a non-zero IEP count in the 2012-2013 and 2013-2014 school years and the average distance from the threshold, showing a similar distance on either side:

	No concentration grant	Concentration grant
Unduplicated pupil percentage $\geq$ 55%	0%	100%
Distance from threshold	-0.22	0.23

The table highlights that we can treat a district's unduplicated pupil percentage as fully determining whether or not the district receives a concentration grant (sharp RDD).

RDD results

Unobserved characteristics of districts–for instance, the density of legal advocacy organizations in a local area–may be an important factor behind cases. This suggests that in addition to a standard RDD that looks at an outcome in a given year, we can improve the RDD by exploiting the fact that we not only observe enforcement activity in districts in the school year *of* the concentration grant, but also enforcement activity in districts in the school year prior to the grant. If unobserved characteristics of a district remain relatively constant across these school years, we can focus on *within-district* estimates that examine how enforcement activity in a district changes *relative to itself* in the year prior to the grant. In particular, when examining the binary outcome of whether a district had a case,

there are four combinations, with the ones of interest highlighted in red:

		2012-2013 school year (before grant)	
		No case	Yes case
2013-2014 school year (after grant)	No case	Case neither year	No case before grant but case after
	Yes case	Case before grant but no case after	Case both years

The RDD examines four outcomes outlined in Table 5.7. The *leaky pipeline* hypothesis predicts that the resources from the concentration grant, instead of solely reaching their intended recipients in categories like ELL and foster youth, may "leak out" to reach students in the disability category. If this diversion occurs, then the extra resources may *decrease* complaints aimed at securing resources for special education students. Table 5.7 shows predictions under the *leaky pipeline* hypothesis. The table shows that two of the three *within-district* measures are statistically significant at the $p < 0.05$ level. Districts that *did not* have a complaint in the year prior to a grant are *less* likely to newly have a complaint if they receive a concentration grant. Districts that had at least one complaint in the year prior to the grant have *fewer* complaints the year the districts received the grant. The signs on the other two coefficients are also consistent with the leaky pipeline hypothesis.

Importantly, the results also rule out the idea that this lower likelihood of having a complaint and lower count of complaints in the concentration grant districts is due to a lower number of students placed in the disability category: there is no difference between districts receiving a grant and those not receiving a grant in whether there's a drop in IEPs. Important to remember is that the RDD estimates are valid for districts around the concentration grant threshold, and thus should not be generalized to districts with low unduplicated pupil percentages (the wealthiest school districts) or high unduplicated pupil percentages (the poorest school districts). Figure 5.45 presents a visual depiction.

Figure 5.45: **Visual depiction of RDD results: reduction in complaints.** The figure uses the plotting method in `rdrobust`. Each dot represents a binned group of districts that dinstance from the threshold. The figure shows a jump up near the threshold where districts receiving the grant are more likely to have *fewer complaints* than in the previous SY.

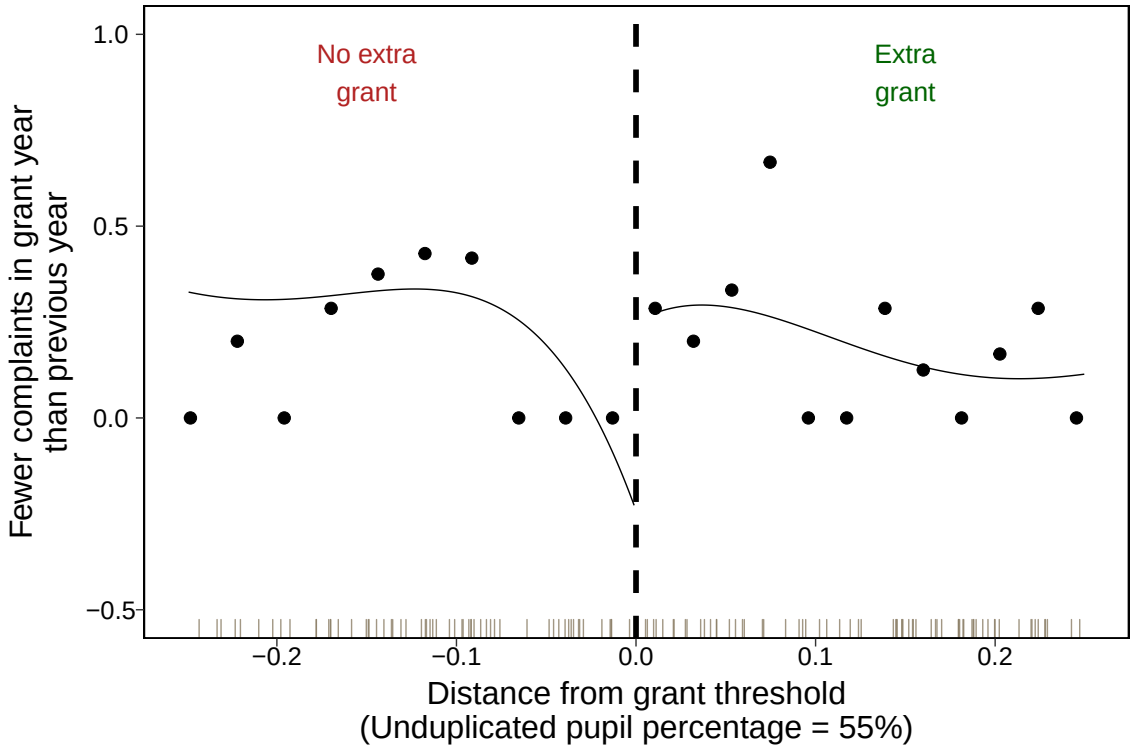


Table 5.7: RDD results

Within-district measures	Prediction	RD estimate	Std. error	P-value	Bandwidth
No complaint year before grant; complaint after grant (1 = yes; 0 = no)	-	-0.71	0.35	p = 0.04*	0.09
Complaint year before grant; no complaint after grant (1 = yes; 0 = no)	+	0.076	0.06	p = 0.21	0.18
For districts with > 0 complaint in prev. year, drop in complaints (1 = yes; 0 = no)	+	0.47	0.23	p = 0.04*	0.12
Between-district measure					
Any complaint (1 = yes; 0 = no)	-	-0.13	0.11	p = 0.25	0.13
Check for alternate mechanisms					
Lower % of IEPs in grant year than previous year (1 = yes; 0 = no)	No effect	0.17	0.31	p = 0.56	0.17

5.3.4 Robustness checks

To investigate the robustness of the present results, I perform the following robustness checks.

Sorting around threshold

The main identifying assumption behind RDD is that units cannot manipulate their position around the threshold–in this case, districts near the cutoff of 55% UPP for the concentration grant cannot manipulate their student characteristics in ways that help the district cross the 55% threshold. We examine this assumption in three ways.

First is via a visual inspection of the distribution of unduplicated pupil percentages in the analytic sample of 221 districts. Figure 9.82 highlights the distribution of percentages across districts, and also focuses on the distribution around the threshold. While there are peaks at 56 and 57%, there are also peaks at 46 and 50-51%; the visual inspection does not provide clear evidence of sorting. Second, we can perform a statistical test that checks for discontinuities in the density of observations around the threshold. In particular, I use a sorting test developed by (**?**). The test is useful for the case where the manipulation around the threshold is *monotonic*–that is, districts either all want to have UPPs above the threshold or districts all want UPPs below the threshold, rather than some districts wanting to be above and other districts wanting to be below the threshold. Since it is most plausible in this case that districts want to monotonically manipulate their percentages to be *above* the concentration grant threshold, the failure to reject the null of no discontinuity is useful in this case. The test fits a local polynomial on either side of the threshold, and then tests the null hypothesis that the limit of the probability density function is the same as you approach the threshold from either side ($lim_{x^+} f(x) = lim_{x^-} f(x)$), where x is the running variable (in this case, the unduplicated pupil percentage) versus the alternative hypothesis that densities are not equal ($lim_{x^+} f(x) \neq lim_{x^-} f(x)$). The McCrary test examines the logged difference between this right and left limits to construct the test statistic ($\hat{\theta} = ln(\hat{f}^+) - ln(\hat{f}^-)$). As a result, failing to reject the null illustrates continuity in the UPP; rejecting the null highlights a discontinuity. With a 10 percent bandwidth, the test yields: $Z = 0.496, p = 0.62$, a failure to reject the null that lends more evidence to the absence of a discontinuity in the threshold in a district's UPP, lending greater weight to the idea that districts did not successfully manipulate their percentages to qualify for a grant.

Third, we can exploit the fact that we observe two "ingredients" for the UPP—a dis-

trict's percentage of students eligible for free or reduced price lunch and a district's percentage of Limited English Proficiency (LEP) students–in two years: the year *directly prior* to the concentration grant receipt and the year *of the* concentration grant receipt, allowing us to investigate whether districts that received a grant seemed to experience greater increases in these categories of need than districts that did not receive a grant.[90] Figure 5.46 shows the distribution of changes in two characteristics used to determine whether a district is eligible for a grant—FRPL and ELL—between districts that did versus did not receive a concentration grant and are within the 10 percent bandwith. A Kolmogorov-Smirnov (K-S) test then tests the null hypothesis that the concentration grant spread of changes and the no concentration grant spread of changes was drawn from the same distribution. In particular, if districts manipulated these percentages to be *over* the threshold, we might expect that for the concentration grant districts, the distribution of change in limited english proficiency (LEP) and free or reduced price lunch students is shifted rightwards compared to the districts that just missed qualifying for a grant.

Figure 5.46 shows the density of changes in the concentration grant districts versus no grant districts near the threshold. For each, the K-S test supports the null of no difference in the distributions, but the change in students classified as having limited english proficiency is closer to failing to reject the null ($p = 0.12$) than the change in FRPL percentage ($p = 0.51$). As I discuss in the Conclusion, this could reflect the fact that districts may have more discretion around who qualifies for ELL than who is free lunch eligible.

Applicability of treatment to districts with different risk pools

Earlier, I discussed how the analytic sample is restricted to districts with roughly similar probabilities of generating a case based on the mechanical relationship between a higher count of IEPs and a higher probability of generating a case. To test the robustness of the results to the lower threshold used for the IEP count, I iterate from a lower IEP threshold of 10 IEPs to a lower threshold of 1000 IEPs in increments of five to show the range of sizes

[90]English Language Learner (ELL) and Limited English Proficiency (LEP) are used interchangeably; here, I refer to these students as LEP because that is the designation provided by the Common Core Data

for which the treatment estimate is most valid for the two significant outcomes: the positive coefficient on the same district having fewer cases in the year of the grant than the year before the grant and the negative coefficient on a district without a case in the year before the grant getting a new case in the year of the concentration grant. Figure 5.47 shows the range of IEP lower thresholds for which the results are most robust. The coefficients are all in the same direction regardless of the threshold—that is, they show that districts that receive a concentration grant have a lower likelihood of a new case and a higher likelihood of fewer cases–but the figures also show that each treatment effect is strongest for districts with at least 200 IEPs (which corresponds to districts with at least 1650 total students in the district).

Placebo test of RDD

Another way to examine the robustness of the results is to: 1) randomly draw placebo thresholds from a uniform distribution of possible thresholds;[91] 2) re-estimate the regression discontinuity, and 3) examine the distribution of treatment effects identified in the discontinuity, which should peak at zero given that there was no actual discontinuity in state grants at those placebo thresholds. Again focusing on the two significant results–whether there is a new case in districts that did not have a case in the previous year and whether there is a drop in cases–Figure 5.48 shows the results. The figures confirm that the treatment effect peaks at zero for these randomly-drawn thresholds, lending weight to the fact that the threshold used to grant or withhold districts extra resources for students *not in* special education has a valid effect on litigation against those districts.

[91] In this case, potential thresholds are from 0 to 1, but the test was conducted between 0.1 and 0.9 to have sufficient data points to estimate the RDD

Figure 5.46: Distribution of changes in Limited English Proficiency and FRPL percentages: 10 percent bandwidth, districts with and without concentration grant

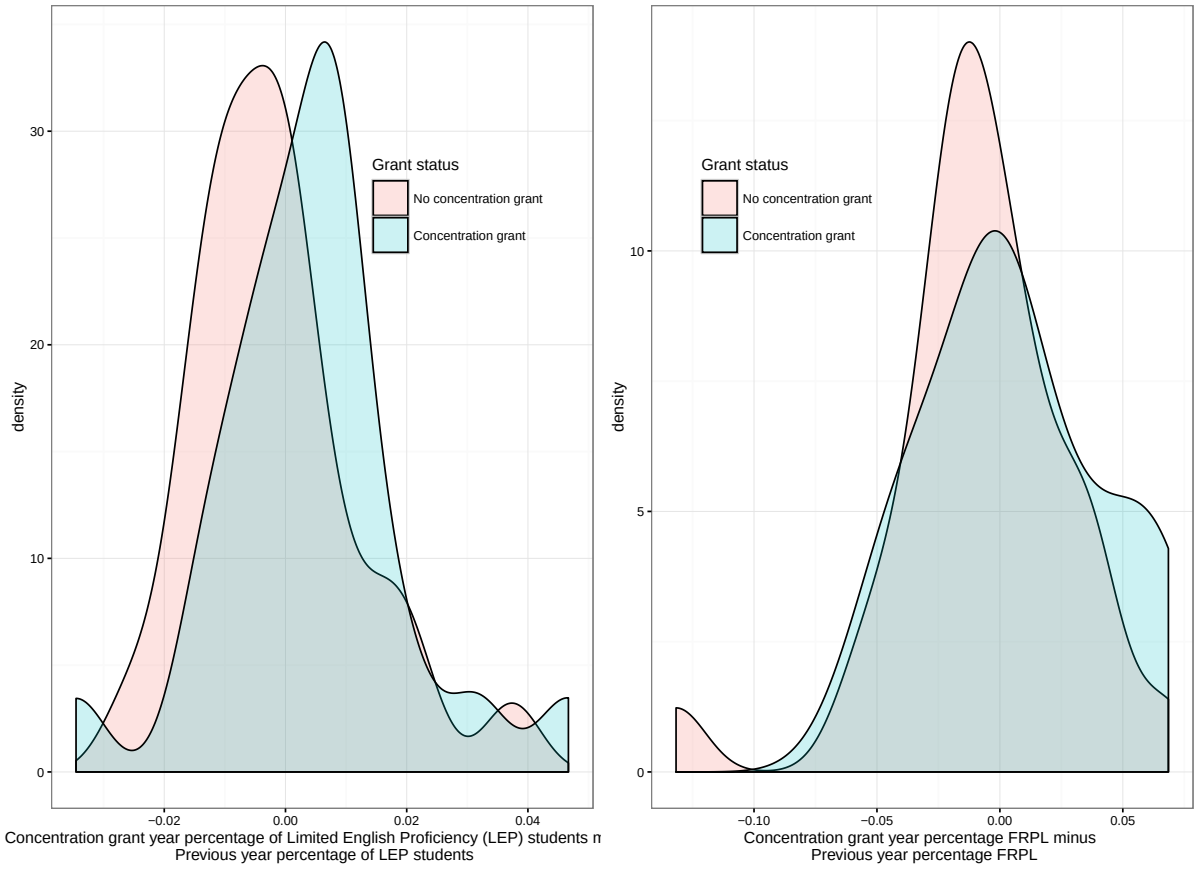


Figure 5.47: Treatment effects across range of lower thresholds for count of IEPs. *Red dashed line* indicates the treatment results presented

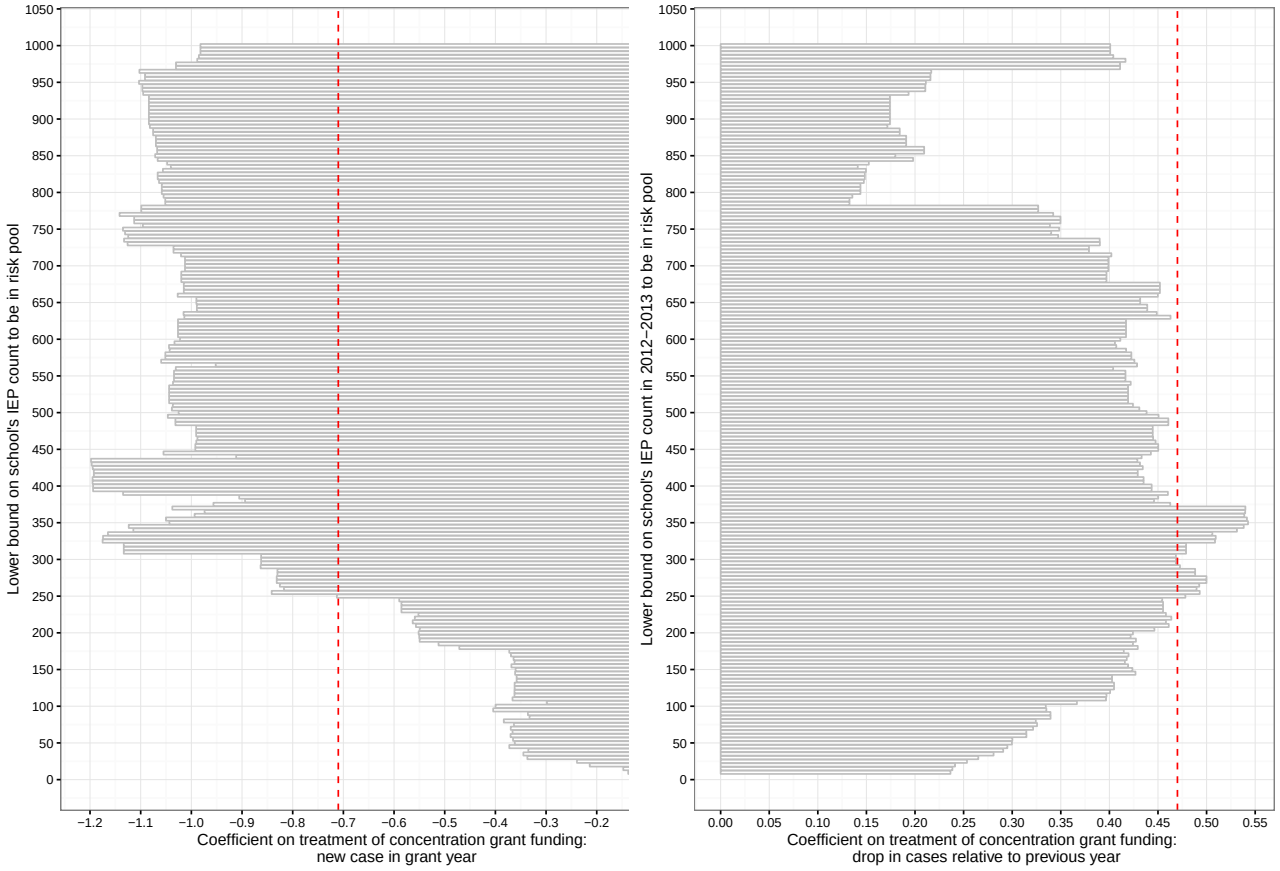
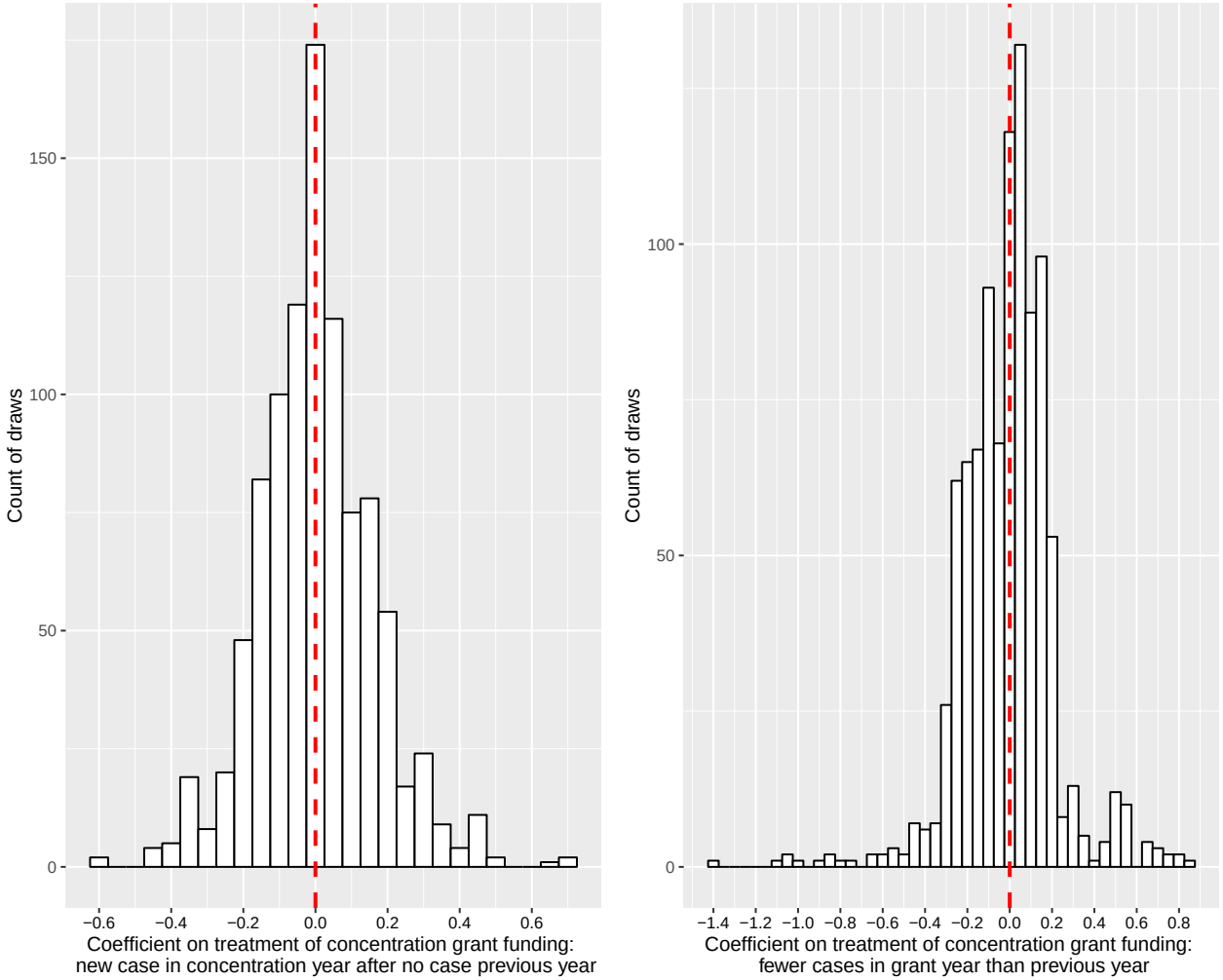


Figure 5.48: Placebo draws of thresholds: distribution of coefficients (red dashed line shows that it should peak at zero)



5.4 Conclusion

The previous Chapters showed that there are inequalities in parent monitoring of districts' disability-related decisions and that these inequalities may leave students with disabilities vulnerable to rationing when there is budget pressure. While one policy solution is to equalize access to monitoring *within* the disability category, this may have spillover effects on other students. Most worrisome for inequality is if resources are diverted from students in other categories reflecting need to the category of disability.

After outlining a framework for why we might see diversion from other categories—the categories have a less clear intended beneficiary than the disability category; parents of students in the category have weaker rights to monitor resource flows—I presented two sets of results. First, I showed that resource boosts to students in the disability category lead to reductions in complaints. Second, I showed that resources that California policymakers intended for non-disability categories reduced complaints about disability services, indicating potential diversion. Here, I outline limitations and future research.

5.4.1 Limitations and future research

Student membership in multiple categories

The analysis suggests that some of the resource boosts that districts receive from the grant is being used to provide disability services. This general finding could stem from a mix of two types of diversion. One form of diversion is between students exclusively in those categories—e.g., an ELL student not receiving an IEP—to students solely in the disability category. A second form of diversion comes from the fact that the same student can have multiple needs—a student living in poverty or an ELL student may also have an IEP. While the grant is supposed to address needs that arise by virtue of their targeted categories, rather than to address services in their IEP, this within-student diversion has fewer implications for inequality.

Unfortunately, we do not have district-level data on what percentage of the unduplicated pupils are also receiving IEPs. However, the grant was clear in urging districts to use the

extra funds to address category-related needs. Districts needed to fill out a Local Control Accountability Plan (LCAP) that outlined how they would spend the extra money on services to address barriers they face as the result of category challenges. However a 2019 state audit of the grant program argued that the LCAP plans were too broad to serve the intended monitoring function:

> Moreover, even when districts did report supplemental and concentration funds in their LCAPs, we had difficulty determining whether or how the districts' use of those funds increased or improved services for intended student groups—a difficulty that stakeholders likely share. One challenge is that the current requirement districts must meet for spending supplemental and concentration funds to benefit intended student groups is essentially meaningless. Specifically, a district must describe in its LCAP how it will increase or improve services for those students in proportion to the amount of supplemental and concentration funds it receives. However, it is unclear how a district would demonstrate that it increased or improved services by a proportion, and neither county offices of education nor the California Department of Education are responsible for verifying whether districts actually met the required proportional increases. Another problem is that the legal requirements for county offices of education to approve districts' LCAPs, such as ensuring that they adhere to the State's LCAP template, are insufficient to ensure that those LCAPs are clear and effective (California State Auditor, 2019).

Since districts are required to post plans publicly, future research could analyze the plans to examine whether the services that the districts outline suggest either between or within-student diversion.

Sample size and power

Within the optimal bandwidths of plus or minus 10-15 percentage points from the threshold, there were 129-142 districts. This reduces our statistical power to detect effects. In our case, however, we were able to improve the power by reducing the variance in the outcome variables through using within-district measures of changes in complaints. Since the LCFF has now been in operation for five school years, future research could use approaches that pool RDD estimates over multiple time periods to improve the statistical power of the analysis.

Supplementary Materials: Chapter Two

Legislative confirmation of year of formula switch

The primary source for financing formula data is a survey conducted to measure financing formulas in the 1999/2000 school year and then again in 2008/2009 school year as part of a cooperative agreement between the Department of Education and the National Association of State Directors of Special Education (NASDSE) Project Forum. The methodology is outlined in Parrish et al. (2003) for the survey of 1999-2000 financing formulas and in Ahearn (2010) for the survey of 2008/2009 financing formulas. The 1999-2000 survey asked each state to provide its formula and the researchers conducting the survey then classified the formulas into the categories outlined in Table 1. The later survey sent state staff a copy of the formula the state had provided in the earlier survey and asked the respondent to indicate whether the state had changed its formula. If a change was indicated, the state was asked to describe the new formula. All states but four (Georgia, New Hampshire, South Carolina, and South Dakota) provided updated formulas for the 1999/2000 survey. For these four states, Parrish (2003) retains the funding formula reported in the 1994/1995 survey. All 50 states provided current formulas for the 2008/2009 survey.

These surveys reliably indicate the following information: 1) a state's formula in the 1999/2000 school year; 2) a state's formula in the 2008/2009 school year; 3) which states switched formulas between these time points. The qualitative descriptions of new formulas reported in Ahearn (2010) sometimes indicate the school year in which the new formula was

implemented. Since this information was inconsistently collected in Ahearn, for all states that switched between the broad block grants and weighting categories, below I outline my independent confirmation of the school year in which the new financing formula was implemented.

Weighting to block grants: New Jersey, West Virginia, and Missouri

New Jersey's Department of Education commissioned and has posted on its official website a program evaluation of its special education reform that confirms implementation began in the 2008/2009 school year (Augenblick, Palaich and Associates, 2011). The text of the New Jersey Bill (The School Funding Reform Act of 2008) also confirms this year of implementation.[92] The finance formula for West Virginia reported in the Ahearn (2010) survey specifies that the switch to no separate special education funding began in the 2008/2009 school year. In addition, information from the West Virginia legislatures confirms this year as the year of implementation of a change to the financing formula.[93] Missouri's Department of Education confirms that the state switched to no separate special education funding in the 2006/2007 school year (Missouri Department of Elementary and Secondary Education, 2014).

Block grants to weighting: Alaska, Colorado, Minnesota

Alaska's new implementation of a mixed funding formula classified within the weighting category began in the 2008/2009 school year. That date of switch is confirmed in the text of the bill Alaska passed–HB 273– where Section 4 amended Alaska's previous census formula to allow for upward adjustment based on the number of students needing intensive special education services a district reports serving.[94] This section went into effect in July 2008, thus affecting the 2008/2009 school year. For Colorado, the bill revising the funding

[92] http://www.njleg.state.nj.us/2006/Bills/AL07/260_.HTM

[93] http://wvde.state.wv.us/finance/files/Data/2011-12/State%20Aid%20(PSSP)/PSSP%2012%20Executive%20Summary%20-%20Final%20Comps.pdf

[94] http://www.legis.state.ak.us/PDF/25/Bills/HB0273Z.PDF

formula (HB06-1375) and related material from state legislative council staff indicate that the new special education funding formula went into effect in the 2005/2006 school year, the same year as the bill's passage.[95] Finally, for Minnesota, Ahearn (2010) and a report from the Minnesota state legislature,[96] each indicate that Minnesota adjusted its financing formula beginning in the fiscal year 2008 (school year 2007/2008) to reimburse districts for a percentage of their expenditures in the present year (percentage reimbursement) rather than to tie funding to a base year (block grant).

Fixed effects analyses of impact of block grants

In these analyses, I estimate the following model where the dependent variable measures the rate of special education placement in a given year t and state i:

$$Y_{i,t} = \beta \times blockgrants(1 = yes; 0 = no)_{it} + \gamma_t + \delta_i + \kappa X_{i,t} + \epsilon_{i,t} \tag{6.7}$$

The coefficient β represents the coefficient of interest–the mean special education rates that result from either a decrease in placement among states that switch *to* block grants or an increase in placement among states that switch *away from* block grants (so to weighting). γ_t represents year fixed effects that control for common shocks to placement rates across all states.

δ_i represents state fixed effects that control for time-invariant features of a state that might influence that state's special education placement rate. These state fixed effects also ensure that the model only estimates the effect of treatment from states shaded in red in Table 6.12 since states with block grants during the entire period under study or weighting during the entire period under study have no deviations in this variable. κ represents

[95] The bill text is here: `http://www.leg.state.co.us/clics2006a/csl.nsf/billcontainers/E2B24623C224397987257147007DC269/$FILE/1375_enr.pdf`. The related material clarifying that the bill's provisions regarding special education apply immediately to the 2005/2006 school year include a fiscal impact study (`http://www.leg.state.co.us/clics2006a/csl.nsf/billcontainers/E2B24623C224397987257147007DC269/$FILE/HB1375_r4.pdf`) and an issue brief (`https://www.colorado.gov/pacific/sites/default/files/06-12IssueBrief_SpecialEd.pdf`)

[96] `http://www.auditor.leg.state.mn.us/ped/pedrep/sped.pdf`

a vector of coefficients on a vector of time-varying control variables that could be either relevant to a state's passage of block grants versus weighting (party control of the state's legislature, unemployment rates that influence state revenue), relevant to a state's special education placement rate because they reflect measures of parent SES that may play a role in placement (percentage of children eligible for Free or Reduced Price Lunch, percentage of children living in a single parent household, also unemployment rate), or that reflect the potential for greater or less volatility in placement rates that is unrelated to financing formulas (the log of the state's total population, with smaller states exhibiting greater potential volatility). Because the outcome variable of special education placement rates are correlated within a state across time, and because the treatment–a legislative change in financing formulas–occurs at the state level, standard errors are clustered at the state level (Bertrand et al., 2004). This correlation is especially likely since although IEPs go through an "annual review" each year where services and progress are discussed and a new IEP is signed, there are likely many students in state i year $t-1$ who retain an IEP in year t in the same state, since the dependent variable measures a state's *stock of placement* rather than *newly placed students in special education* (a flow measure), since administrative data for the latter are not available.[97]

Table 6.13 presents results for the coefficient of interest. Tables 6.14 and 6.15 present the coefficients on the control variables, as well as show that the aggregate effects are driven by switches *to capitation* rather than switches to weighting financing, motivating the paper's focus on fiscal retrenchment.

[97]In addition to being a stock rather than a flow measure, while IEPs are signed on a yearly basis, the IDEA only requires that a child's eligibility be re-evaluated every three years ("Triennial review"), which parents and school districts can agree to waive if this agreement is documented in writing. As a result, the effects of a change in financing formula result from a mix of students graduating from special education eligibility (which ends at age 21) and not being fully replaced by new cohorts of students, and fewer students in "entering cohort" of special education placement. But these occur at the margins of placement and there remain a group of students who are likely to remain in special education for the duration of their school-age years after their initial placement. Thus, there might be larger effects of financing reforms if we were to look at the effect on *newly issued IEPs*, but the data do not permit us to distinguish between newly issued and existing IEPs in a given state and year.

Table 6.8: Special education state financing formula descriptions

Category	**Description**
Weighting	
Service and diagnosis linked	
Multiple pupil weighting	Each special education student is counted as a multiple of a general education student; higher multiples are assigned to disabilities or placement settings associated with higher costs
Service linked	
Single pupil weighting	Same as above but each special education student assigned the same weight
Resource based	Funding based on extra resources, mainly staff, devoted to special education students. Often based on set staff/student ratio
Percentage reimbursement	Districts reimbursed for some percentage of special education program expenditures
Combination of any of the above	
Block grants	
Census-based	Funding based on count of all students in district, often average daily membership, rather than count of special education students or resources
Block grant	Funding fixed to a base year or fixed percentage of special education students in the state
No separate special education funding	Special education funding distributed as part of general state aid to school districts with no separate weighting or reimbursement for special education

Table 6.9: Data sources for state-level analysis

Dependent variables: all by year/state from 2000 to 2011	
Percentage of students enrolled in special education	Numerator: NCES Common Core data on IDEA Part B (3-21) recipients; Data Accountability Center IDEA Part B child count data for state/year used for missing data from Common Core; Denominator: NCES total students in state enrolled in public school
Independent variables: all by year/state from 2000 to 2011	
Financing formula	Parrish et al. (2003) and Ahearn (2010) 50-state surveys of financing formula (conducted by partnership between Department of Ed. Office of Special Education Programs (OSEP) and National Association of State Directors of Special Education (NASDSE)
State unemployment rate	Bureau of Labor Statistics
Percentage of children eligible for free or reduced price lunch	NCES Common Core data
Percentage children living in single-parent households	American Community Survey (via Kids Count)
Party controls state legislature[98] (0 = Republicans control both chambers; 0.25 = Republicans control one chamber, other chamber evenly split; 0.5 = Republicans control one chamber, Dems control other chamber; 0.75 = Dems control one chamber, other chamber evenly split; 1 = Dems control both chambers	Klarner database[99]; table that follows shows how legislative sessions coded to school years

Table 6.10: Legislative sessions versus school years

Legislative session year	School year (fall-spring)
1999	1999-2000
2000	2000-2001
2001	2001-2002
2002	2002-2003
2003	2003-2004
2004	2004-2005
2005	2005-2006
2006	2006-2007
2007	2007-2008
2008	2008-2009
2009	2009-2010
2010	2010-2011

Figure 6.49: Correlation between predictor variables for state-level models (at midpoint year: 2005-2006 school year)

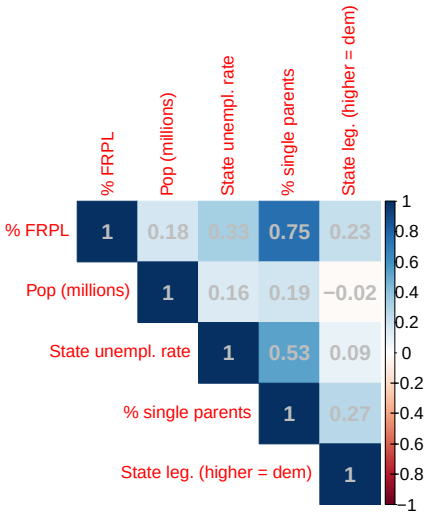


Table 6.11: Descriptive statistics: variables in state-year fixed effect models (all switches combined). Note this is the mean across all years so states values are counted multiple times. Means are *not* weighted by a state's population

Variable	N	Mean	St. Dev.	Min	Max
% students in special education	600	13.862	2.101	8.519	20.984
% students eligible FRPL	600	39.067	10.791	15.000	71.000
% children living in single parent household	600	31.123	5.202	17	48
Party control of state legislature (1 = dems control both; 0 = repub. control both)	600	0.517	0.442	0.000	1.000
Unemployment rate	600	5.767	2.113	2.200	14.400
Total population in millions (logged)	600	1.297	1.012	−0.705	3.629

Figure 6.50: For the states with no change in their financing formulas, the following figure illustrates the full distribution of placement rates. It shows that while block grant states had lower *average* rates, the formulas were certainly not fully determinative of rates, as we see some block grant states with high placement rates throughout the period (e.g., Massachusetts)

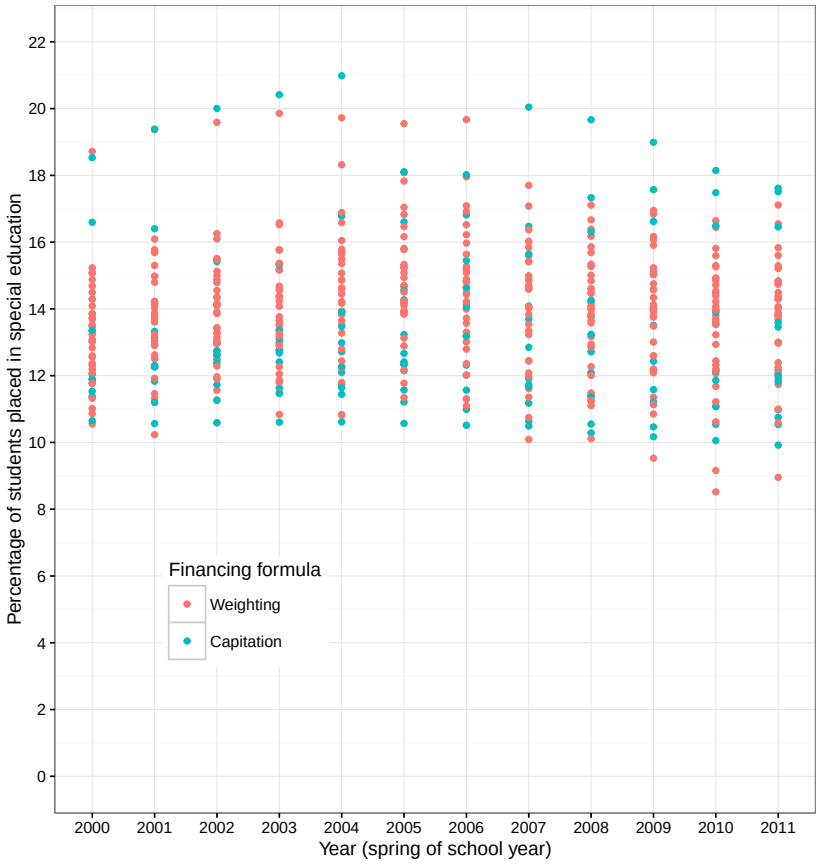


Table 6.12: Financing formula possibilities (red = treatment states)

red!10Switch from weighting red!10 to block grant	Block grant entire period
Weighting entire period	red!10Switch from block grant red!10 to weighting

Table 6.13: Fixed effects results: does placement change in the wake of financing changes?

	Dependent variable: Percentage of students placed in special education		
	(1)	(2)	(3)
Block grant (1 = yes; 0 = no; reflects switches in both directions)	−0.689***	−0.662**	
	(0.196)	(0.266)	
Switch from weighting to block grant (1 = yes; 0 = no; control states are weighting entire time)			−0.885**
			(0.290)
State fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
SE clustered by state	Yes	Yes	Yes
Controls included?	No	Yes	Yes
Observations (N states × 12 years)	600	600	420
Adjusted R^2	0.012	0.060	0.075
F Statistic	7.247***	6.414***	5.781***
	(df = 1; 538)	(df = 6; 533)	(df = 6; 368)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6.14: Full models: state and year fixed effect models of switch to or away from block grants

	Dependent variable: Percentage of students placed in special education	
Capitation	-0.689^{***}	-0.662^{**}
(1 = yes; 0 = no)	(0.196)	(0.266)
% Students		-0.032
eligible for FRPL		(0.025)
Unemployment rate		-0.019
		(0.082)
% children living		-0.010
in single-parent		(0.040)
households		
Party control of		0.629^{*}
state legislature		(0.354)
(1 = dems control both;		
0 = repub. control both)		
Logged population in		-5.773
millions		(3.653)
State fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
SE clustered by state	Yes	Yes
Observations	600	600
(50 states × 12 years)		
Adjusted R^2	0.012	0.060
F Statistic	7.247^{***} (df = 1; 538)	6.414^{***} (df = 6; 533)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.15: Full models: separating switch to block grants from switch away from block grants

	Dependent variable: Percentage students placed in special education	
	(Switch from weighting to block grants)	(Switch from block grants to weighting)
Switch to capitation (1 = yes; 0 = no)	−0.885** (0.290)	
Switch to weighting (1 = yes; 0 = no)		0.594 (0.660)
% students eligible FRPL	−0.048* (0.028)	0.114*** (0.035)
State unemployment rate	0.119 (0.111)	−0.438*** (0.118)
% children living in single parent household	−0.037 (0.050)	0.006 (0.022)
Party control of state legislature (1 = dems control both; 0 = repub. control both)	0.658* (0.368)	1.215 (0.870)
Logged population in millions (4.118)	−5.842 (6.167)	−13.205**
State fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
SE clustered by state	Yes	Yes
Observations	420	180
(For block grants: 3 states that switch + 32 states that have weighting entire time × 12 years; For weighting: 3 states that switch + 12 states with block grants entire × 12 years)		
Adjusted R^2	0.075	0.211
F Statistic	5.781*** (df = 6; 368)	8.530*** (df = 6; 148)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.16: Switch to block grants: separating post-treatment years

	Dependent variable:
Three school years before capitation	−0.238 (0.463)
Two school years before capitation	−0.256 (0.327)
One school year before capitation	−0.241 (0.370)
First school year of capitation	−0.873* (0.517)
Second school year of capitation	−0.632 (0.430)
Third school year of capitation	−1.115** (0.459)
State fixed effects	Yes
Year fixed effects	Yes
SE clustered by state	Yes
Observations	420
Controls included?	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

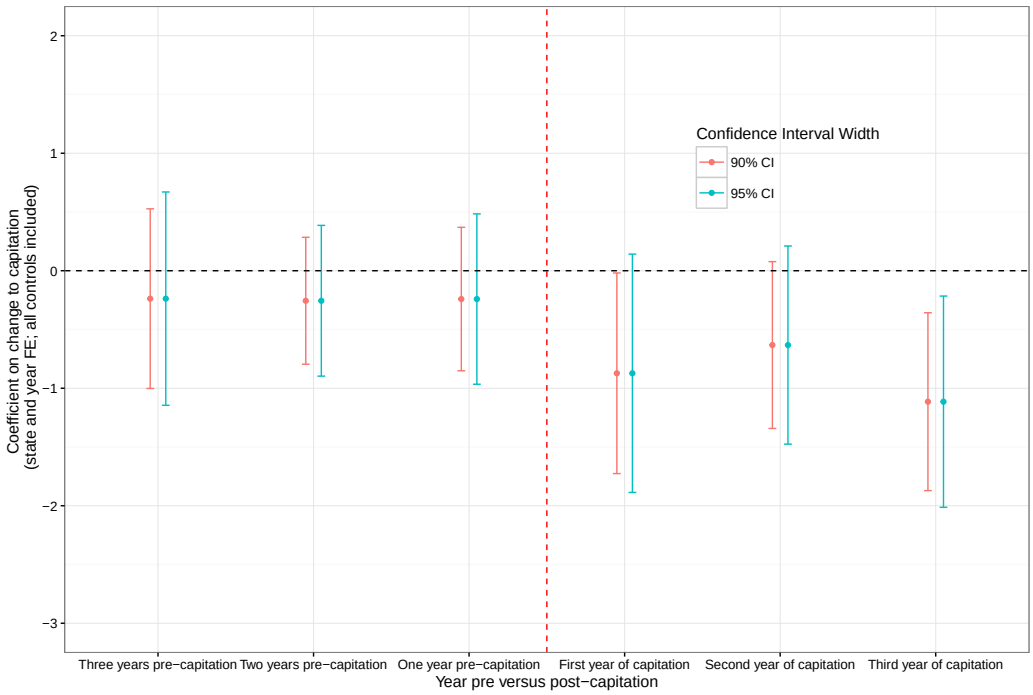
Robustness check: pre and post-treatment effects by leading and lagged treatment indicators

The models in the above tables focus on *average* levels of placement in the pre-treatment versus post-treatment periods. Focusing on states that switch from weighting to capitation, which are driving the aggregate drops in placement, I also estimate the following model where the treatment states are those that switch from weighting to capitation and the control states are those that had weighting financing during the entire period under study (so were at risk for this switch to capitation):

$$Y_{i,t} = \beta_1 \times capitation(1 = yes)_{it-3} + \beta_2 \times capitation_{it-2} + \beta_3 \times capitation_{it-1} + \beta_4 \times capitation_t + \beta_5 \times capitation_{t+1} + \beta_6 \times capitation_{t+2} + \gamma_t + \delta_i + \kappa X_{i,t} + \epsilon_{i,t} \quad (6.8)$$

The model serves two functions. First, coefficients β_1, β_2, and β_3 serve as robustness

Figure 6.51: Coefficient on capitation: lead and lag treatments



checks on the results. If the switch to capitation affects special education rates, we would hope to see non-significant coefficients in each of the pre-treatment years and significant coefficients in each of the post-treatment years. Second, coefficients β_4, β_5 and β_6 serve as estimates of how the treatment effect varies in three periods: the first school year of implementation (β_4) and the two school years that follow. γ_t, δ_i, and $\kappa X_{i,t}$ remain the the same as in Equation 1 (year fixed effects, state fixed effects, and a vector of controls respectively). Appendix Table 6.16 presents the coefficients and Figure 6.51 presents the results of this model. Though we see diminished power when we move from examining pooled post-treatment effects to treatment effects for each year, the results generally show no statistically significant changes in placement relative to control states in the school years directly preceding capitation and drops in placement in the school years following the policy change. These continued lagged effects have face validity since the stock of special education students might slowly adapt to the new financing formula in place when graduating cohorts of students are not fully replaced by new IEP's.

Selection into treatment?

The results from the fixed effects models are unbiased if states that switched their financing formulas exhibit similar trends in special education rates to states that do not switch their formulas (parallel trends assumption). In addition, the table below highlights four categories of confounders that, if associated with both a state's likelihood of switching its financing formula and that state's special education placement rates, bias the interpretation of the legal change's causal impact. In particular, while state fixed effects address unobserved time-invariant features of a state that might affect its choice of formula and placement rates, there might be unobserved time-variant features of a state that predict both outcomes (Besley and Case, 2000). If these features are present and are time-variant, the estimate of a new financing formula's effect can only remain relatively unbiased if the variables change in a similar manner between treatment and control states. While it is impossible to test for the presence of these unobserved, time-variant features, understanding the context in which special education financing formulas change is useful for showing why the change is plausible exogenous to placement rates after controlling for features of a state like measures of its fiscal health and family demographics (state fixed effects analysis) or these controls *and* the state's special education placement trends in the years prior to passing a policy (synthetic control analysis).

	Observed	Unobserved
Time-invariant	Time-invariant observed: addressed by controlling for as long as pre-treatment	Time-invariant unobserved: addressed with state fixed effect
Time-variant	Time-variant observed: addressed by controlling for as long as pre-treatment	Time variant unobserved: No formal way to address

The main contextual feature of switches in special education financing is that these changes to *special education* financing are often embedded within larger, more highly politicized changes to *general education* financing formulas. As a result, the public attention and political pressure that might differ between treatment and control states in unobserved, time-variant ways generally focus on other provisions of the statute in which the special ed-

ucation financing change is embedded, with the special education provisions of the statute more subject to the control of state special education directors in consultation with task forces (Whiteboard Advisors, 2013).

For instance, for one of the states that switched from weighting to capitation, New Jersey, the change was embedded in the larger School Funding Reform Act (SFRA). Evidence on the focus of public debate of this legislation comes from the Joint Legislative Committee on Public School Funding Reform, a committee convened in 2006 to solicit public feedback on the design of a new funding formula, which solicited comments on the proposed changes via email from New Jersey residents and published a breakdown of the topics of these comments. Figure 6.52 highlights their breakdown of topics: only 19 emails out of over 1000 focused on the proposed changes to special education financing, with most focusing on issues such as whether smaller districts should be consolidated to reduce property tax burdens and on teacher compensation. Meanwhile, it is difficult to find *any* public discussion of the other five states' financing formula shifts.

This lack of public attention to specifics of special education formulas echoes state special education directors' description of their processes for changing formulas as largely led by task forces, comparative studies where the directors examine formulas of states that in some cases appear far from being fiscal or political neighbors (e.g., Tennessee's Special Education Director reporting that they looked to Pennsylvania, Delaware, and Florida as useful models), and other technocratic processes (Whiteboard Advisors, 2013) While this context does not definitively prove that unobserved, time-variant factors do not influence which states switch their formulas, it does reduce the possibility of the presence of this selection since switches occur as the result of protracted deliberations that are somewhat insulated from unobserved shifts between states.

Figure 6.52: Breakdown of email topics from public comments on proposed financing change. *Source: Adler and Conaway (2006), page 9*

Summary

As of November 1, 2006, 1,043 e-mails were received by the Joint Committee. The e-mails were categorized by topic. Some e-mails addressed more than one topic and were categorized as such, resulting in 1,563 categorized entries that break down as follows:

336 addressed administrative costs and regionalization/shared services/consolidation;
260 addressed employee and teacher benefits;
191 addressed the potential shift of property taxes to other revenue sources;
92 addressed who the sender thought should pay for education;
88 addressed the relationship between senior citizens and property taxes;
74 addressed issues related specifically to Abbott districts;
62 addressed the broad issue of the school funding formula;
56 addressed the New Jersey Education Association (NJEA);
43 addressed waste and abuse;
26 addressed school budgets;
19 addressed special education;
12 addressed nonAbbott districts;
6 addressed amending the thorough and efficient clause of the New Jersey State Constitution; and
4 addressed a constitutional convention.

Synthetic control: additional information

Table 6.17: New Jersey synthetic control: Donor states with non-zero weights

Weight	State
0.718	Indiana
0.129	Illinois
0.085	Maine
0.067	Nebraska

Table 6.18: Missouri synthetic control: Donor states with non-zero weights

Weight	State
0.183	New Mexico
0.171	Michigan
0.161	Indiana
0.072	New Hampshire
0.053	Nebraska
0.045	New York
0.030	Wisconsin
0.029	Illinois
0.021	Oregon
0.020	Maine
0.016	Iowa
0.016	Kansas
0.016	Washington
0.014	Kentucky

Weight	State
0.013	Vermont
0.013	Wyoming
0.012	Tennessee
0.011	North Carolina
0.011	Ohio
0.010	Maryland
0.010	Nevada
0.010	South Dakota
0.009	Arizona
0.009	Delaware
0.009	South Carolina
0.008	Georgia
0.008	Oklahoma
0.007	Virginia
0.005	Louisiana
0.004	Florida
0.004	Mississippi
0.001	Texas

Table 6.19: West Virginia synthetic control: Donor states with non-zero weights

Weight	State
0.637	Indiana
0.363	New Mexico

Figure 6.53: Synthetic control analysis of Missouri shows no apparent effect of a less dramatic shift to capitation. Instead, we see capitation begin at a time of declining special education rates

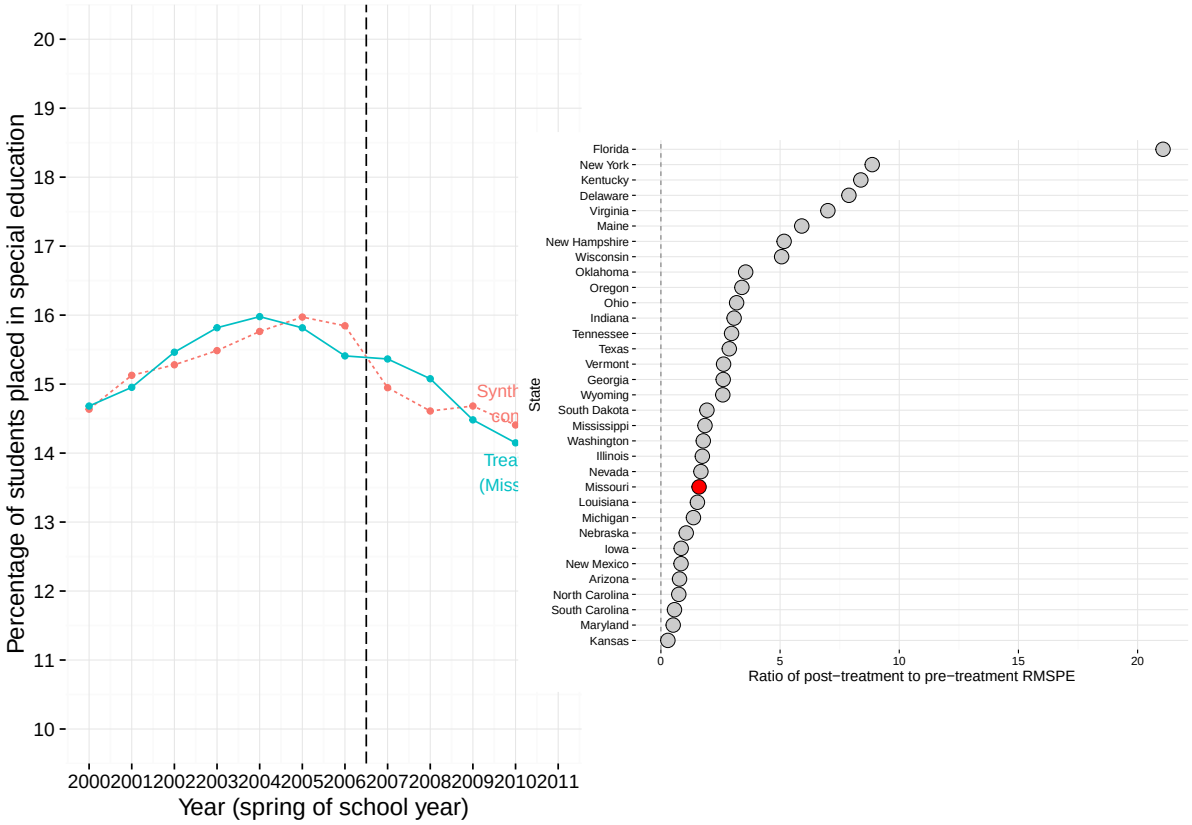
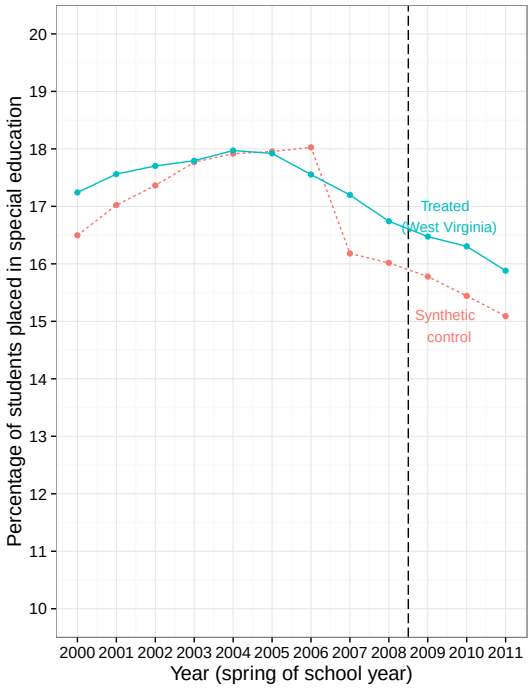
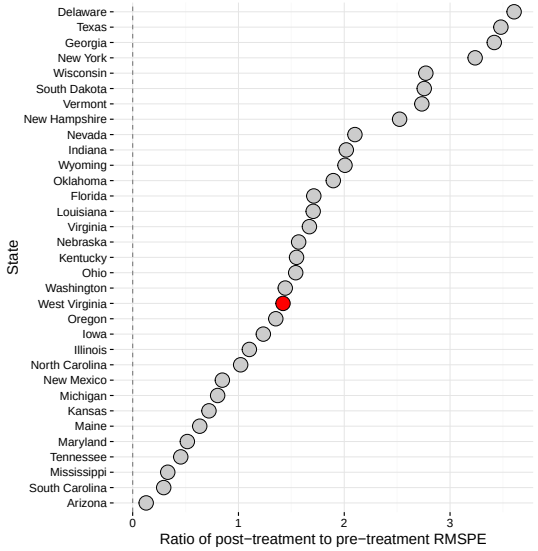


Figure 6.54: Synthetic control analysis of West Virginia shows no apparent effect of a less dramatic shift to block grants, but also highlights difficulty finding a good match for West Virginia in the pre-treatment period. In addition, since West Virginia had some of the highest FRPL percentages in the country, that variable was excluded from the donor selection process to create a better pre-treatment fit





States: switch from block grants to weighting (Alaska, Colorado, Minnesota)

Table 6.20: Summary of RMSPE rankings

State	Rank	Percentile
Alaska	$\frac{1}{13}$	0.07
Colorado	$\frac{6}{13}$	0.46
Minnesota	$\frac{8}{13}$	0.61

Supplementary Materials: Chapter Three

The first assumption in the main results comes in the coding of "any monitoring" as any parent monitoring from the beginning of the pre-treatment period (the 2000-2001 school year) to the school year immediately preceding the fiscal reform. This assumes that an intervention has a substantial enough effect, possibly through mechanisms like a school putting in place procedures to forestall future cases in the presence of the first case, for its effects to persist in years beyond the school year immediately following the year the case was filed. We can test the robustness of the results to different assumptions about how far back a case could be filed to significantly moderate the effects of the fiscal reform. More specifically, I use the following procedure to test the results' robustness to different windows in which a complaint can be filed:

1. *Change the window size for the treatment variable of any case:* Vary the coding of any case from any case in $t-1$ (a district is coded as having a case only if the case was filed in the 2007-2008 school year immediately preceding the reform) , $t-2$ (the district is coding as having a case if the case was filed in the 2007-2008 school year immediately preceding the reform or the 2006-2007 school year), $\ldots t-8$ (the district is coded has having a case if the case was filed anytime between the start of the observation period (2000-2001 school year) to the year immediately preceding the reform (2007-2008 school year))

2. *Perform CEM using that new treatment variable*: since changing the window size

results in a slightly different set of treatment units, I then used CEM to match the new set of treatment units with control units

3. *Estimate the models described in equation 1 and equation 2*: if the results are robust across different window sizes of when a case can occur, we would expect the coefficient on "any monitoring" to be consistent across these window sizes (though likely attenuated when we restrict to cases in more recent years because we switch from measuring the cumulative impact of cases across many school years to the short-term impact of a single case)

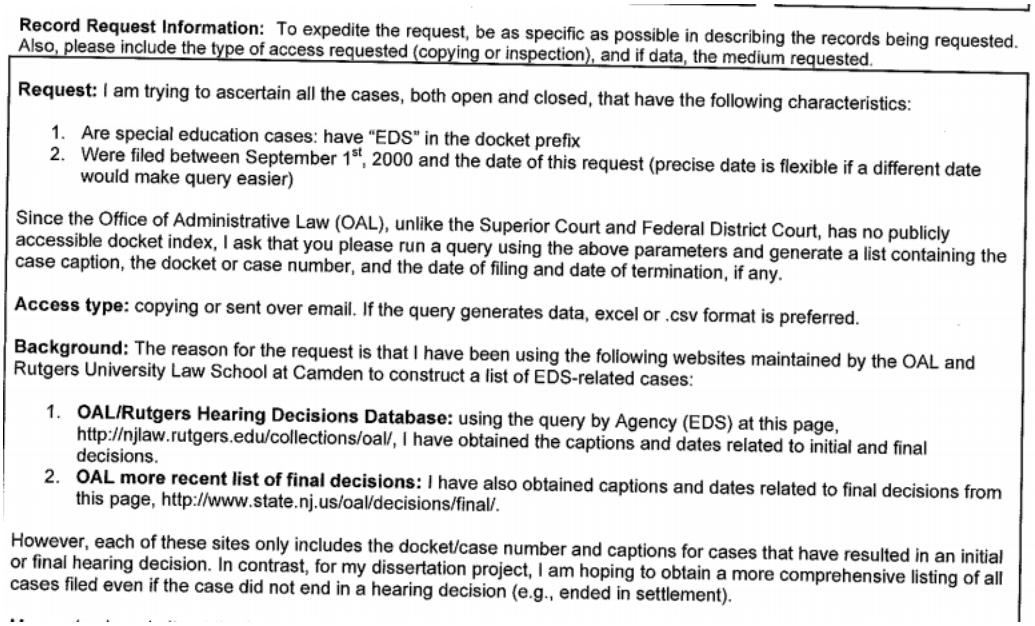
The Figure in the main text show the results from the linear lagged dependent variable model.

Figure 7.66 display the results for the logistic regression examining whether having any case reduces the probability of any drop in post-reform placement. The findings show the robustness of the results across different window sizes for when a parent intervention can occur in order to moderate the district's response to the fiscal reform.

The second assumption in the analysis is the *ignorability* or *selection on observables* assumption discussed previously: conditioning on covariates, a district's treatment status is unrelated to its potential outcomes (in this case, a drop in categorization following cost pressure relative to itself the year before). CEM strengthens that assumption by restricting the sample to treatment and control districts with similar *observed* characteristics. But we can also test the sensitivity of the results to confounding based on *unobserved characteristics*. In particular, we can ask the question: how large would an unobserved confounder need to be to "explain away" the relationship of interest (a case lowering a district's probability of post-reform drops in placement?)

To address this question, I use an approach to sensitivity analysis outlined in Blackwell (2014). Broadly, I first use logistic regression to estimate a district's probability of experiencing a parent intervention based on observed characteristics. This regression returns a set of predicted probabilities for each district–some districts have a high likelihood based on observed characteristics; other districts have a low likelihood of an intervention. I then use

Figure 7.55: Text of Open Public Records Act Request



Record Request Information: To expedite the request, be as specific as possible in describing the records being requested. Also, please include the type of access requested (copying or inspection), and if data, the medium requested.

Request: I am trying to ascertain all the cases, both open and closed, that have the following characteristics:

1. Are special education cases: have "EDS" in the docket prefix
2. Were filed between September 1st, 2000 and the date of this request (precise date is flexible if a different date would make query easier)

Since the Office of Administrative Law (OAL), unlike the Superior Court and Federal District Court, has no publicly accessible docket index, I ask that you please run a query using the above parameters and generate a list containing the case caption, the docket or case number, and the date of filing and date of termination, if any.

Access type: copying or sent over email. If the query generates data, excel or .csv format is preferred.

Background: The reason for the request is that I have been using the following websites maintained by the OAL and Rutgers University Law School at Camden to construct a list of EDS-related cases:

1. **OAL/Rutgers Hearing Decisions Database:** using the query by Agency (EDS) at this page, http://njlaw.rutgers.edu/collections/oal/, I have obtained the captions and dates related to initial and final decisions.
2. **OAL more recent list of final decisions:** I have also obtained captions and dates related to final decisions from this page, http://www.state.nj.us/oal/decisions/final/.

However, each of these sites only includes the docket/case number and captions for cases that have resulted in an initial or final hearing decision. In contrast, for my dissertation project, I am hoping to obtain a more comprehensive listing of all cases filed even if the case did not end in a hearing decision (e.g., ended in settlement).

each district's predicted probability to create a "confounding-adjusted" outcome for each district's yes or no drop in categorization under the scenario of "one-sided bias": I assume that districts that *did* experience a parent intervention have unobserved characteristics that put them at risk of *no* drops in tagging, and adjust the outcome accordingly. I then re-estimate the model described in equation 2, but replace a district's observed outcome with its confounding adjusted outcome. I then calculate the range of unobserved confounding needed to "explain away" the effect of a case on categorization. Figure 7.67 displays the results. We see that an unobserved confounder would need to explain over 25% of the variation in parent interventions in order to change the significance and main direction of the causal effect of these interventions on drops in categorization. This would be a very powerful confounder–by comparison, a district's poverty level only explains about 1.4% of the variation in whether a district had any monitoring.[100]

[100]For implementation, since the present version of the `causalsens` package only allows for adjusting outcomes for a linear model, I implement a version of the confounding-adjusted outcome that allows for any form of predicted value using code I provide as part of the present article's replication package.

Figure 7.56: Details of merging monitoring with districts

With the analytic sample of cases (cases against districts in pre-treatment years), to match requests with the district it was filed against, I parsed the case caption, examples of which are highlighted below, and then used partial string matching algorithms (e.g., Levenshtein Distance using *agrep* in R) to merge cases with the Common Core and NJ DOE data on district characteristics and placement rates, e.g., the first caption below would be merged with the Morris Regional school district, the second with the Lawrence Township district (the images refer to Decisions to get a sense of the structure of the captions but the request yielded captions for all settlements and other requests also):

DECISION
OAL DKT. NO. EDS1583-98
AGENCY DKT. NO. 98-9137

G.M., BY HIS FATHER, G.M. SR.,
Petitioner,
v.
WEST MORRIS REGIONAL SCHOOL DISTRICT BOARD OF EDUCATION,
Respondent.

DECISION
OAL DKT. NO. EDS50-04
AGENCY REF. NO. 2002 8507

D.C. and J.P. o/b/o K.C.,
Petitioners,
v.
LAWRENCE TOWNSHIP BOARD
OF EDUCATION,
Respondent.

This matching process was not perfect due to ambiguous referents to districts (e.g., a case caption referring to "Freehold" which could correspond to one of three distinct districts: Freehold Borough, Freehold Township, or Upper Freehold Regional) and the previous exclusion of small districts from the 598 districts in the analytic sample on the the grounds that the district either didn't survive to make it to the post-treatment period or didn't emerge until this period. In the present analyses, 4021 (3821 + 200 cases matched but with parents as defendent) of the 4082 cases against districts in the pre-treatment period (97%). were successfully matched with a district. Case captions for the unmatched cases are presented in Table 7.21 and are composed of vocational schools not classified as districts in administrative datasets, charter schools that were not present in both the pre-treatment year and post-treatment year, state-wide administrative agencies, or an ambiguous school district in one case ("BRIDGE TWP" could refer to Old Bridge Township, Bridgewater-Raritan, Bridgeton City, or High Bridge). The captions also highlight a phenomenon–repeated cases that appear to be filed by the same plaintiffs–that leads to the analytic choice to collapse cases into a yes or no indicator rather than summed count in the district-level analysis.

Figure 7.57: Histogram of special education placement rates: year before capitation versus year after capitation. The histogram and tests of equality in distribution show a significant shift leftwards (towards lower rates) following the formula change

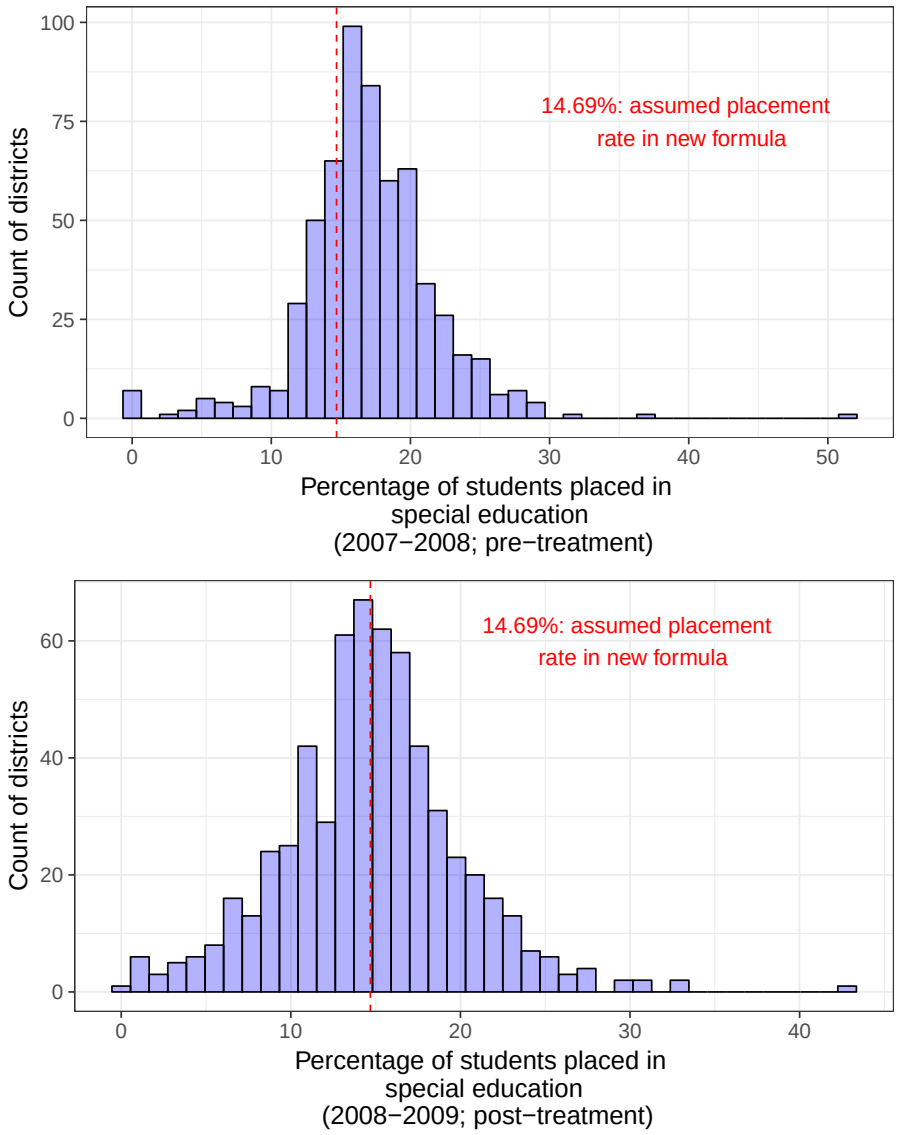


Figure 7.58: Students placed pre policy versus students placed post policy. The dashed 45-degree line represents if a district had the same placement rate pre and post-policy. Note that most districts are clustered around this line, but the ones that deviate from this line in the direction of fewer students placed appear to be higher poverty districts (closer to red on the color scale)

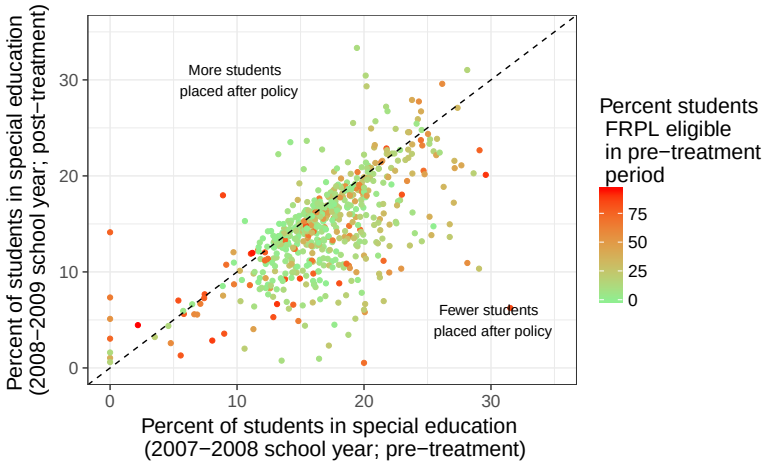


Figure 7.59: District factor group rating versus drop in categorization: *x axis* shows a district's composite measure of socioeconomic status, while the *y axis* shows the drop in tagging as a percentage of initial levels, with a loess-smoothed line. The figure highlights that although there's a general trend where higher SES districts (higher DFG) districts had smaller drops, there is also significant heterogeneity within each demographic category that means demographics do not fully explain the change in tagging.

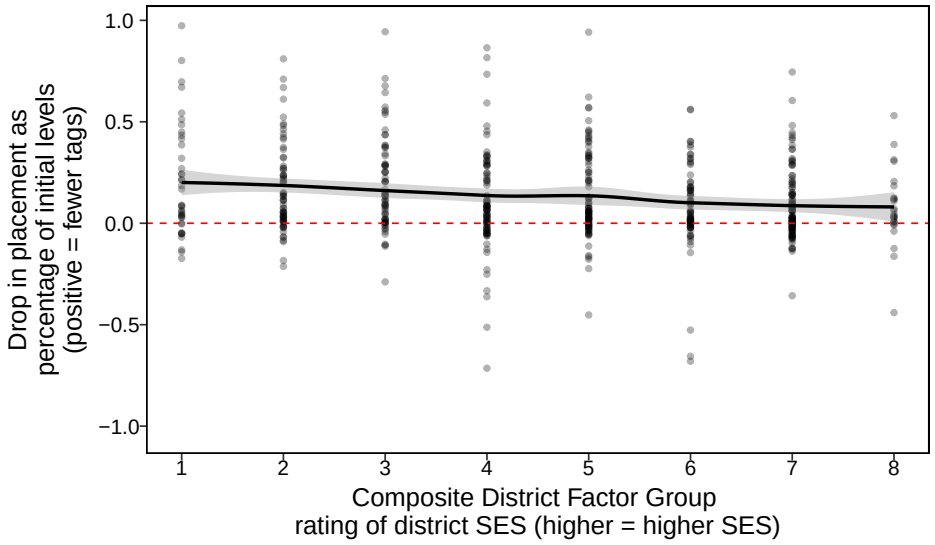


Table 7.21: Case captions not matched/merged with a district

J.V. ON BEHALF OF I.R. V. BAYONEN BOE
M.P. ON BEHALF OF E.G. V. BELOVED COMMUNITY CHARTER SCHOOL BOE
L.L. O/B/O L.L. BRIDGE TWP BOE
R.K. O/B/O A.K. CAMDEN COUNTY BOARD OF EDUCATION
B.C. O/B/O B.C. CAMDEN COUNTY TECHNICAL BOE
T.D. O/B/O G.D. V. CAMDEN COUNTY VOCATIONAL SCHOOL DISTRICT BOE
G.B. ON BEHALF OF J.J. V. CENTRAL JERSEY ARTS CS BOE
L.S. ON BEHALF OF C.S. CENTRAL JERSEY ARTS CS BOE
L.S. ON BEHALF OF C.S. CENTRAL JERSEY ARTS CS BOE
L.S. ON BEHALF OF C.S. CENTRAL JERSEY ARTS CS BOE
G.B. O/B/O J.J. V CENTRAL JERSEY ARTS CS BOE & PLAINFIELD
M.I. AND C.I. O/B/O M.I. V. CLINTON-GLEN GARDNER BOARD OF EDUCATION
N.W. ON BEHALF OF M.W. V. COLLEGE ACHIEVE CENTRAL CHARTER SCHOOL
P.C. ON BEHALF OF G.C. NJ DEPT. OF CHILDREN AND FAMILIES
G.C. AND M.E. ON BEHALF OF L.P. DHS-OFFICE OF EDUCATION BOE
J.L.E. O/B/O O.G.E. V. WASHINGTON TOWNSHIP BOE
P.M. ON BEHALF OF D.M. VS. FOUNDATION ACADEMY CHARTER SCHOOL, BOE
C.J. O/B/O C.J. V. GRANVILLE CHARTER HIGH SCHOOL
D.W. O/B/O B.B. V. GRANVILLE CHARTER HIGH SCHOOL
T.H. O/B/O R.H. V. GRANVILLE CHARTER HIGH SCHOOL BOE
D.W. O/B/O B.B. V. GRANVILLE CHARTER HIGH SCHOOL BOE
K.W. O/B/O A.I. V. GRANVILLE CHARTER HIGH SCHOOL BD OF EDUCATION
V.W. O/B/O J.W. V. GRANVILLE CHARTER HS BOARD OF EDUCATION
D.W. O/B/O N.S. V. GRANVILLE CHARTER MIDDLE SCHOOL BOE
S.A. O/B/O N.A. V. GRANVILLE CHARTER MIDDLE SCHOOL
J.C. O/B/O J.C. V. GRANVILLE CHARTER MIDDLE SCHOOL
D.W. O/B/O N.S. V. GRANVILLE CHARTER MIDDLE SCHOOL BOE
S.A. O/B/O N.A. V. GRANVILLE CHARTER MIDDLE SCHOOL BOE
S.F. O/B/O I.F. V. GRANVILLE CHARTER SCHOOL BOE
S.F. O/B/O I.F. GRANVILLE CHARTER SCHOOL BOE
D.W. O/B/O N.S. V. GRANVILLE CHARTER SCHOOL BOE
B.C. O/B/O D.O. V. GRANVILLE CHARTER SCHOOL
J.L.H. O/B/O W.F.H. V. PACE CHARTER SCHOOL OF HAMILTON BOE
J.S. O/B/O A.C. V HATIKYAH INTERNATIONAL ACADEMY CHARTER BOE
L.A. O/B/O J.A. V. JOHN P. HOLLAND CHARTER BOE
T.D. O/B/O G.D. V. LOWER CAMDEN COUNTY REGIONAL BOE
B.M. O/B/O T.M. V. MERCER COUNTY SPECIAL SVCS SCH DIST. BOE
D.P. AND A.P. O/B/O H.P. V. MONMOUTH CO. VOCATIONAL BOARD OF EDUCATION
K.R. AND M.R. O/B/O T.R. V. MONMOUTH COUNTY VOCATIONAL BOARD OF EDUCATION
S.E. O/B/O J.E. V. MONMOUTH COUNTY VOCATIONAL SCH. DIST. BOE
B.O. AND E.B. ON BEHALF OF J.O. MORRIS-UNION JOINTURE COMMISSION BOE
P.C. ON BEHALF OF G.C. NEW JERSEY DEPT. OF CHILDREN AND FAMILIES
R.O. ON BEHALF OF S.O. V. NEWARK EDUCATORS CHARTER SCHOOL BOE
R.O. ON BEHALF OF S.O. V. NEWARK EDUCATORS CHARTER SCHOOL BOE
J.L. O/B/O T.D. V. NORTH STAR ACADEMY CHARTER SCHOOL OF NEWARK BOE
S.W. ON BEHALF OF K.W. V. NORTH STAR ACADEMY CHARTER SCHOOL OF NEWARK BOE
J.S. O/B/O Y.S. V PASSAIC COUNTY BD OF SOC SVCS
L.W. O/B/O K.L. V. PLEASANTVILLE CHARTER SCH FOR ACADEMIC EXCELLEN
M.E.F. ON BEHALF OF D.A. VS. SOARING HEIGHTS CHARTER SCHOOL BOE
G.L. O/B/O W.L. V. STATE OF NJ, DHS, OFFICE OF EDUCATION
J.S. ON BEHALF OF N.S. VS. SUSSEX CO. CHARTER SCHOOL FOR TECHNOLOGY BOE
M.G. & S.M. O/B/O H.G. V THE ETHICAL COMMUNITY CHARTER SCHOOL BOE
T.I. O/B/O A.I. V THE PAULO FREIRE CS FOR LIBERTY
G.B. O/B/O J.J. V. CENTRAL JERSEY ARTS CS BOE
N.A. ON BEHALF OF A.A. V. M.E.T.S. CHARTER BOE
E.S. ON BEHALF OF N.B. V. ESSEX COUNTY DEPARTMENT OF CORRECTIONS
S.M. & E.M. O/B/O B.M. V. GARDEN ACADEMY
K.P. AND M.P. O/B/O A.P. V. VINELAND PUBLIC CHARTER SCHOOL BOARD OF EDUCATION
T.T. ON BEHALF OF S.B. V. VISIONS ACADEMY CHARTER HIGH SCHOOL BOE
R.O. ON BEHALF OF S.O. V. NEWARK EDUCATORS CHARTER SCHOOL BOE
P.A. AND M.A. ON BEHALF OF A.A. V. WOODLAND PARK BOARD OF EDUCATION

Table 7.22: Data sources: district-level analysis

Variable	Sources	Notes
% FRPL (2007-2008 school year)	National Center for Education Statistics Common Core of Data (CCD), Local Education Agency (School District) Universe Survey, "Public Elementary/Secondary School Universe Survey"	31 districts missing 2007-2008 school year, so assigned to 2006-2007 or 2005-2006 % (whichever was complete + most recent) all complete after this assignment
% Black; % ELL (2007-2008 school year)	Ibid.	Refers to public school students rather than all residing in district
Percent revenue from non-local sources (100 - % revenue from local sources)	National Center for Education Statistics, Common Core of Data (CCD),Local Education Agency (School District) Universe Survey, 2013-14 v.1a; Survey of Local Government Finances, School Systems (F-33)	
District Factor Group (DFG)	NJ DOE	
Due process intervention history	OPRA request; NJ Office of Administrative Law (OAL)	
Logged enrollment (2007-2008 school year)	NJ Department of Education	

Figure 7.60: Identification for district-level analysis. i indexes districts; $t-1$ indexes the pre-treatment school year; t indexes the post-treatment school year. The figure highlights that we reply on a selection on observables assumption, but this assumption is strengthened by controlling for a district's pre-reform tagging rates

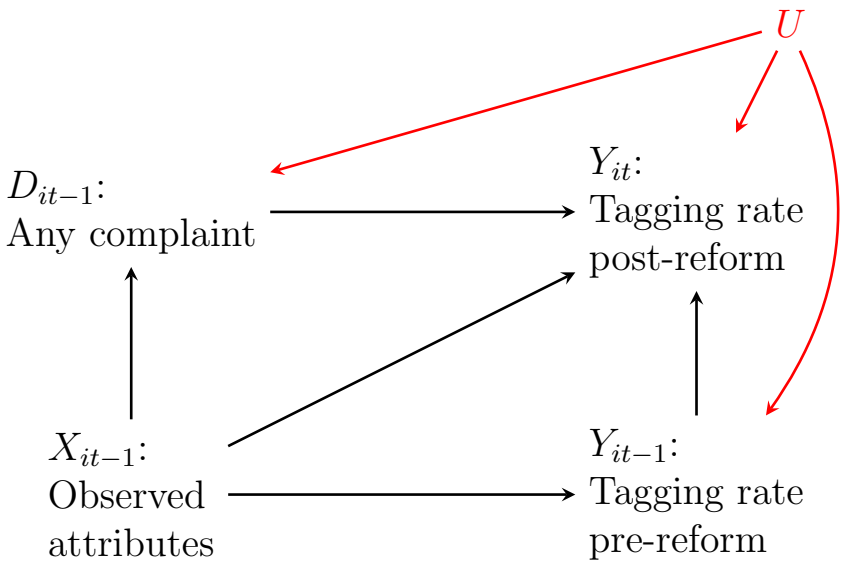


Figure 7.61: Descriptives: variables used in district-level regression model.

Statistic	N	Mean	St. Dev.	Min	Max
% special education placement (post-treatment)	598	14.745	5.298	0.530	43.330
% special education placement (pre-treatment)	17.027	4.843	0.000	51.430	
Any drop in placement	598	0.749	0.434	0	1
Any pre-treatment case	598	0.734	0.442	0	1
District Factor Group (converted to integer)	543	4.611	2.010	1	8
% revenue from non-local sources (pre-treatment)	598	36.438	20.922	9.500	96.500
% Black (pre-treatment)	598	13.278	20.885	0.000	97.906
% ELL (pre-treatment)	596	1.970	3.489	0.000	34.703

Figure 7.62: Correlation between district-level predictor and outcome variables

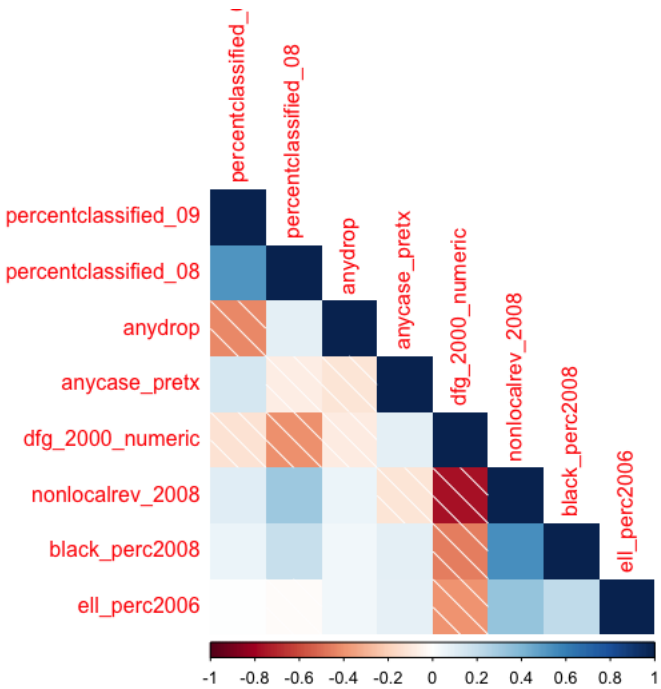


Figure 7.63: *Top panel*: Cutpoints used in coarsened exact matching. All cutpoints chosen by default "Sturges" setting except for the percentage of special education students in the pre-treatment year and the district factor groups. *Bottom panel*: units pruned

	Percent classified (pre-tx year)	District Factor Group	% Non-Local Rev. (pre-tx year)	% Black (most recent pre-tx year)	% ELL
1	5.000	1.000	9.500	0.000	0.000
2	10.000	2.000	18.200	9.791	3.470
3	15.000	3.000	26.900	19.581	6.941
4	20.000	4.000	35.600	29.372	10.411
5	25.000	5.000	44.300	39.162	13.881
6		6.000	53.000	48.953	17.352
7		7.000	61.700	58.743	20.822
8		8.000	70.400	68.534	24.292
9			79.100	78.325	27.763
10			87.800	88.115	31.233
11			96.500	97.906	34.703

	No case pre-tx	Any case pre-tx
All	150	448
Matched	77	205
Unmatched	73	243

Figure 7.64: Coarsened exact matching for district-level regression: univariate and multivariate imbalance measures. *Top panel:* before matching, there is a high degree of univariate imbalance on covariates like the district factor grouping (a measure of school SES/used for funding allocations), with treatment districts (those with at least one intervention in pre-treatment period) having a higher SES, and percent classified before capitation, with treatment districts having more students classified in special education. *Bottom panel*: we see reductions in imbalance on those variables post-matching, as well as a reduction in multivariate imbalance.

	Mean difference (treatment - control)	ℓ_1
% placed in special education (pre-tx year)	1.208	0.213
District Factor Group (higher = higher SES)	0.50	0.224
% Non-local revenue (pre-tx year)	-7.63	0.000
% Black (pre-tx year)	-5.30	0.000
% ELL (most recent pre-tx year)	0.94	0.094
Global multivariate $\mathcal{L}_1$: 0.86		

	Mean difference (treatment - control)	L_1
% placed in special education (pre-tx year)	-0.542	0.048
District Factor Group (higher = higher SES)	0.00	0.000
% Non-local revenue (pre-tx year)	0.048	0.000
% Black (pre-tx year)	0.152	0.000
% ELL (most recent pre-tx year)	0.02	0.000
Global multivariate $\mathcal{L}_1$: 0.55		

Figure 7.65: Visual illustration of reduction in imbalance post-CEM depicted in Table 7.64: *Top panel* depicts pre-matching density of covariates (though DFG is an ordinal variable coded as 1 through 8) and *bottom panel* depicts post-matching density. We see for instance that schools without any special education placement in the pre-treatment period (e.g. charter schools with very low percentages placed) are removed due to a lack of cases-controls in the same strata. Likewise, districts in the lowest tier of District Factor Groups (lowest SES) are also removed.

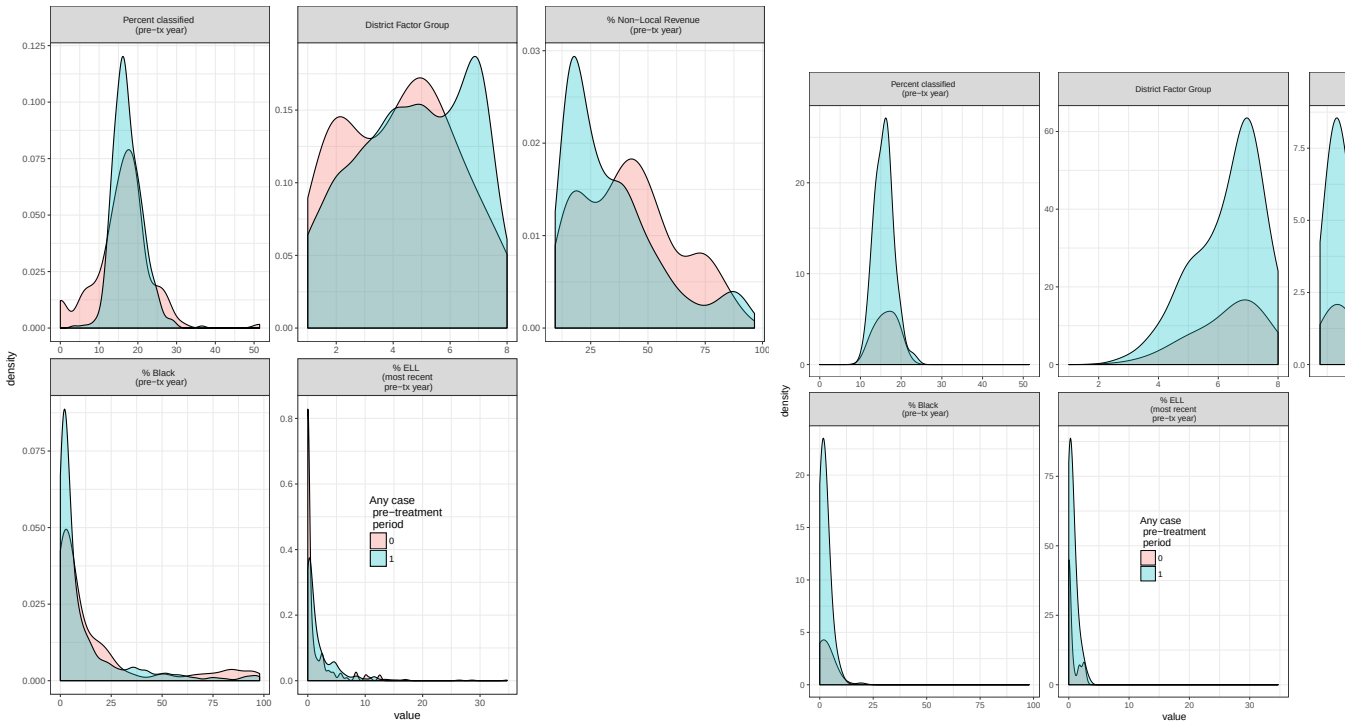


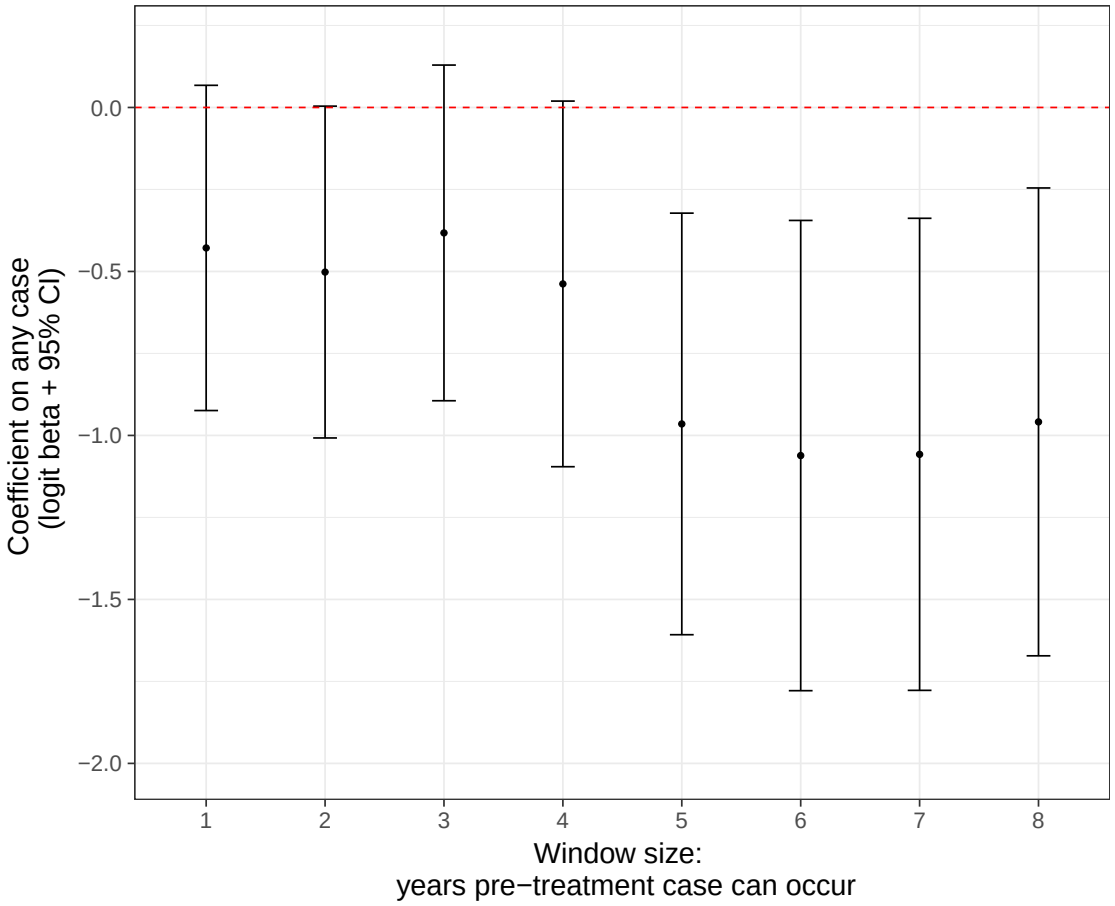
Table 7.23: Effect of parent monitoring on change in special education placement following reform (linear regression; lagged DV)

	Dependent variable:					
	Percentage of students placed in special education (post-treatment school year)					
	(Full sample)	(CEM sample)	(Full sample)	(CEM sample)	(Full sample)	(CEM sample)
Any pre-treatment case	1.768*** (0.373)	1.911*** (0.457)	2.096*** (0.433)	1.930*** (0.464)		
Controls						
% placed (pre-tx yr)	0.700*** (0.033)	0.685*** (0.067)	0.744*** (0.052)	0.706*** (0.082)	0.741*** (0.053)	0.698*** (0.084)
District factor group			0.248* (0.142)	0.182 (0.226)	0.290** (0.144)	0.184 (0.232)
% non-local revenue			0.005 (0.014)	0.013 (0.027)	−0.003 (0.014)	0.012 (0.028)
% Black (pre-tx yr)			−0.011 (0.013)	−0.008 (0.079)	0.002 (0.013)	0.017 (0.081)
% ELL (most recent pre-tx yr)			0.055 (0.053)	0.163 (0.161)	0.089* (0.054)	0.131 (0.166)
Constant	1.504** (0.628)	1.638 (1.168)	−0.899 (1.561)	−0.223 (2.496)	0.737 (1.556)	1.274 (2.543)
Observations	598[101]	282	543	280	543	280
Adjusted R^2	0.448	0.297	0.305	0.280	0.276	0.237
F Statistic	243.676*** (df = 2; 595)	60.494*** (df = 2; 279)	40.616*** (df = 6; 536)	19.078*** (df = 6; 273)	42.283*** (df = 5; 537)	18.333*** (df = 5; 274)
Note:			*p<0.1; **p<0.05; ***p<0.01			

Table 7.24: Effect of parent monitoring on change in special education placement following reform (logistic regression; any drop in placement relative to pre-treatment levels)

	Dependent variable:					
	Any drop in placement (1 = yes; 0 = no)					
	(Full sample)	(CEM sample)	(Full sample)	(CEM sample)	(Full sample)	(CEM sample)
Any pre-treatment case	-0.378^{*} (0.225)	-0.982^{***} (0.359)	-0.752^{***} (0.287)	-0.959^{***} (0.364)		
District factor group			-0.084 (0.081)	0.042 (0.147)	-0.094 (0.080)	0.035 (0.145)
% non-local revenue (pre-tx yr)			-0.005 (0.009)	0.021 (0.019)	-0.002 (0.008)	0.022 (0.019)
% Black (pre-tx yr)			0.007 (0.008)	0.030 (0.063)	0.003 (0.008)	0.016 (0.061)
% ELL (most recent pre-tx yr)			0.026 (0.034)	0.235 (0.156)	0.015 (0.033)	0.261^{*} (0.154)
Constant	1.305^{***} (0.199)	1.795^{***} (0.326)	2.117^{***} (0.679)	0.790 (1.290)	1.503^{**} (0.626)	0.087 (1.242)
Observations	598	282	543	280	543	280
Log Likelihood	-344.854	-153.231	-305.019	-148.142		
Akaike Inf. Crit.	693.708	310.463	622.038	308.285		

Figure 7.66: Logistic regression results are robust to changing the size of a window for when an intervention can occur. The graph presents the coefficient and 95% confidence interval around the "any intervention" variable, which has a significant effect on reducing a district's likelihood of any drop in placement. Similar to the linear lagged DV specification, which shows significant results across the range of window sizes, the logistic regression results show consistent results, though the strength of the coefficient attenuates to $p < 0.1$ rather than $p < 0.05$ when we restrict "any intervention" to only more proximate years



Window size for pre-tx intervention	β on any intervention	p-value
School year immediately before reform $(t-1)$	-0.4283	0.0904
$t-2$	-0.5019	0.0518
$t-3$	-0.3825	0.1429
$t-4$	-0.5380	0.0585
$t-5$	-0.9649	0.0033
$t-6$	-1.0614	0.0037
$t-7$	-1.0576	0.0040
Any time between start of window and school year immediately before reform $(t-8)$	-0.9587	0.0084

Figure 7.67: Sensitivity analysis for the magnitude of unobserved confounding needed to explain away the effect of parent interventions on drops in tagging

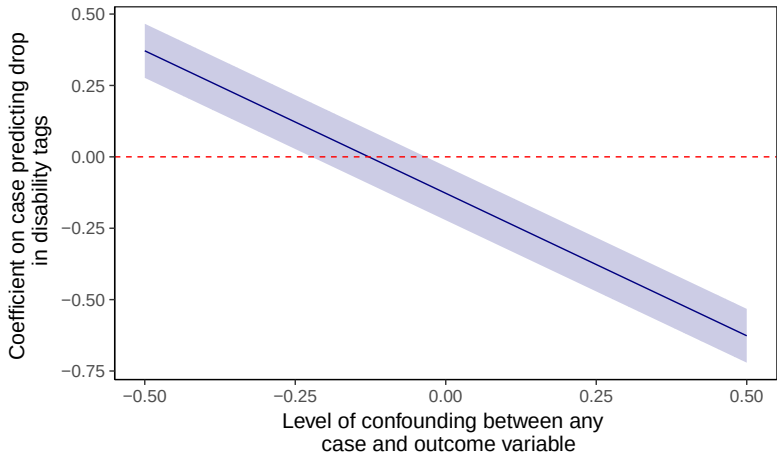
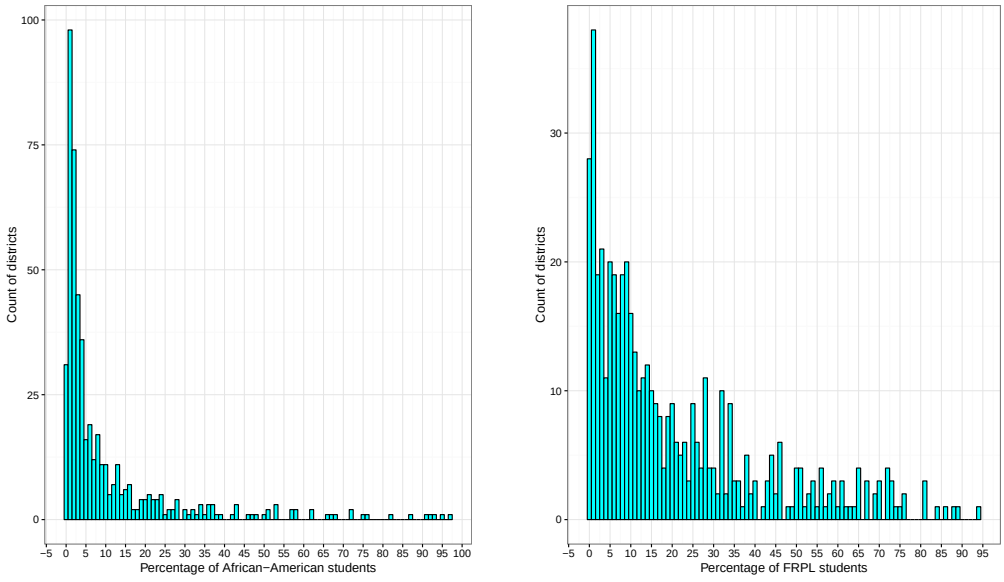


Figure 7.68: Distribution of districts across racial and parental SES ranges. *Note: there are the same number of districts in each graph but note that the y axes have different scales*



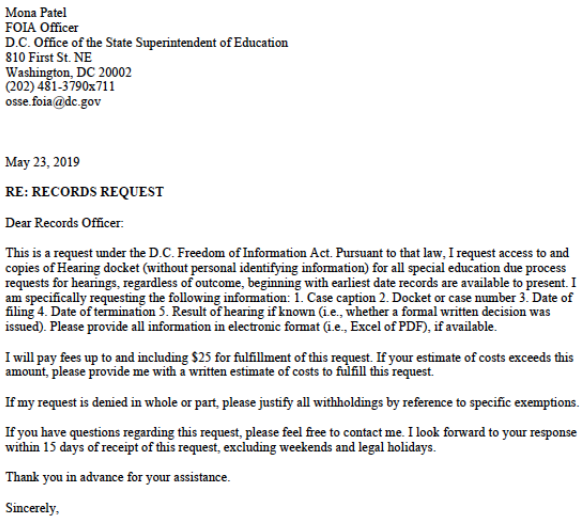
Supplementary Materials: Chapter Four

8.1 Details on DC filings data

Table 8.25: DC filings data: schools mentioned in filings that could not be matched with a Common Core Data school

school_against_cleaned
ACCOTINK ACADEMY
ARCHBISHOP CARROLL HIGH SCHOOL
BELL MULTICULTURAL SENIOR HIGH SCHOOL
BUILD ING FOR THE FUTURE
CARDOZO HIGH SCHOOL
CARE CENTER AT SHAW JHS-ELEMENTARY CAMPUS
CHELSEA SCHOOL
CHILDRENS GUILD • BALTI MOR E
CHOICE ACADEMY MS/SHS · HOME SCHOOL
CHOICE ACADEMY MS/SHS • HOME SCHOOL
CLINTON GROVE ELEMENTARY SCHOOL
CUMBERLAND HOSPITAL
DC DETENT ION FACILITY
DCPS PRIVATE AND RELGIOUS OFFICE IPRO)
DEVEREUX
EARLY STAGES AM
ELEMENTARY SCHOOL @ WILKINSO N
ELEMENTARY SCHOOL @ WILKINSON
EMERSON PREPARATORY
FORBUSH SCHOOL @ OAKMONT
FOUNDATION SCHOOL OF P.G. COUNTY
FRANCIS•STEVENSEDUCATIONC ENTER
FROST SCHOOL • ROCKVILLE
HAMILTON CENTER
HARBOUR SCHOOL
HART M I DD IE SCHOOL
HEIGHTS EDUCATION CENTER HIGH SCHOOL
HIGH ROAD DC KATHERINE THOMAS
KENNEDY INST ITU TE
KINGSBU RY DAY SCHOOL
KINGSBURY DAY SCHOOL
LAB SCHOOL OF WASHINGTON
LVYMOUNT
MCLEA N SCHOOL
MCLEAN SCHOOL
N.H. BURRO UGHIGH SCHOOL
N.H. BURROUGHIGH SCHOOL
NATIONAL CHILDREN'S CENTER (N-Z)
NEW BEGINNINGS VOCATIONAL SCHOOL
PARK MOUNT SCHOOL
PHILLIPS SCHOOL
REGINALD LOURIE CENTER SCHOOL
SCHOOL-WITHIN-SCHOOL@ PEABODY
SENIOR HIGH SCHOOL
STANSBURY ACADEMY
VILLAGE ACADEMY

Figure 8.69: **Open records request**. The request was filed in May 2019 and eventually fulfilled in September of 2019.



Mona Patel
FOIA Officer
D.C. Office of the State Superintendent of Education
810 First St. NE
Washington, DC 20002
(202) 481-3790x711
osse.foia@dc.gov

May 23, 2019

RE: RECORDS REQUEST

Dear Records Officer:

This is a request under the D.C. Freedom of Information Act. Pursuant to that law, I request access to and copies of Hearing docket (without personal identifying information) for all special education due process requests for hearings, regardless of outcome, beginning with earliest date records are available to present. I am specifically requesting the following information: 1. Case caption 2. Docket or case number 3. Date of filing 4. Date of termination 5. Result of hearing if known (i.e., whether a formal written decision was issued). Please provide all information in electronic format (i.e., Excel of PDF), if available.

I will pay fees up to and including $25 for fulfillment of this request. If your estimate of costs exceeds this amount, please provide me with a written estimate of costs to fulfill this request.

If my request is denied in whole or part, please justify all withholdings by reference to specific exemptions.

If you have questions regarding this request, please feel free to contact me. I look forward to your response within 15 days of receipt of this request, excluding weekends and legal holidays.

Thank you in advance for your assistance.

Sincerely,

Table 8.26: DC filings data: schools that could be matched with a Common Core data school but that didn't submit data meeting Common Core data quality standards

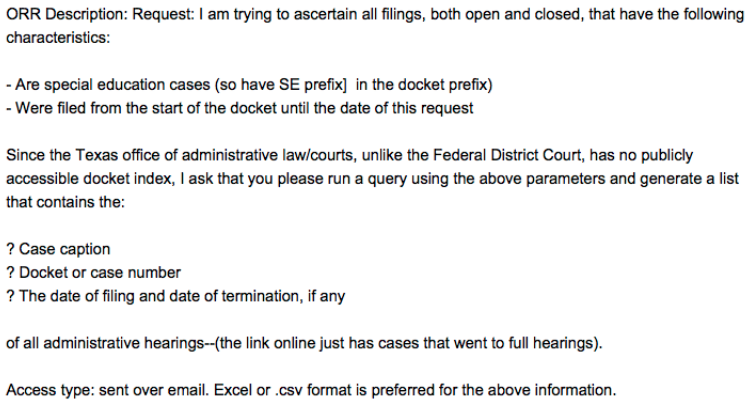
school_name
ACADEMY OF HOPE ADULT PCS
ADAMS ELEMENTARY SCHOOL
ADVANCED PATH ACADEMY
APPLETREE EARLY LEARNING CENTER PCS AMIDON
APPLETREE EARLY LEARNING CENTER PCS PARKLAND
BREAKTHROUGH MONTESSORI PCS
BROOKLAND MS
CAPITAL CITY UPPER PCS
CARLOS ROSARIO INTERNATIONAL PCS S STREET CAMPUS
CHILD AND FAMILY SERVICES REGULAR ED
COMMUNITY ACADEMY RAND TECH
CONSOLIDATED HEADSTART
DAVIS ES
DC PREPARATORY ACADEMY PCS ANACOSTIA ELEMENTARY
DC YOUTH RE ENGAGEMENT CENTER
DEMOCRACY PREP CONGRESS HEIGHTS PCS
DISTRICT OF COLUMBIA INTERNATIONAL SCHOOL
DOROTHY I HEIGHT ES
EAGLE ACADEMY PCS HOWARD U
EXCEL ACADEMY PCS LEAD
FEREBEE HOPE ES
FRIENDSHIP PCS ARMSTRONG
FRIENDSHIP PCS CHAMBERLAIN
FRIENDSHIP PCS ONLINE
FRIENDSHIP PCS TECHNOLOGY PREPARATORY ACADEMY HIGH
FRIENDSHIP PCS WOODRIDGE CAMPUS
GOODWILL EXCEL CENTER PCS
HARMONY DC PCS SCHOOL OF EXCELLENCE
HOWARD ROAD ACADEMY PCS MLK CAMPUS
HOWARD ROAD ACADEMY PCS PENNSYLVANIA AVENUE
HOWARD UNIVERSITY MIDDLE SCHOOL OF MATH AND SCIENC
JEFFERSON MS
KENILWORTH ES
KINGSMAN ACADEMY PCS
KIPP DC ARTS AND TECHNOLOGY ACADEMY PCS
KIPP DC NORTHEAST ACADEMY PCS
KIPP DC QUEST ACADEMY PCS
KIPP DC VALOR ACADEMY PCS
LASHAWN DCPS NON PUBLIC
LEE MONTESSORI PCS
M C TERRELL ES
MACFARLAND MS
MACFARLAND MS LINCOLN HILL CLUSTER
MARSHALL EC
MAYA ANGELOU TRANSITION CENTER
MONUMENT ACADEMY PCS
PRE K INCENTIVE PROGRAM
PROSPECT LC
RESIDENTIAL SCHOOLS
RICHARD WRIGHT PCS FOR JOURNALISM AND MEDIA ARTS P
RIVER TERRACE EC
RIVER TERRACE ES
ROCKETSHIP DC PCS RISE ACADEMY
RON BROWN COLLEGE PREPARATORY HIGH SCHOOL
RON BROWN MS
ROOTS PCS NORTH CAPITOL STREET CAMPUS
SEPTIMA CLARK PCS
SHAW MS AT GARNET PATTERSON
SPINGARN SHS
SPINGARN STAY
SUSTAINABLE FUTURES PCS
THE CHILDRENS GUILD PCS
TUITION GRANT DCPS NON PUBLIC
TWO RIVERS PCS MIDDLE SCHOOL
TWO RIVERS PCS YOUNG
VAN NESS ES
WASHINGTON GLOBAL PCS
WASHINGTON LEADERSHIP ACADEMY PCS
WILLIAM E DOAR PCS NW SOLDIERS HOME
WINSTON EC

8.2 Details on Texas filings data

Table 8.27: Texas filings data: schools mentioned in filings that could not be matched with a Common Core Data school based on state ID-NCES ID crosswalk

school
TEXAS SCH FOR TH E D EAF (227906)
UPLIFT EDUCATION (057803)
STAR CHARTER SCHOOL (227814)
IDEA ACADEMY (108807)
NORTH FOREST ISD (101909)
SOUTHWEST SCHOOL (101838)
LA MARQU E ISD (084904)
VANGUARD ACADEMY (108808)
NYOS CHARTER SCHOOL (227804)
SOUTH TEXAS ISD (031916)
ARROW ACADEMY (021805)
IDEA PUBLIC SCHOOLS (108807)
KIPP SAN ANTONIO (015826)
WAYSID E SCHOOLS (227803)
HARRIS COUNTY DEPT OF ED
NEW FRONTIERS CHARTER SCHOOL
BAY AREA CHARTER SCHOOL
LA AMISTAO LOV E & LEARNING
HOUSTON CAN ACADEMY CHARTER
S EASHOR E CHART ER SCHOOLS
S EASHOR E L EARNING CTR CHARTER
BRAZOS RIVER CHARTER SCHOOL
HARMONY SCI ENC E ACAD (EL PASO)
SCHOOL OF EXC ELL ENC E IN
HARMONY SCI ENC E ACAD
HOUSTON ALTERNATIVE
ACAO EMY OF CAREERS ANO
EAGL E ADVANTAG E SCHOOLS
ACCELERATED INTERMEDIAT E
YES PREPARATORY PUBLIC
WINDHAM SCHOOL DISTRICT
JUBIL EE ACAD EMIC CENTER
DALLAS CAN ACADEMY CHARTER
HARMONY SCI ENC E ACAD (SAN
HARMONY SCI ENC E ACAD EMY
TWO DIMENSIONS PREPARATORY
TEXAS COLL EG E PR EPARATORY
KIPP AUSTIN PUBLIC SCHOOLS INC
DR M L GARZA-GONZALEZ CHARTER
FALLBROOK COLL EG E PR EPARATORY
SCHOOL OF SCI ENC E AND
AUSTIN DISCOVERY SCHOOL
TH E EAST AUSTIN COLL EG E PR EP
RICHARD MILBURN ALTER HIGH
UPLIFT EDUCATION - HAMPTON
TRINITY BASIN PREPARATORY
TEXAS YOUTH COMMISSION
TEXAS EDUCATION AGENCY
AMBASSADORS PREPARATORY
BURNHAM WOOD CHARTER SCHOOL
HARMONY SCHOOL OF EXCELLENCE
BROOKS ACADEMY OF SCI ENC E AND
W ESTLAK E ACAD EMY CHARTER
WAXAHACHI E FAITH FAMILY
PRIORITY CHARTER SCHOOLS
HARMONY SCI ENC E ACAD (FORT
IMAGIN E INT ERNATIONAL ACADEMY
KIPP TEXAS PUBLIC SCHOOLS

Figure 8.70: **Open records request**. The request was filed in May 2019 and fulfilled in June of 2019.



ORR Description: Request: I am trying to ascertain all filings, both open and closed, that have the following characteristics:

- Are special education cases (so have SE prefix] in the docket prefix)
- Were filed from the start of the docket until the date of this request

Since the Texas office of administrative law/courts, unlike the Federal District Court, has no publicly accessible docket index, I ask that you please run a query using the above parameters and generate a list that contains the:

? Case caption
? Docket or case number
? The date of filing and date of termination, if any

of all administrative hearings--(the link online just has cases that went to full hearings).

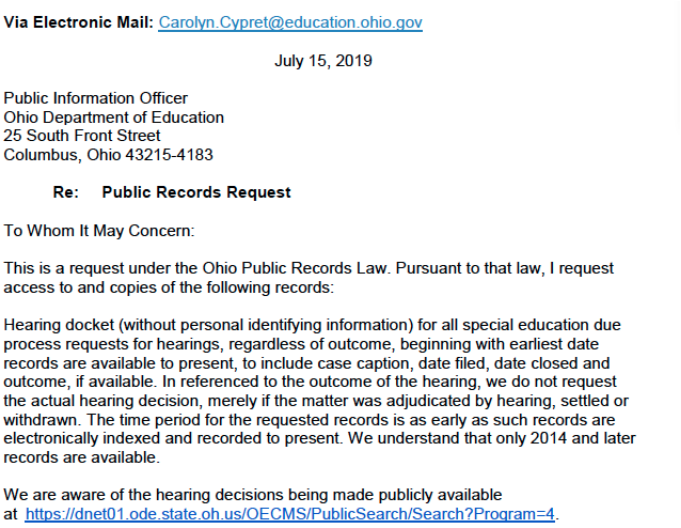
Access type: sent over email. Excel or .csv format is preferred for the above information.

Table 8.28: Texas filings data: schools that could be matched with a Common Core data school but that didn't submit data meeting Common Core data quality standards

school_name
A+ UNLIMITED POTENTIAL
AL PRICE STATE JUVENILE CORRECTIONAL FACILITY
ALPHONSO CRUTCH'S-LIFE SUPPORT CENTER
AUSTIN CAN ACADEMY CHARTER SCHOOL
BENJI'S SPECIAL EDUCATIONAL ACADEMY CHARTER SCHOOL
BETA ACADEMY
BRIDGEWAY PREPARATORY ACADEMY
BYERS ISD
CARPE DIEM SCHOOLS
CHILDREN FIRST ACADEMY OF DALLAS
CHILDREN FIRST ACADEMY OF HOUSTON
COMPASS ROSE ACADEMY
CORSICANA RESIDENTIAL TREATMENT CENTER
CROCKETT STATE SCHOOL
EL PASO LEADERSHIP ACADEMY
EL PASO SCHOOL OF EXCELLENCE
ENCINO SCHOOL
ETOILE ACADEMY CHARTER SCHOOL
EVINS REGIONAL JUVENILE CENTER
FORT WORTH CAN ACADEMY
FRUIT OF EXCELLENCE
GABRIEL TAFOLLA ACADEMY
GAINESVILLE STATE SCHOOL
GEORGE I SANCHEZ CHARTER HS SAN ANTONIO BRANCH
GIDDINGS STATE SCHOOL
GOODWATER MONTESSORI SCHOOL
GREAT HEARTS TEXAS
GUARDIAN ANGEL PERFORMANCE ARTS ACADEMY
HARMONY SCHOOL OF INNOVATION
HARMONY SCHOOL OF SCIENCE AUSTIN
HARMONY SCIENCE ACAD (BEAUMONT)
HARMONY SCIENCE ACAD (COLLEGE STATION)
HARMONY SCIENCE ACADEMY - LAREDO
HARRIS COUNTY DEPT OF ED
HIGH POINT ACADEMY
HOUSTON ALTERNATIVE PREPARATORY CHARTER SCHOOL
HOUSTON CAN ACADEMY CHARTER SCHOOL
JESSE JACKSON ACADEMY
JUAN B GALAVIZ CHARTER SCHOOL
KAUFFMAN LEADERSHIP ACADEMY
KENDLETON ISD
KI CHARTER ACADEMY
KIPP SOUTHEAST HOUSTON
LA ESCUELA DE LAS AMERICAS
LEGACY SCHOOL OF SPORT SCIENCES
LONE STAR LANGUAGE ACADEMY
MCLENNAN CO ST JUVENILE CORRECTION FACILITY I
MCLENNAN CO ST JUVENILE CORRECTION FACILITY II
METRO ACADEMY OF MATH AND SCIENCE
MONTESSORI FOR ALL
NORTH FOREST ISD
NORTH HOUSTON H S FOR BUSINESS
NOVICE ISD
OUTREACH ACADEMY
PIONEER TECHNOLOGY & ARTS ACADEMY
REG 1 EDUCATION SERVICE CENTER
REG 10 EDUCATION SERVICE CENTER
REG 11 EDUCATION SERVICE CENTER
REG 12 EDUCATION SERVICE CENTER
REG 13 EDUCATION SERVICE CENTER
REG 14 EDUCATION SERVICE CENTER
REG 15 EDUCATION SERVICE CENTER
REG 16 EDUCATION SERVICE CENTER
REG 17 EDUCATION SERVICE CENTER
REG 18 EDUCATION SERVICE CENTER
REG 19 EDUCATION SERVICE CENTER
REG 2 EDUCATION SERVICE CENTER
REG 20 EDUCATION SERVICE CENTER
REG 3 EDUCATION SERVICE CENTER
REG 4 EDUCATION SERVICE CENTER
REG 5 EDUCATION SERVICE CENTER
REG 6 EDUCATION SERVICE CENTER
REG 7 EDUCATION SERVICE CENTER
REG 8 EDUCATION SERVICE CENTER
REG 9 EDUCATION SERVICE CENTER
RICHARD MILBURN ACADEMY (BEAUMONT)
RON JACKSON STATE JUVENILE CORR COMPLEX UNIT I
RON JACKSON STATE JUVENILE CORR COMPLEX UNIT II
SAM HOUSTON STATE UNIVERSITY CHARTER SCHOOL
SAMNORWOOD ISD
SAN ANTONIO CAN HIGH SCHOOL
SAN ANTONIO PREPARATORY ACADEMY
SCHOOL OF SCIENCE AND TECHNOLOGY CORPUS CHRISTI
SEASHORE LEARNING CTR CHARTER
SOMERSET CHARTER SCHOOL
TEXAS YOUTH COMMISSION
THE EXCEL CENTER
THE EXCEL CENTER (FOR ADULTS)
THE LEGENDS ACADEMY
THE SCHOOL OF LIBERAL ARTS AND SCIENCE
THERESA B LEE ACADEMY
TRINITY ENVIRONMENTAL ACADEMY
TRIVIUM ACADEMY
UTPB STEM ACADEMY
VALOR PUBLIC SCHOOLS
VICTORY FIELD CORRECTIONAL ACADEMY
WAYSIDE SCHOOLS

8.3 Details on Ohio's filings data

Figure 8.71: **Open records request**. The request was filed in July 2019 and fulfilled in August 2019.



Via Electronic Mail: Carolyn.Cypret@education.ohio.gov

July 15, 2019

Public Information Officer
Ohio Department of Education
25 South Front Street
Columbus, Ohio 43215-4183

Re: Public Records Request

To Whom It May Concern:

This is a request under the Ohio Public Records Law. Pursuant to that law, I request access to and copies of the following records:

Hearing docket (without personal identifying information) for all special education due process requests for hearings, regardless of outcome, beginning with earliest date records are available to present, to include case caption, date filed, date closed and outcome, if available. In referenced to the outcome of the hearing, we do not request the actual hearing decision, merely if the matter was adjudicated by hearing, settled or withdrawn. The time period for the requested records is as early as such records are electronically indexed and recorded to present. We understand that only 2014 and later records are available.

We are aware of the hearing decisions being made publicly available at https://dnet01.ode.state.oh.us/OECMS/PublicSearch/Search?Program=4.

Table 8.29: Ohio filings data: schools that could be matched with a Common Core data school but that didn't submit data meeting Common Core data quality standards

school_name
ACADEMY OF COLUMBUS
ACADEMY OF NEW MEDIA MIDDLE
AKRON ACADEMY OF EXCELLENCE THE
ALADDIN ACADEMY
AREA COOP COMP ED SERV SYS
BAJIM VILLAGE ACADEMY
BEACON HILL MIDDLE/HIGH ACADEMY
BIO-MED SCIENCE ACADEMY
BRIDGE ACADEMY OF OHIO
CAMPBELL SCHOOL FOR GIRLS
CANTON LOCAL DIGITAL ACADEMY
CENTRAL HIGH SCHOOL
CLASSICAL ACADEMY OF COLUMBUS GOVENING COUNCIL
COLLEGE HILL LEADERSHIP ACADEMY
CRITTENTON COMMUNITY SCHOOL
CUYAHOGA VALLEY ACADEMY
DAYTON LEADERSHIP ACADEMIES-EARLY LEARNING ACADEMY
EARLY CAREER ACADEMY OHIO THE
EDUCATIONAL ACADEMY AT LINDEN
FIRST TIME LEARNERS ACADEMY
FIVE R'S ACADEMY
FOUNDATION ACADEMY OF AKRON
FOUNDATION ACADEMY OF CANTON
FOUNDATION ACADEMY OF CLEVELAND
GAHANNA COMMUNITY SCHOOL
GAIN PRODUCTIVE SKILLS ACADEMY
GALLIA-VINTON ESC
GCESC COMMUNITY SCHOOL
GEORGE V. VOINOVICH RECLAMATION ACADEMY
HAMILTON BD OF EDUC-DATA PROC
HOPE ACADEMY EAST CAMPUS
KELLEYS ISLAND LOCAL
L.E.A.D. ACADEMY
L.E.A.R.N. ACADEMY
LAKE ERIE ED COMP ASSOC
LAKE-GEAUGA COMP NETWORK
LANCASTER DIGITAL ACADEMY
LAWRENCE COUNTY ESC
LEADERSHIP ACADEMY OF MATHEMATICS & SCIENCE FOCUS
LEADERSHIP ACADEMY OF MATHEMATICS & SCIENCE OF CINCINNATI
LIBERTY PREPARATORY SCHOOL
LICKING AREA COMPUTER ASSOC
LION OF JUDAH ACADEMY
MASON RUN HIGH SCHOOL
MELROSE PREPARATORY ACADEMY
METRO DAYTON ED COOP ASSOC
METROPOLITAN EDUC COUNCIL
MIAMI VALLEY ED COMP ASSOC
MIDDLE BASS LOCAL
MUSKINGUM VALLEY STEMM ACADEMY
N CENTRAL OHIO COMP COOP
NE OHIO MGMNT INFO NETWORK
NEW DIRECTIONS ACADEMY
NORTH BASS LOCAL
NORTHERN OHIO ED COMP ASSOC
NORTHWEST OHIO COMP ASSOC
NOTTEN SCHOOL FOR SCIENCE TECHNOLOGY ENGINEERING AND MATHE
NW OHIO AREA COMP SVCS COOP
O.N.E. ACADEMY THE
OH MID EAST-REG ED SERV AG
OHIO CENTRAL SCHOOL SYSTEM
OHIO CYBER ACADEMY
OLYMPUS K-12 ONLINE SCHOOL
PEGASUS ACADEMY
PERRY-HOCKING ESC
PHOENIX VILLAGE ACADEMY PRIMARY 1
PORTAGE PATH PREPARATORY ACADEMY
PSCHTECIN PUBLIC SCHOOL
QUEST ACADEMY COMMUNITY
RIVER VALLEY ACADEMY
ROMIG ROAD COMMUNITY SCHOOL
SCHOLARTS PREPARATORY AND CAREER CENTER FOR CHILDREN
SHELBY COUNTY ESC
SOUTH CENT OH-REG ED SER AG
SOUTH EAST OH VOL ED COOP
SOUTHWEST OHIO COMPUTER ASSOC
STARK COUNTY BD ED DATA PROC
STEVE SANDERS ACADEMY THE
THE GATEHOUSE SCHOOL
THE ISUS INSTITUTE OF HEALTH CARE
THE OPEN SCHOOL OF OHIO
TOWPATH TRAIL HIGH SCHOOL
TRI-RIVERS ED COMP ASSOC
UNITED PREPARATORY ACADEMY
URBAN PATHWAYS YOUNGSTOWN
WALTON INSTITUTE FOR SCHOLARLY EDUCATION
WESTERN OHIO COMP ORG
WINGS ACADEMY 1
WINWIN ACADEMY
WORLD COLLEGIATE PREPARATORY SCHOOL
YOUNG SCHOLARS PREP SCHOOL - SOUTH
YOUTH EXPERIENCING SUCCESS

8.4 Additional summaries of relationship between school or district demographics and filings

Table 8.30: **Relationship between district poverty share and parent monitoring (GAM results): Texas**

B. smooth terms	edf	Ref.df	F-value	p-value
	Total filings			
s(frpl_eligible_rate)	1.0000	1.0000	5.0985	0.0241
s(total_students)	8.6560	8.9620	170.7626	< 0.0001
	Any filing			
s(frpl_eligible_rate)	1.0002	1.0004	1.6159	0.2037
s(total_students)	4.8111	4.9871	247.8499	< 0.0001

Table 8.31: **Relationship between district poverty share and parent monitoring (negative binomial and logistic regression results): Texas**

	Dependent variable:	
	Any filing	Total filings
	Logit	*Negative binomial*
	(1)	(2)
Free lunch share	−0.630	−0.738
	(0.455)	(0.289)
	p = 0.166	p = 0.011**
log(total_students)	1.339	1.124
	(0.085)	(0.042)
	p = 0.000***	p = 0.000***
Constant	−11.023	−9.171
	(0.689)	(0.379)
	p = 0.000***	p = 0.000***
Observations	1,189	1,189
Log Likelihood	−375.964	−879.492
θ		0.913*** (0.130)
Akaike Inf. Crit.	757.928	1,764.985
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 8.32: **Relationship between district poverty share and parent monitoring (GAM results): DC**

Total filings				
B. smooth terms	edf	Ref.df	F-value	p-value
s(Free lunch share)	5.8536	6.9796	4.9755	< 0.0001
s(total_students)	7.5481	8.4168	4.5520	< 0.0001
Any filing				
B. smooth terms	edf	Ref.df	F-value	p-value
s(Free lunch share)	6.1661	6.9249	47.1720	< 0.0001
s(total_students)	1.4921	1.8417	1.8424	0.2903

Table 8.33: **Relationship between district poverty share and parent monitoring (logistic regression results): DC**. The negative binomial model does not converge.

	Dependent variable:
	Any filing
Free lunch share	-0.630
	(0.455)
	p = 0.166
log(total_students)	1.339
	(0.085)
	p = 0.000***
Constant	-11.023
	(0.689)
	p = 0.000***
Observations	1,189
Log Likelihood	-375.964
Akaike Inf. Crit.	757.928
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 8.34: **Relationship between district poverty share and parent monitoring (GAM results): Ohio**

B. smooth terms	edf	Ref.df	F-value	p-value
	Total filings			
s(frpl_eligible_rate)	8.0311	8.7446	3.3797	0.0008
s(total_students)	8.9927	9.0000	404.0159	< 0.0001
	Any filing			
s(frpl_eligible_rate)	1.0003	1.0005	0.0067	0.9347
s(total_students)	5.6944	6.7702	212.3199	< 0.0001

Table 8.35: **Relationship between district poverty share and parent monitoring (logistic regression and negative binomial results): Ohio**.

	Dependent variable:	
	Any filing	Total filings
	Logit	*Negative binomial*
	(1)	(2)
Free lunch share	0.166	−0.033
	(0.388)	(0.274)
	p = 0.670	p = 0.903
log(total_students)	1.288	1.193
	(0.098)	(0.062)
	p = 0.000***	p = 0.000***
Constant	−10.131	−9.265
	(0.777)	(0.500)
	p = 0.000***	p = 0.000***
Observations	1,003	1,003
Log Likelihood	−422.403	−853.690
θ		0.886*** (0.126)
Akaike Inf. Crit.	850.806	1,713.380
Note:		*p<0.1; **p<0.05; ***p<0.01

8.5 Details on topic modeling

Figure 8.72: **Choosing the number of topics** The figure shows the tradeoffs between semantic coherence and exclusivity in the corpus comprised of Texas and DC hearings. The plot shows that $k = 16$ and $k = 17$ strike a good balance between high exclusivity without too low of semantic coherence.

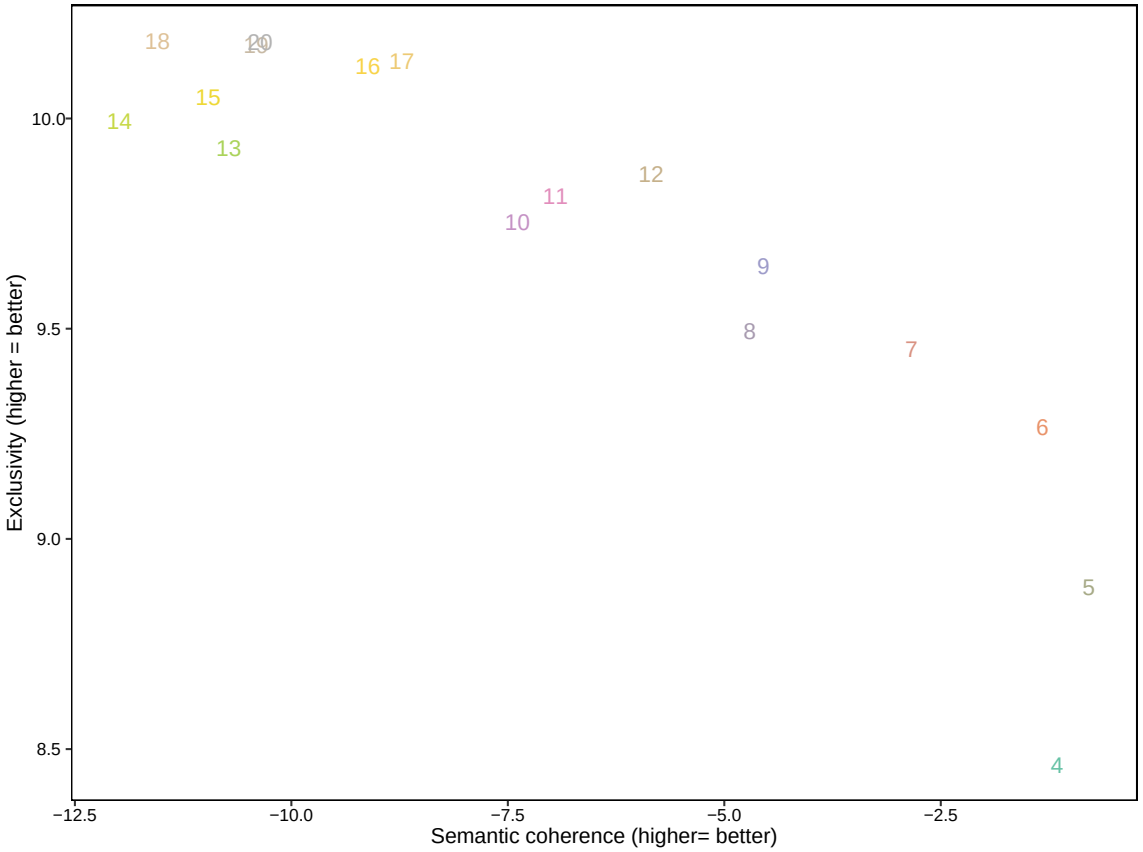


Figure 8.73: **Comparing themes in hearings: Texas versus DC** The figure shows topics with no difference in prevalence between Texas and DC.

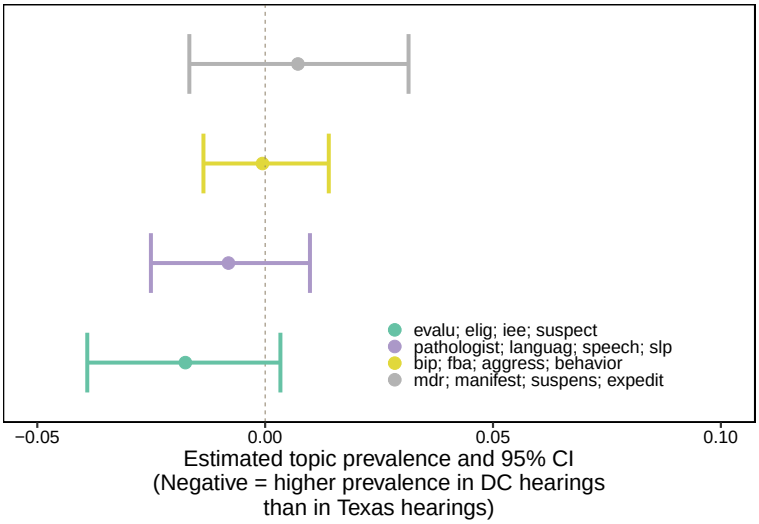
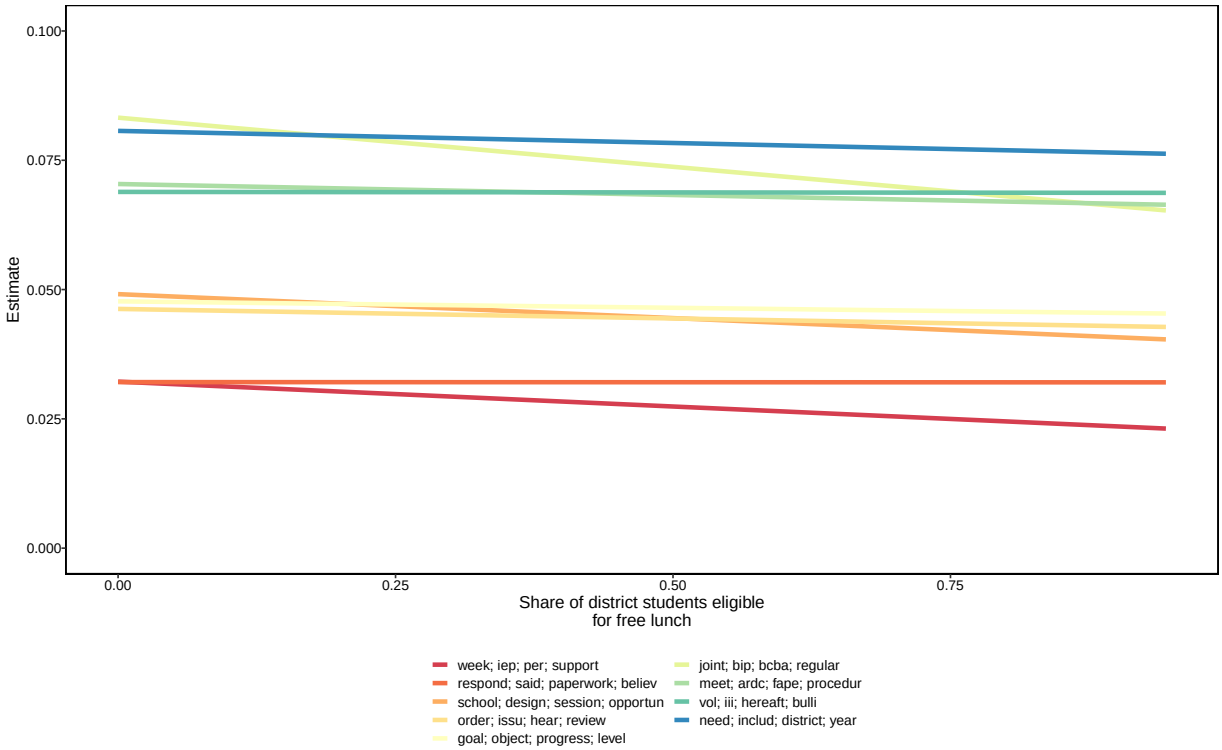


Figure 8.74: **Themes that do not vary across poverty levels in Texas**



Supplementary Materials: Chapter Five

Table 9.36: Data sources for analysis of ARRA's effect on parent complaints about disability services

Dependent variables: all by state/year from 2004/2005 to 2011/2012 school year	
Real outcome	
Disputes per 10,000 special education students	Numerator: IDEA Part B (3-21) Section 618 dispute counts Denominator: CCD with, IDEA Part B Section 618 counts used for missing CCD values
Robustness check outcome	
Disputes per 10,000 students	Numerator: same as above Denominator: CCD
Placebo outcome	
Child-focused malpractice claims per 10,000 children	Numerator: NPDB public-use data file count of claims in 4 age categories: fetus, < 1 year, Age 1-9, Age 10-19. States were coded using recommended logic of first using the practitioner's work state, and then, if missing using the practitioner's home state
Independent variables: all by state/year from 2004/2005 to 2011/2012 school year	
ARRA financing years (2008/2009 and 2009/2010)	Legislation
Financing formula	Parrish et al. (2003) and Ahearn (2010) 50-state surveys of financing formula (conducted by partnership between Department of Ed. Office of Special Education Programs (OSEP) and National Association of State Directors of Special Education (NASDSE)
Controls (calendar year corresponding to fall of SY)	
% children living in poverty	Census; ACS
Annual unemployment rate	BLS
% educ. revenue from federal sources	CCD Public Education Financial Survey
State expense-revenue ratio	Pew state fiscal health database, derived from state Comprehensive Annual Financial Reports

Figure 9.75: Correlation between outcome and predictors: state-level ARRA analysis

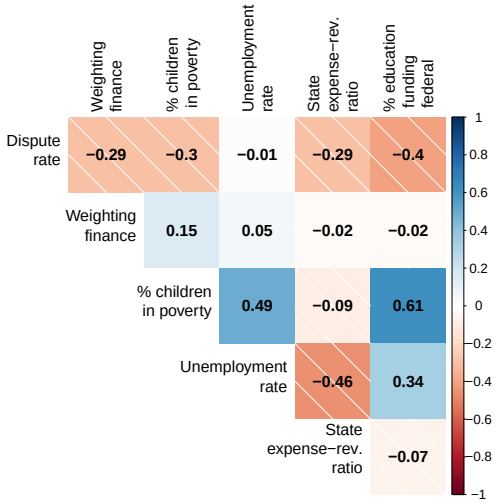


Figure 9.76: Trends in disputes in individual states (states ordered alphabetically)

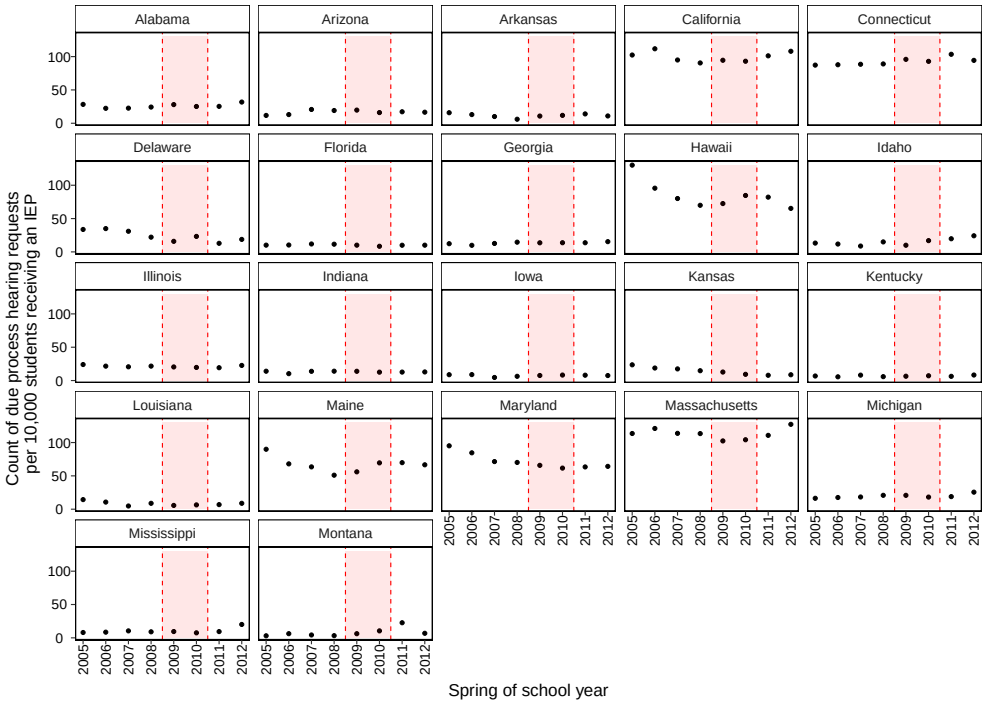


Figure 9.77: Trends in disputes in individual states (states ordered alphabetically)

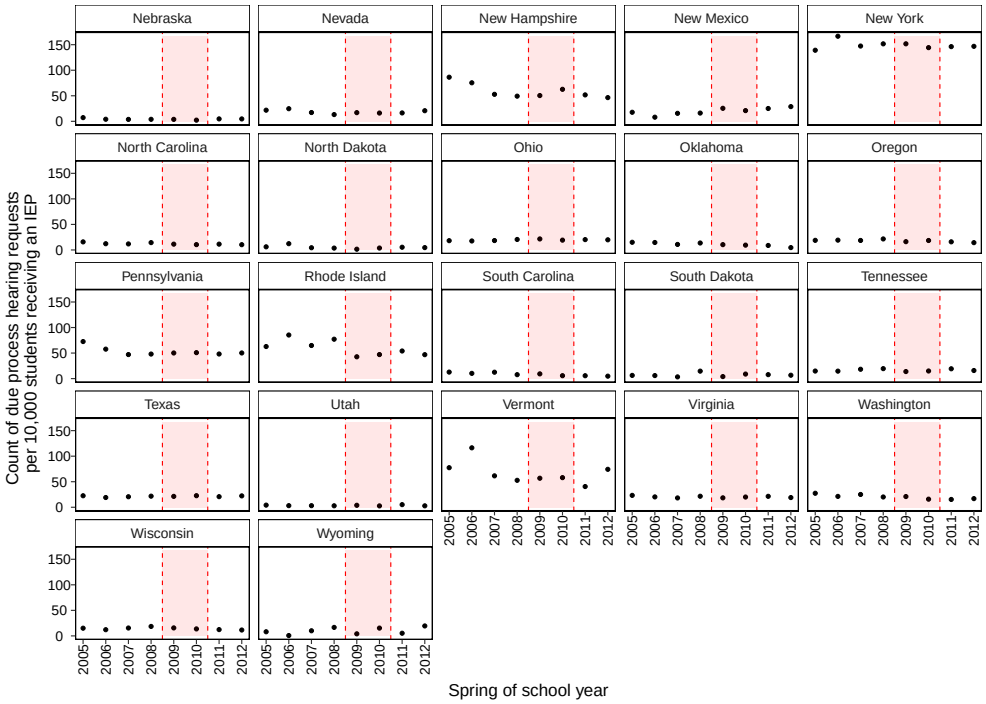


Figure 9.78: Placebo analysis of child-focused malpractice claims: trends across states and years

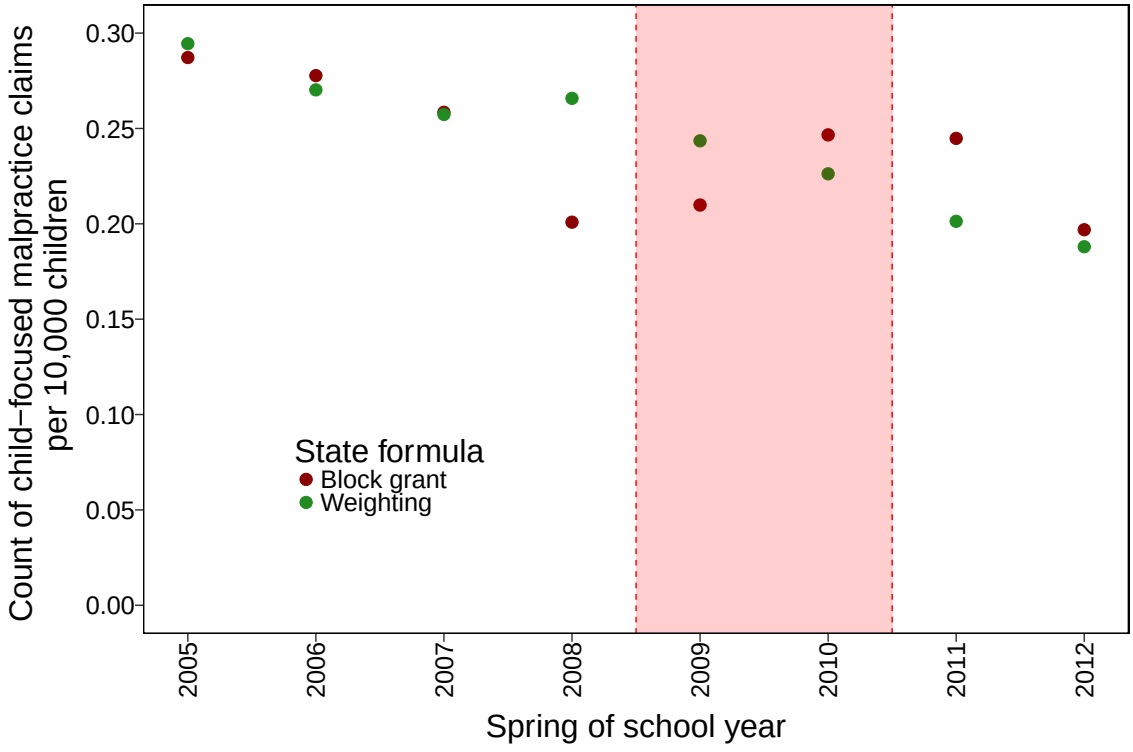


Table 9.37: Robustness check: effect of ARRA grant on alternate definition of dispute rate ($\frac{\text{count disputes}}{\text{all students}}$ rather than $\frac{\text{count disputes}}{\text{IEP students}}$)

	β (SE) p	
ARRA grant year (1 = yes)	-0.538 (0.27) 0.04	-0.424 (0.21) 0.04
Weighting financing (1 = yes)	-0.606 (0.29) 0.04	-0.695 (0.28) 0.01
ARRA grant year (1 = yes) × weighting financing (1 = yes)	0.285 (0.28) 0.31	0.290 (0.25) 0.25
Observations (50 states × 8 years)	400	400
State fixed effects?	Yes	Yes
Clustered SE by state?	Yes	Yes
Other controls?	No	Yes

Table 9.38: Placebo test: effect of ARRA grant on child-focused malpractice claim rates

	β (SE) p	
ARRA grant year (1 = yes)	-0.011 (0.01) 0.39	-0.012 (0.02) 0.42
Weighting financing (1 = yes)	0.059 (0.03) 0.05	0.042 (0.02) 0.07
ARRA grant year (1 = yes) × weighting financing (1 = yes)	0 (0.02) 0.99	0 (0.02) 0.99
Observations (50 states × 8 years)	400	400
State fixed effects?	Yes	Yes
Clustered SE by state?	Yes	Yes
Other controls?	No	Yes

Table 9.39: Data sources: predictor variables for district-level analysis

Variable	**Data Source**
Main predictor	
Unduplicated pupil % used in funding threshold	California Dept. of Ed. LCFF Source Data
Controls	
Count and % of students with IEP	NCES Common Core Data
Pre-grant per-pupil expenditures	NCES Common Core Data
Student demographics in district (race; FRPL ELL)	NCES Common Core Data

Figure 9.79: IEPs versus count of districts

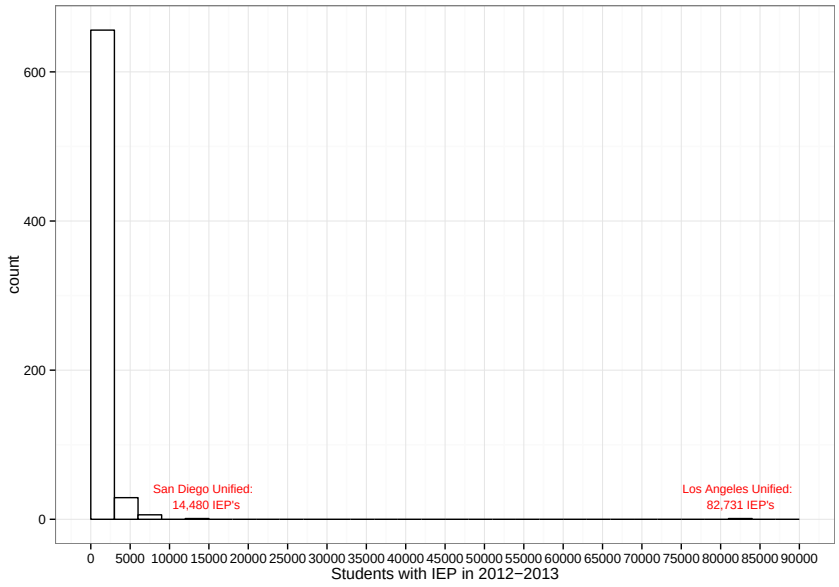


Figure 9.80: Count of IEPs versus predicted probability of having a case. **Left**: shows the predicted probability of case across the range of IEP counts in the data– shows that all districts with IEPs $>\approx 5000$ have a case; **Right**: restricts the window for the graph to districts with below a 0.9999 probability of having a case

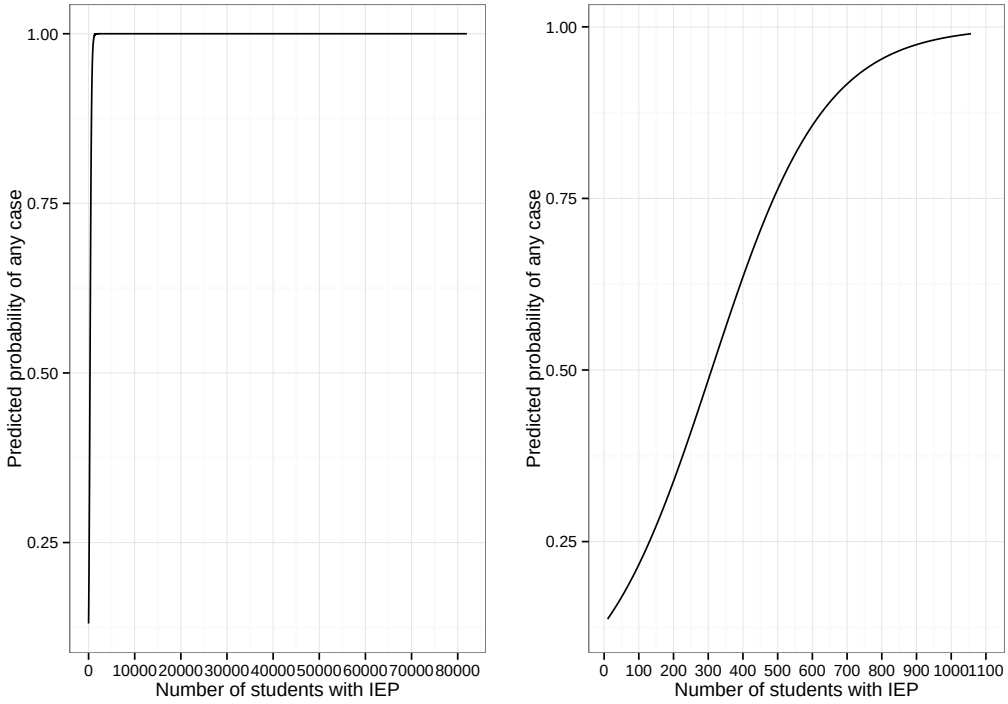


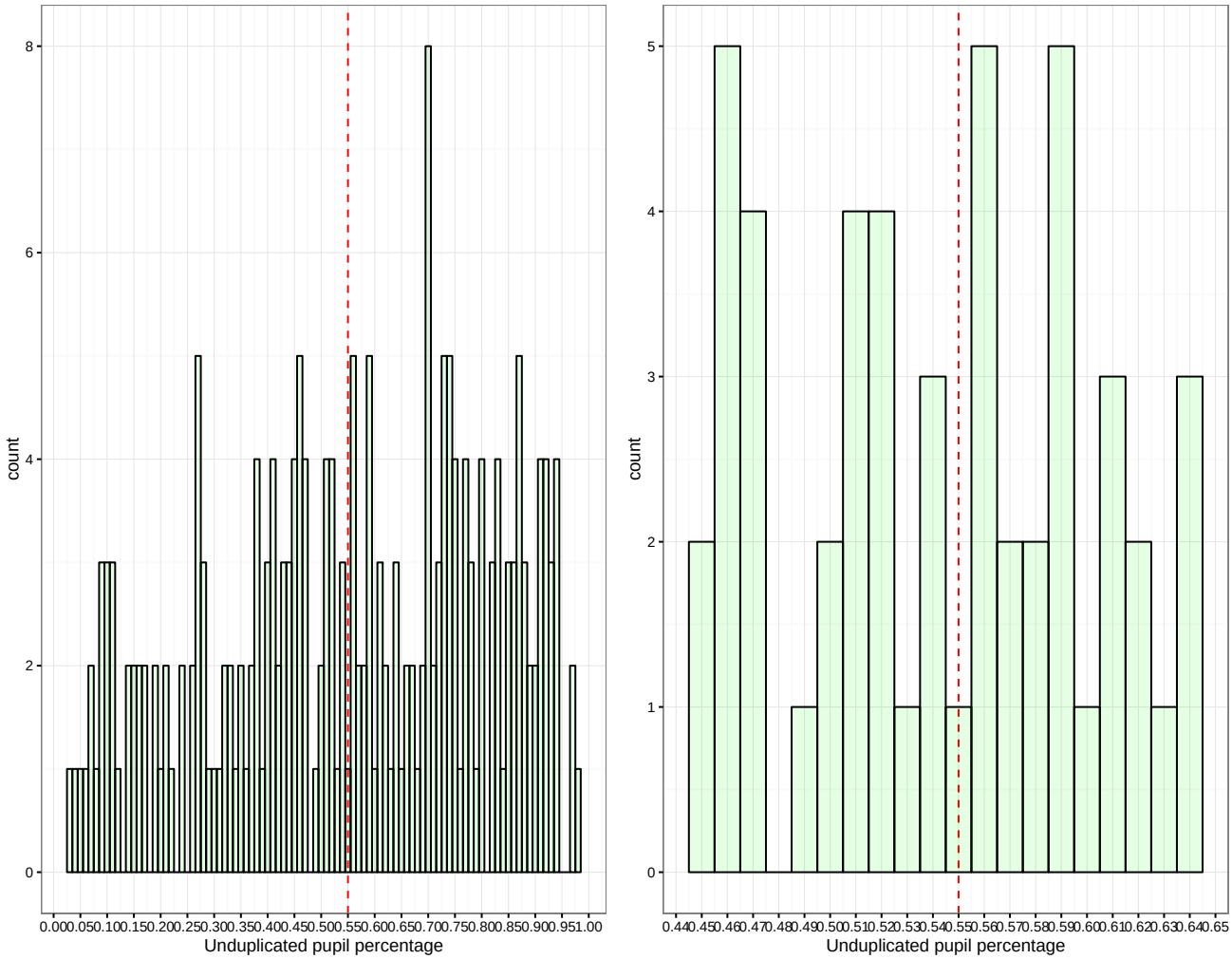
Figure 9.81: School districts in analytic sample for RDD

	District
1	Acalanes Union High
2	Adelanto Elementary
3	Alameda Unified
4	Albany City Unified
5	Alhambra Unified
6	Alisal Union
7	Alta Loma Elementary
8	Amador County Unified
9	Apple Valley Unified
10	Arcadia Unified
11	Atwater Elementary
12	Azusa Unified
13	Bellflower Unified
14	Belmont-Redwood Shores Elementary
15	Berkeley Unified
16	Berryessa Union Elementary
17	Beverly Hills Unified
18	Bonita Unified
19	Brawley Elementary
20	Brea-Olinda Unified
21	Buena Park Elementary
22	Burbank Unified
23	Calaveras Unified
24	Campbell Union
25	Campbell Union High
26	Carlsbad Unified
27	Castro Valley Unified
28	Center Joint Unified
29	Centinela Valley Union High
30	Central Elementary
31	Central Unified
32	Central Union High
33	Charter Oak Unified
34	Claremont Unified
35	Coachella Valley Unified
36	Corcoran Joint Unified
37	Coronado Unified
38	Cotati-Rohnert Park Unified
39	Covina-Valley Unified
40	Culver City Unified
41	Cupertino Union Elementary
42	Cypress Elementary
43	Davis Joint Unified
44	Del Mar Union Elementary
45	Delano Joint Union High
46	Delano Union Elementary
47	Delhi Unified
48	Dixon Unified
49	Dry Creek Joint Elementary
50	Duarte Unified
51	Dublin Unified
52	Eastside Union Elementary
53	El Monte City
54	El Rancho Unified
55	El Segundo Unified
56	Empire Union Elementary
57	Encinitas Union Elementary
58	Enterprise Elementary
59	Escondido Union High
60	Etiwanda Elementary
61	Eureka City Unified
62	Fallbrook Union High
63	Fillmore Unified
64	Fountain Valley Elementary
65	Franklin-Mckinley Elementary
66	Fremont Union High
67	Fullerton Elementary
68	Fullerton Joint Union High
69	Garvey Elementary
70	Gilroy Unified
71	Glendora Unified
72	Goleta Union Elementary
73	Hawthorne Elementary
74	Hilmar Unified
75	Hollister
76	Huntington Beach City Elementary
77	Huntington Beach Union High
78	Inglewood Unified
79	Jefferson Elementary (Daly City)
80	Jefferson Elementary (Tracy)

	District
81	Jefferson Union High
82	Julian Union Elementary
83	Keppel Union Elementary
84	King City Union
85	Kings Canyon Joint Unified
86	La Canada Unified
87	La Mesa-Spring Valley
88	Lafayette Elementary
89	Lancaster Elementary
90	Las Virgenes Unified
91	Lawndale Elementary
92	Lemon Grove Elementary
93	Lennox
94	Liberty Union High
95	Lincoln Unified
96	Little Lake City Elementary
97	Los Alamitos Unified
98	Los Altos Elementary
99	Los Banos Unified
100	Lowell Joint Elementary
101	Lucia Mar Unified
102	Lynwood Unified
103	Magnolia Elementary
104	Manhattan Beach Unified
105	Martinez Unified
106	Menifee Union Elementary
107	Mill Valley Elementary
108	Modesto City High
109	Monrovia Unified
110	Monterey Peninsula Unified
111	Moreland
112	Morgan Hill Unified
113	Mountain View Elementary (El Monte)
114	Mountain View Whisman
115	Mountain View-Los Altos Union High
116	Mt. Pleasant Elementary
117	National Elementary
118	Natomas Unified
119	Nevada Joint Union High
120	New Haven Unified
121	New Jerusalem Elementary
122	Newark Unified
123	Newhall
124	North Monterey County Unified
125	Novato Unified
126	Oak Grove Elementary
127	Oak Park Unified
128	Oakley Union Elementary
129	Ojai Unified
130	Orcutt Union Elementary
131	Oroville City Elementary
132	Oroville Union High
133	Oxnard Elementary
134	Oxnard Union High
135	Palo Alto Unified
136	Palos Verdes Peninsula Unified
137	Paramount Unified
138	Paso Robles Joint Unified
139	Patterson Joint Unified
140	Perris Union High
141	Petaluma City Elementary
142	Petaluma Joint Union High
143	Piedmont City Unified
144	Pittsburg Unified
145	Placer Union High
146	Pleasanton Unified
147	Ramona City Unified
148	Ravenswood City Elementary
149	Redondo Beach Unified
150	Redwood City Elementary
151	Rim Of The World Unified
152	Rio Elementary
153	Robla Elementary
154	Rocklin Unified
155	Romoland Elementary
156	Rosedale Union Elementary
157	Roseville City Elementary
158	Roseville Joint Union High
159	Rowland Unified
160	Salinas City Elementary

	District
161	Salinas Union High
162	San Bruno Park Elementary
163	San Carlos Elementary
164	San Dieguito Union High
165	San Gabriel Unified
166	San Jacinto Unified
167	San Leandro Unified
168	San Lorenzo Unified
169	San Luis Coastal Unified
170	San Marino Unified
171	San Mateo Union High
172	San Mateo-Foster City
173	San Rafael City Elementary
174	San Ysidro Elementary
175	Santa Cruz City Elementary
176	Santa Cruz City High
177	Santa Maria-Bonita Elementary
178	Santa Monica-Malibu Unified
179	Santa Rita Union Elementary
180	Santa Rosa Elementary
181	Santa Rosa High
182	Santee
183	Saugus Union
184	Selma Unified
185	Sequoia Union High
186	Silver Valley Unified
187	Snowline Joint Unified
188	Solana Beach Elementary
189	Soledad Unified
190	Sonoma Valley Unified
191	South San Francisco Unified
192	South Whittier Elementary
193	Spencer Valley Elementary
194	Stanislaus Union Elementary
195	Sulphur Springs Union
196	Sunnyvale
197	Sylvan Union Elementary
198	Tahoe-Truckee Unified
199	Tamalpais Union High
200	Temple City Unified
201	Tracy Joint Unified
202	Turlock Unified
203	Ukiah Unified
204	Upland Unified
205	Vacaville Unified
206	Vallejo City Unified
207	Ventura Unified
208	Victor Elementary
209	Victor Valley Union High
210	Walnut Valley Unified
211	Washington Unified (West Sac)
212	Waterford Unified
213	West Covina Unified
214	Western Placer Unified
215	Westminster
216	Westside Union Elementary
217	Whittier City Elementary
218	Whittier Union High
219	Woodland Joint Unified
220	Yuba City Unified
221	Yucaipa-Calimesa Jt. Unified

Figure 9.82: Distribution of districts in analytic sample by percentage unduplicated. **Left**: all percentage unduplicated; **Right**: focusing on districts within 10% bandwidth of threshold



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