Optimal Special Education Identification Under State Finance Policies

by

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THESIS ABSTRACT

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Title: Optimal Special Education Identification Under State Finance Policies

All state education systems allocate additional funding to schools serving students with specialized needs, including those in special education and English language learner (ELL) programs. Although this creates a mechanical increase in revenue where identification rates are higher, empirical evidence suggests that schools may also adjust identification and placement decisions in response to funding policy changes. This paper develops a theoretical model to examine how schools classify students under information asymmetry about individual needs and with differing finance structures. I frame schools' decision as a signal extraction problem where schools maximize aggregate student performance subject to a non-negative budget constraint. The model predicts that when specialized resources are more effective than general resources at improving the performance of students at the margin of receiving support, or are perceived to be, schools will classify a larger proportion of their student body for specialized support. Funding policies effectively impose an upper-bound on the number of students schools can identify for support; a more generous environment enables schools to approach their unconstrained optimal resource allocation. I derive comparative statics with respect to key parameters and outline testable hypothesis for future empirical research. Although motivated by special education finance research, the model is generalizable to other fiscally incentivized student-resource matching programs such as those for ELLs.

ACKNOWLEDGMENTS

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CHAPTER I

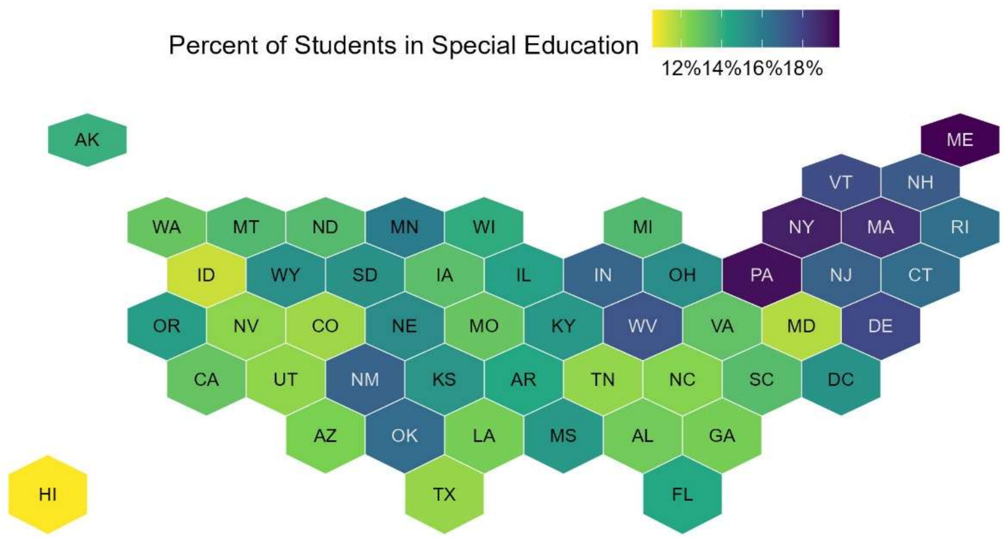
INTRODUCTION

Students with disabilities represent a significant and expanding subgroup among the school-aged population in the United States, representing 15% of the school-going population or over seven million students (National Center for Education Statistics [NCES], 2024). Eighty percent of special needs students receive services for specific learning disabilities (e.g., dyslexia), speech and language impairments, other health impairments (e.g., attention deficit hyperactivity disorder, asthma, diabetes), and autism. (NCES, 2024). About two-thirds of special needs students spend 80% or more of their school day in general education classrooms (NCES, 2024). Despite this overall trends, there is substantial geographic variation in special education identification rates (see Figure 1 and 2). For example, the state-level identification rate ranges from 13% in Texas to 20% in Massachusetts (NCES, 2024), with notable variation between districts within states (Office of Special Education Programs [OSEP], 2022).

Two research traditions have sought to explain the variation in identification rates. The first focuses on disproportionality in special education identification. Prevalence studies consistently indicate that certain demographic groups are overrepresented in special education (e.g., boys, African American and American Indian students, and students from low-income backgrounds) whereas other groups are often underrepresented (NCES, 2024). However, these patterns may arise from a range of factors, including differential sorting of students into settings, cumulative effects of intersectional socioeconomic identities, or differential treatment and implicit bias within settings.

Figure 1

State-wide variation in special education identification rates for 2022-23 school year.



Note: Data from NCES (2024) and OSEP (2022).

Figure 2A

District-wide variation in special education identification rates for Oregon in 2022-23 school year.

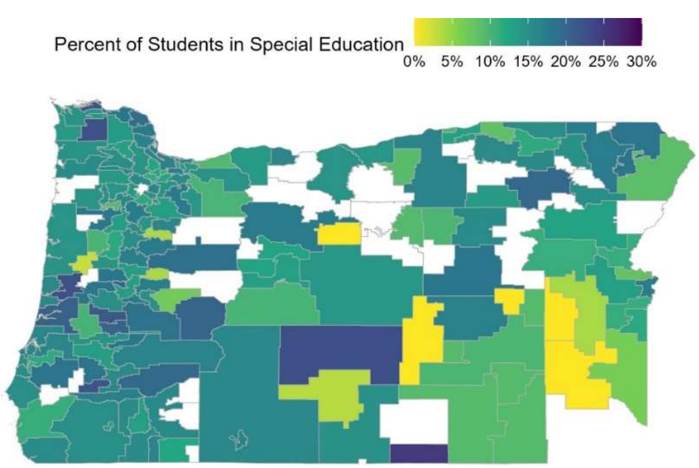
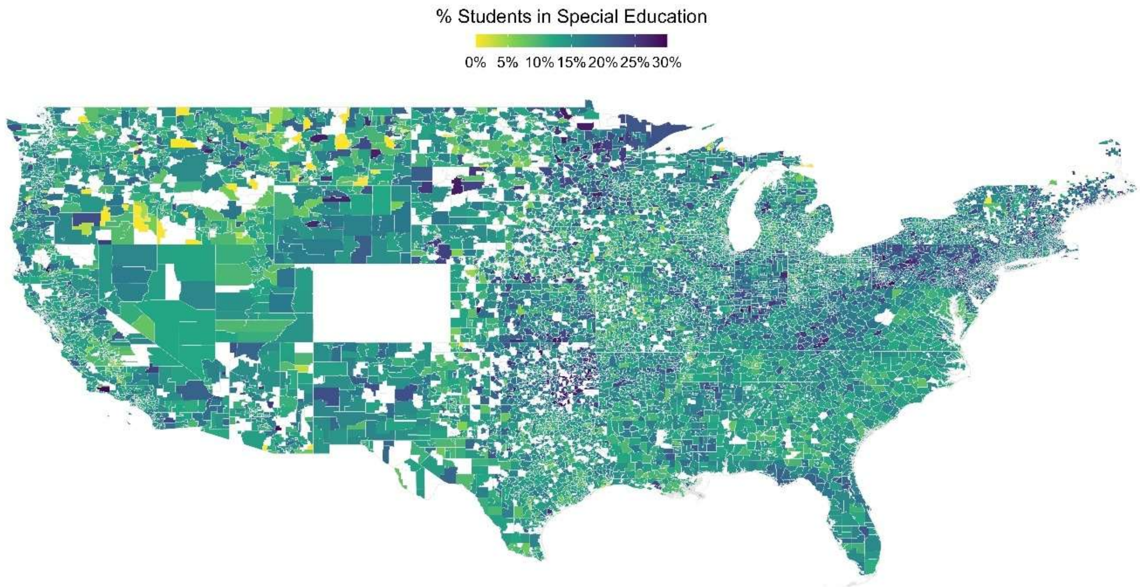


Figure 2B

District-wide variation in special education identification rates for the United States in 2022-23 school year.



Note: Data from NCES (2024) and OSEP (2022). The white area shows districts with missing data.

A second line of research investigates the relationship between school funding and special education identification rates. The federal Individuals with Disabilities Education Act (IDEA, 2004) mandates that public schools provide a "free and appropriate education" for all students with disabilities. Because specialized services typically incur higher costs than general education, both federal and state funding mechanisms provide additional resources to school districts for special education (Kolbe, 2019). Consequently, the revenue allocated to school districts increases with an increase in the number of students identified for special education. However, empirical studies show that state funding formulas may shape identification and placement decisions, indicating that financial incentives can influence resource allocation (Dhuey & Lipscomb, 2011; Greene & Forster, 2002; Kwak, 2010; Morrill, 2018).

Although these literatures have developed separately, special education identification rates and schools' funding decisions are fundamentally linked: schools must provide "appropriate" services for every identified student, and their capacity to do so depends on available resources constrained by funding mechanism. To better understand this connection, I develop a theoretical model drawing from Lucas's (1972) signal-extraction theory. I conceptualize schools as decision-making agents operating with incomplete information about which students require specialized services. Schools use assessment data to gauge student needs and optimally match students to specialized or general resources with the goal of maximizing student performance within their budget constraints. The framework highlights the dimensions along which schools set an optimal threshold and respond to funding policies, generating predictions for future empirical work.

A central assumption of the model is that allocating specialized resources is a beneficial strategy for a performance-maximizing school. Students with disabilities experience persistent disparities in academic achievement, grade retention, disciplinary actions, and postsecondary attainment (Morgan et al., 2014; Newman et al., 2011; Wagner et al., 2005). Special education services are designed to mitigate these gaps, and intervention research demonstrates that targeted services yield meaningful academic and behavioral improvements (e.g., Fuchs &Vaughn, 2012; What Works Clearinghouse). Further, IDEA reinforces the use of evidence-based interventions and inclusive education practices (IDEA, 2004). However, estimating the causal effects of special education remains challenging due to selection bias and the heterogeneity of disabilities, services, and implementation quality across settings. Critics raise concerns about potential negative effects, including stigmatization from disability labels (Shifrer, 2013), increased academic tracking and segregation (Parrish, 1994; Parrish, 2000), and adverse spillovers on peers in inclusive classrooms (Balestra et al., 2022; Friesen et al., 2010; Justice et al., 2014; Salas García & Rentería, 2024). Despite these concerns, a growing literature using within-student designs and exogenous policy variation find that special education services improve outcomes for those receiving the services without adversely affecting the peers (Ballis & Heath, 2021; E. Hanushek et al., 2002; E. A. Hanushek et al., 2003; Hurwitz et al., 2020; Schwartz et al., 2021). These findings suggest that, on average, special education services are beneficial educational strategy for schools.

To preview the key results, the model predicts that schools classify more students for specialized support when they perceive specialized resources as more effective than general resources in improving performance for students at the identification margin. Funding policies effectively impose an upper bound on identification rates that can be realized given schools' budget; in a more generous funding environment, schools can approach their unconstrained optimal resource allocation. This paper contributes to three strands of literature: research on dynamic school-level factors explaining variation in identification rates, formal mechanisms linking identification and funding policies, and the application of economic signal extraction models to special education decision-making. The thesis progresses as follows: Chapter II reviews the legislative background and relevant literature. Chapter III presents the theoretical model. Chapter IV illustrates the model's results and outlines hypotheses for empirical testing. Section V presents concluding remarks.

CHAPTER II

BACKGROUND

Legislative Context

The Individuals with Disabilities Education Act (IDEA), originally enacted in 1975 and most recently reauthorized in 2004, is the primary federal law ensuring services to children with disabilities throughout the United States (IDEA, 2004). IDEA guarantees students with disabilities the right to a “free and appropriate public education” in the “least restrictive setting.” One of its foundational provisions is the “Child Find” mandate, which requires states and local educational agencies to identify, locate, and evaluate all children with disabilities who may need special education and related services (IDEA, 20 U.S.C. § 1412(a)(3)(A)). Schools fulfill this mandate through a combination of universal screeners, teacher referrals, parent or guardian requests, and pre-referral interventions such as multi-tier systems of support (Frey, 2019). The law requires multiple measures for identification to ensure accuracy and equity (Fuchs & Fuchs, 2006; IDEA Regulations, 34 CFR § 300.304(b)). Once a concern is raised, schools initiate an evaluation process to determine the child's eligibility for special education services under one of IDEA's thirteen disability categories. Following identification, a multidisciplinary team including parents and general education teachers develops an individualized education program to outline the specialized supports, which is legally binding.

Critically, IDEA positions schools as the primary agents responsible for operationalizing the Child Find mandate (i.e., identifying and matching students to specialized resources). However, implementation varies significantly across districts, influenced by resource constraints, staff training, and local policy interpretations (Frey, 2019; Schifter, 2019; Zirkel, 2013). This variation in implementation creates the foundation for understanding how schools make identification decisions within their resource constraints.

Prevalence and Correlates of Identification Rate

Over seven million students currently receive special education services nationwide (NCES, 2024). Although IDEA recognizes thirteen disability categories, four high-incidence categories account for approximately 80% of students served: specific learning disabilities, speech and language impairments, other health impairments, and autism (NCES, 2024). As of 2022, 67% of students with disabilities spend 80% or more of their school day in general education classrooms, compared to 61% a decade ago (NCES, 2024). Identification patterns reveal significant demographic disparities. Relative to their representation in the general student population, American Indian/Alaska Native and Black students are overrepresented in special education; Asian students are underrepresented (NCES, 2024). Boys comprise approximately two-thirds of students in special education, with this disparity most pronounced in high-incidence disability categories (NCES, 2024). These patterns have remained relatively stable over time, motivating extensive research about disproportionality and factors driving identification decisions.

Extant research on disproportionality has examined various correlates, including students' and caregivers' demographic characteristics (Artiles et al., 2006; Guarino et al., 2010; Hibel et al., 2010; Oswald et al., 1999; Oswald et al., 2006), neonatal health indicators (Elder et al., 2020), schools' demographic composition (Fish, 2019), teacher-student demographic matching (Fish, 2019), community-level values (Wiley et al., 2014), and state-level correlates (Westling, 2019). When summarizing disparities in identification rates on racial and ethnic characteristics, a synthesis of 26 studies through 2016 noted a "stark contrast in conclusions" based on data source, level of aggregation, and statistical method (Cruz & Rodl, 2018). Whereas gender differences in high-incidence disability categories persist across studies, findings on racial disparities yield mixed conclusions (Cruz & Rodl, 2018). Examining the African American-White gaps in identification rates, some studies suggest that African American students are overrepresented in special education (Oswald et al., 1999; Skiba et al., 2005) while others find evidence of underidentification (Morgan et al., 2019; Elder et al., 2019; Hibel et al., 2010). Similarly, the explanatory power of socioeconomic status appears sensitive to operationalization (Cruz & Rodl, 2018). Notably, this literature has largely overlooked school-level resources and decision-making, factors that are more adaptable to policy changes, as a mechanism for explaining variation in identification rates.

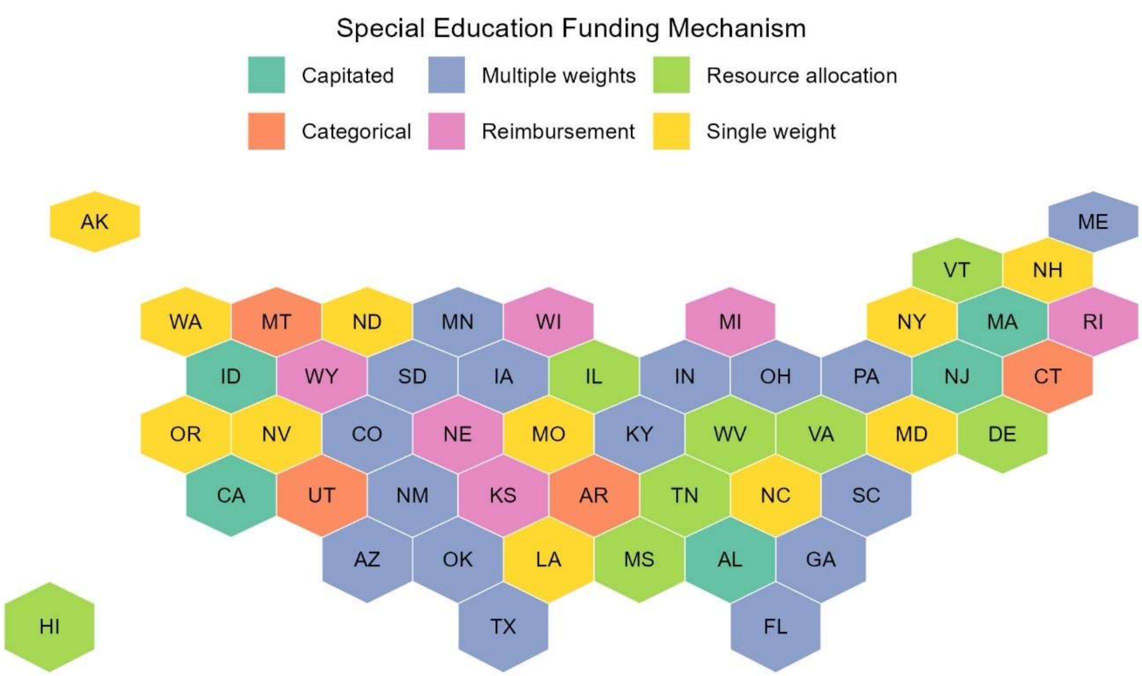
Funding Special Education

State special education funding models are designed to reflect policy priorities while shaping district behavior. IDEA is not only a legal mandate but also a fiscal statute that channels federal funds to states and districts to offset costs related to special education services. However, federal contributions remain limited, covering less than 20% of the total special education expenditure (Zembar, 2018). As a result, most revenue allocation takes place via state and local streams. All 50 states and the District of Columbia have distinct mechanisms to allocate resources, varying in both structure and generosity. For instance, Wyoming reimburses 100% of the special education costs incurred by the local school districts, whereas Connecticut only provides state funding for those students whose education plans require high-cost services (Kolbe, 2019).

State special education funding models are designed to reflect policy priorities while shaping district behavior. Kolbe (2019) classified state-level special education funding policy into one of the six categories: single-weight student-based, multiple-weight student-based, categorical, census-based/capitated, reimbursement, and resource allocation. Figure 3 shows the state-variation in funding policies for special education, as classified by Kolbe (2019). More than half of U.S. states use some form of student-based formula, i.e., additional funding weights are applied to students based on specific categories or service requirements (Kolbe, 2019), and census-based and student-weights are examined most in empirical work.

Figure 3

State variation in special education financial policies, as classified by Kolbe (2019).



Census-based funding, in which a fixed amount is allocated per student based on total enrollment, is valued for its administrative simplicity and for reducing incentives to overidentify students by decoupling funding from special education enrollment. It may also promote investment in early general education (Dhuey & Lipscomb, 2013; Kolbe, 2019). However, it assumes uniform disability prevalence across districts, a notion contradicted by research, and may lead to under identification in high-need areas (Baker & Ramsey, 2010). In contrast, student-weighted models promote equity but can create incentives for strategic classification. For instance, New York schools in the 1990s disproportionately placed students in costly, segregated settings in response to placement-based funding incentives (Mahitivanichcha & Parrish, 2005). Reimbursement models can support expensive services but risk inefficiencies or inflated spending if reimbursement levels are too high, while narrow definitions of allowable costs may prompt rationing of services (Kolbe, 2021; Parrish, 1994). Additionally, funding caps or thresholds may stabilize state budgets but can disadvantage districts with larger special education populations and encourage efforts to under-identify (Kolbe, 2021; Parrish & Verstegen, 1994). Currently, seven states maintain funding caps limiting the number of students eligible for additional special education funding, with at least one state—Oregon—actively considering cap removal in its current legislative session (Oregon Legislature, 2025).

Existing quantitative research suggests that state funding policies can influence special education identification and placement decisions. In Texas, Cullen (2003) found that a policy change increasing special education funding for less-resourced districts explained 40% of the growth in student identification. In California, Kwak (2010) observed a decline in identification rates following the shift to a census-based funding formula. Similarly, Dhuey and Lipscomb (2011), using national data, found that census-based funding reduced identification rates and increased the use of out-of-school placements. Morrill (2018), in a nationwide panel study, reported that states offering differentiated funding incentives for an attention-deficit/hyperactivity disorder (ADHD) diagnosis had higher identification rates and greater likelihood of medication use. While there is some evidence suggesting that school decision-making processes are influenced by funding, the specific mechanism and the margins along which schools respond to these fiscal changes remain unclear and is the subject of the current paper.

Schools' Role: Fiscally-incentivized matching problem

Signal extraction theory is a macroeconomic framework that describes how agents interpret noisy signals to infer the true state of the world and make decisions under uncertainty and incomplete information (Lucas, 1972; Mills, 1982, Bao & Duffy, 2021). In the original formulation by Lucas (1972), agents cannot directly observe economic shocks (e.g., price changes driven by changes in demand vs. inflation) and must infer their source based on observable but ambiguous signals. Schools face an analogous challenge: they must determine which students require specialized resources versus general education services based on imperfect and noisy indicators of need. Signals available to schools—such as assessment results used in child-find procedures—rarely reveal students' needs with certainty and instead provide only indirect evidence

Under IDEA, one of schools' primary responsibilities is to identify student needs and allocate resources accordingly. When identifying students for special education, schools thus face a signal extraction problem that is both legally binding and fiscally incentivized. In this paper, I propose a model to predict how performance-maximizing schools use noisy assessment data to infer students' true needs and make decisions about identifying students for special education. I also describe how these relationships adjust in response to changes in funding policies. While grounded in the context of special education finance, the theoretical framework has broader applicability to other programs where school-level discretion intersects with fiscal incentives—for example, the identification and support of English Language Learners.

CHAPTER III

MODEL

Model Set-Up

To examine the potential implication of funding policies, we first need to define the schools' role and its decision-making process. I model schools as aggregate student performance-maximizing agents, where performance for student i is generated through an education production function, $Y_i(.)$, which takes student- and school-level inputs. In alignment with the Individuals with Disabilities Education Act (IDEA), which mandates that schools provide a "free and appropriate public education" to all students, I assume that schools aim to optimally match educational resources to students based on individual needs. Specifically, consider a setting in which the student population consists of two distinct groups[1] based on educational needs: those whose learning can be supported by generalized or status-quo inputs, G, and those requiring specialized support, S. Let α denote the probability that a randomly selected student requires generalized resources, and $(1 - \alpha)$ the probability that the student requires specialized resources.

To facilitate student-resource matching, and in line with child-find mandates, schools rely on baseline assessment data (e.g., screeners) as proxies for students' underlying abilities and resource needs (see e.g., Fuchs & Fuchs, 2006; Shinn, 2007). However, these instruments are noisy, i.e., $\widehat{A_i} = A_i + \epsilon, \epsilon \sim N(0, \sigma)$, where A_i denotes student i's true ability and ϵ is classic measurement noise. I assume that the average ability meaningfully differs between students with

[1] In practice, student needs exist along a continuum, and IDEA recognizes thirteen distinct disability categories that are often grouped into high-incidence and low-incidence classifications. The two-group assumption represents a simplification for analytical tractability. The model can be generalized to accommodate n different student profiles with n-1 identification probabilities; however, this added computational complexity does not yield additional theoretical insights.

specialized and generalized resource needs, making statistical inference about required needs using baseline assessments possible, which can be represented as, $E[A_i|Need = S] = \mu_S < E[A_i|Need = G] = \mu_G$. Further, I assume that the marginal change in performance of assigning the correct resource is larger for students with specialized needs. There are two intuitions behind the assumption: first, although all students might experience some performance gains from receiving more intensive, specialized support, the returns are greater for those who genuinely need it; second, specialized support will have diminishing returns in terms of performance for students with general needs. In mathematical notation, this implies that:

$$E[Y_i \mid N = S, R = S] - E[Y_i \mid N = S, R = G] > E[Y_i \mid N = G, R = S] - E[Y_i \mid N = G, R = G] \quad (1)$$

where the performance of student i is Y_i, N denotes a students' true needs and R denotes the resources allocated to students. Thus, schools are incentivized to differentiate students as a means of maximizing their objective function—expected student performance.

If the assessment measuring baseline ability were precise enough, the estimated ability scores for the two groups would form a non-overlapping, bimodal distribution, allowing for perfect student-service matching (see Figure 4). Were schools able to perfectly identify student needs, following up with appropriate resources would exactly equate with the maximum possible value of schools' objective function, denoted V^*, representing the first-best allocation.

Figure 4

The distribution of estimated abilities, proxied through a baseline assessment tool, across the two groups of students. In this scenario, the distributions don't overlap and allow for perfect inference of the true nature of the world, student-resource matching.

However, given that IDEA recommends the use of multiple measures to assess disability and allow local school actors to exercise discretion in identification decisions (Fuchs & Fuchs, 2006), it is unlikely that students with and without specialized needs form clearly separable groups in practice. Furthermore, the National Center on Intensive Intervention (2024) recommends that screening tools achieve at least 80% sensitivity and 80% specificity to be considered acceptable. These thresholds imply that even high quality screeners are expected to misclassify a notable proportion of students. Mathematically, this suggests that the distributions of estimated abilities for the two groups will overlap (Figure 2), requiring schools[2] to set a threshold $\boldsymbol{t}$ to classify students. That is, those with estimated ability below the threshold are assigned specialized resources, and those above receive generalized services.

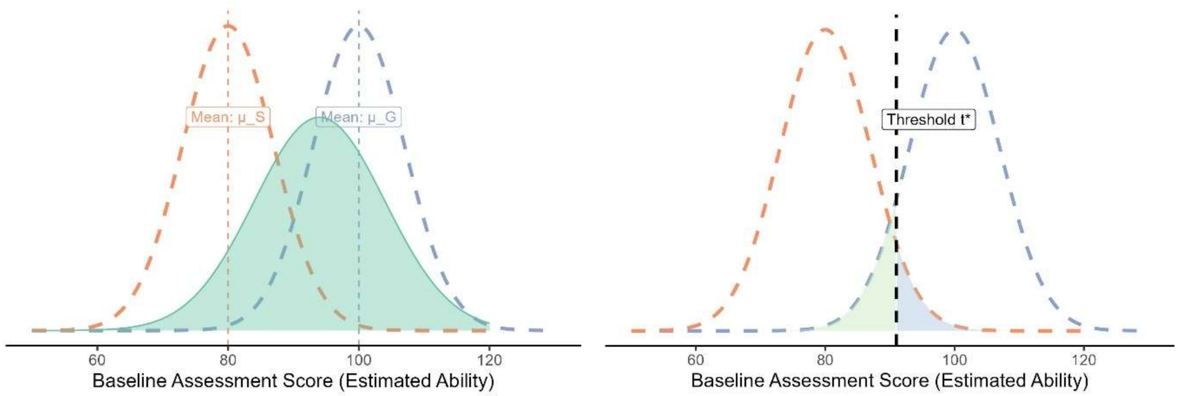
$$\widehat{A_\iota} < t \longrightarrow R = R_S$$

$$\widehat{A_\iota} > t \longrightarrow R = R_G \qquad (2)$$

[2] While screeners include classification thresholds and districts provide guidelines to schools, the final identification decision ultimately rests with schools

Figure 5

Left panel: Distributions of estimated ability for students with generalized (G) and specialized (S) needs. Due to overlapping distributions, some students are misclassified. The overlaid green curve represents the joint distribution of observed ability scores when there are more students with general education needs attending the school. Right panel: Schools set a threshold on estimated ability to allocate resources; given the null hypothesis that a student has specialized needs, the highlighted area represents incorrect classification corresponding to Type 1 (false negative: a student with specialized needs is assigned general resources) and Type 2 (false positive: a student with general needs is assigned specialized resources) errors.



The imperfect classification introduces misalignments: some students with specialized needs receive generalized resources (Type 1 error), and some students with generalized needs receive specialized resources (Type 2 error), thereby reducing the realized value from the first-best to

$$V = V^* - Pr(Type\ 1\ error)\Psi_{\mathrm{SG}}(.) - \mathrm{P\,r}(Type\ 2\ error)\,\Psi_{GS}(.) \tag{3}$$

where V^* denotes the maximum value based on the first-best allocation and $\Psi(.)$ denotes error specific penalty function which is multiplied by the relative probability of the error rates. The subscripts in the above notation and throughout the paper are ordered as follow: the first letter denotes the student's true underlying need, and the second denotes the allocated resources based on threshold setting. Therefore, GS refers to a student with generalized needs who is incorrectly assigned specialized resources, while SG refers to a student with specialized needs who is incorrectly assigned generalized resources.

As a conceptual aside, if both student groups are equally represented and school's realized value depends solely on classification accuracy, meaning the weighted penalties for Type 1 and Type 2 errors exactly offset each other, $Pr(Type\ 1\ error)\Psi_{\mathrm{SG}}(.) = \Pr(Type\ 2\ error)\,\Psi_{GS}(.)$, the optimal threshold would lie at the midpoint between the two group means due to symmetry, i.e., $\frac{A_S+A_G}{2}$. More generally, the first-order condition for the threshold optimization problem reflects a trade-off between the weighted probabilities of the two types of errors. For instance, if Type 2 errors (i.e., incorrectly assigning general education students to special education) incur higher marginal value penalty, the optimal threshold decreases, and schools identify fewer students for special education services.

The primary objective of the paper is to build intuition about relationships affecting identification decisions. In summary, I formalize the schools' role in a two-step framework. First, schools use baseline ability assessments to classify student needs via a threshold-based rule; second, student performance is realized through the education production function conditional on the classification and subsequent resource allocation.

Education Production Function

Several factors can influence student performance, including the general school environment, class size, and peer composition. In this model, I focus on two key inputs.

Consistent with prior research on education production functions (e.g., Hanushek, 1979; Todd & Wolpin, 2003), I adopt a Cobb-Douglas functional form to model individual student performance as a function of their baseline ability and school-provided resources:

$$Y_i(A_i, Ri) = A_i^x \cdot R_i^y \tag{4}$$

where Y_i represents individual student i's performance as a function of their baseline ability A_i and allocated school resources R_i. I set $x + y \leq 1$, reflecting the natural assumption of positive but declining marginal returns to both inputs, $A_i{}' > 0, R_i{}' > 0, A_i{}'' < 0, R_i{}'' < 0$. Peer effects and related factors such as classroom setting and composition are excluded from the model[3].

The school's objective is to maximize aggregate student performance, represented by the weighted average of individual outcomes, adjusted by penalties for misclassification errors. Formally, the first-best value function is denoted as $V^*(Y_i)$ and the penalties are given by $\Psi(\rho_i, Y_i)$, where $\rho_i > 0$ quantifies the cost in value-terms of incorrect classification. The objective function can be simplified as follows:

$$V = V^*(Y_i) - Pr(Type\ 1\ error)\Psi_{SG}(.) - P\,r(Type\ 2\ error)\,\Psi_{GS}(.)$$

$$V = E[\Sigma Y_i - \rho_{GS} \cdot \Sigma_{i \in GS} Y_i - \rho_{SG} \cdot \Sigma_{i \in SG} Y_i]$$

[3] Peer effects can be incorporated mathematically—for example, by introducing group-specific reinforcement or penalty parameters that capture the degree of homogeneity in classrooms, as in Lazear (2001). In such models, student outcomes may be enhanced when peers are correctly matched (i.e., similar needs and classifications), and diminished when mismatched. However, I exclude peer effects from the current model for two reasons: (1) the primary focus is on the relationship between financial resources and identification rates, which relies on aggregate-level data and fine-grained classroom composition data are typically unavailable, and (2) empirical evidence on the specific shape and magnitude of peer effects in special education is limited.

To understand the performance function expansion, consider group GG (i.e., students correctly placed in general education). This group's expected value contribution equals the product of: (a) the group's relative size among all students—given by the prevalence rate multiplied by the cumulative distribution function at the threshold, $\alpha \cdot \left(1 - \mathrm{F}_G(t|\mu_G, \sigma)\right)$, and (b) the group's average performance, $\overline{\mathrm{Y_{GG}}}$. Similarly, we can expand the performance function for each of the two correctly identified groups, GG and SS, and two incorrectly identified groups, SG and GS. There is an additional penalty term for the two incorrectly identified groups.

$$V = \alpha \cdot \left(1 - \mathrm{F}_G(t|\mu_G, \sigma)\right) \cdot \overline{\mathrm{Y_{GG}}} + (1-\alpha) \cdot \mathrm{F}_S(t|\mu_S, \sigma) \cdot \overline{\mathrm{Y_{SS}}} + \alpha \cdot \mathrm{F}_G(t|\mu_G, \sigma) \cdot \overline{Y_{GS}} + (1-\alpha) \cdot \left(1 - \mathrm{F}_S(t|\mu_S, \sigma)\right) \cdot \overline{Y_{SG}} - \rho_{\mathrm{GS}} \cdot \alpha \cdot \mathrm{F}_G(t|\mu_G, \sigma) \cdot \overline{\mathrm{Y}_{GS}} - \rho_{SG} \cdot (1-\alpha) \cdot \left(1 - \mathrm{F}_S(t|\mu_S, \sigma)\right) \cdot \overline{Y_{SG}}$$

Simplifying like terms, we get,

$$V = \alpha \cdot \left(1 - \mathrm{F}_G(t|\mu_G, \sigma)\right) \cdot \overline{\mathrm{Y_{GG}}} + (1-\alpha) \cdot \mathrm{F}_S(t|\mu_S, \sigma) \cdot \overline{\mathrm{Y_{SS}}} + (1 - \rho_{\mathrm{GS}}) \cdot \alpha \cdot \mathrm{F}_G(t|\mu_G, \sigma) \cdot \overline{\mathrm{Y}_{GS}} + (1 - \rho_{SG}) \cdot (1-\alpha) \cdot \left(1 - \mathrm{F}_S(t|\mu_S, \sigma)\right) \cdot \overline{Y_{SG}} \tag{5}$$

Here α represents the probability that a student has general resource needs, $F(.)$ represents the cumulative distribution function for the two student groups with means centered at μ_S and μ_G respectively, σ denotes the measurement noise in the baseline ability assessment, $\bar{Y}$ is the expected performance for different student groups, and ρ_{GS} and ρ_{SG} are penalties for incorrect classification, Note that in this formulation, the realized outcome for misclassified students, is modeled as a fraction of the Cobb-Douglas production output.

School Constraints – Revenue and Cost

Let C_G, C_S denote the unit costs of generalized and specialized resource bundles, respectively. Therefore, the total cost is a student-weighted sum of costs. Again, we can use the prevalence rate and the cumulative distribution functions to represent the relative size of each group. Therefore, the total cost is

$$Cost = \Big(\alpha \cdot \big(1 - \mathrm{F}_G(t|\mu_G, \sigma)\big) + (1-\alpha) \cdot \big(1 - \mathrm{F}_S(t|\mu_S, \sigma)\big)\Big) . C_G + \big((1-\alpha) \cdot \mathrm{F}_S(t|\mu_S, \sigma) + \alpha \cdot \mathrm{F}_G(t|\mu_G, \sigma)\big) . C_S \tag{6}$$

I consider three revenue regimes to explore the implications of fiscal policy on resource allocation.

1. No Budget Constraint (Full Reimbursement): Schools are fully reimbursed for all student services, implying that costs do not influence allocation decisions.
2. Fixed Per-Pupil Allocation: Schools receive a uniform per-student allocation, M, regardless of student classification. This represents a student-based flat-funding model with no differentiation.
3. Differentiated Per-Pupil Allocation: Schools gets differentiated allocations based on assigned services: $M_G = M$ for students assigned generalized services and M_S for students assigned specialized services.

In all cases, I assume a non-negative budget and that funding is sufficient to cover at least the generalized resource bundle for all students.

$$C_S > M \geq C_G; M_S \geq M_G, M; C_S \geq C_G$$

Note that the revenue structure effectively modifies the relative cost burden schools bear for specialized versus generalized resources.

Optimization Problem

A priori, schools operate with fixed resource bundles and known costs. While they do not observe the true prevalence of need, the ability gap between groups of students needing specialized or generalized resources, or the underlying distribution of student abilities, they do observe the distribution of estimated ability using a screener. Based on this distribution and assuming the existence of two underlying distributions of needs, the schools select a classification criterion. Thus, the school's objective is to select a threshold t to maximize post-allocation aggregate student performance

$$\max_{\{t\}} V \tag{7}$$

subject to a non-negative budget. V is defined in equation 3.

CHAPTER IV

RESULTS

First, I compare the optimal classification threshold that emerges from the school's maximization problem with the benchmark symmetric solution - namely, the midpoint between the group means. Second, I characterize the relationship between the optimal threshold and the exogenous parameters in the model. Finally, I describe how the optimal threshold shifts in response to different state finance policies.

Solution for Maximization Problem

Consider a school where students are equally likely to have generalized or specialized resource needs ($\alpha = 0.5$). Suppose the average ability of students with specialized needs is two standard deviations below the average ability mean of students with generalized resources (i.e., 80 and 100 respectively), where the standard deviation of the ability distribution is 10. If threshold was purely a function of classification accuracy, the optimal threshold would be at 90. Next, assume that specialized resources are no more effective than general resources in producing outcomes ($R_S = R_G$), that schools face no budget constraint, and that the penalty for misclassification fully offset performance gains for misclassified students ($\rho_{SG} = \rho_{GS} = 1$). Under these priors, the optimal classification threshold from the maximization problem falls below the midpoint of the two group means of 90.

Compared to a symmetric solution, this decrease in optimal threshold arises because, under a Cobb-Douglas production function, the marginal gains from correctly identifying a student with generalized resources are larger ($A_G^x \cdot R_G^y > A_S^x \cdot R_G^y$). As a result, the school is incentivized to reduce Type 2 errors, misclassifying students with generalized needs, leading to a decrease in the optimal threshold compared to the symmetric solution. Looking ahead at the comparative statics, an interior solution of 90 (or mid-point of the distribution) emerges when the marginal returns in performance from correctly identifying both student groups is equal, i.e.,

$$A_S{}^x \cdot R_S^y = A_G{}^x \cdot R_G^y \tag{8}$$

This condition represents ex-post symmetry in the performance space and renders the school indifferent between misclassification in either direction. When specialized resources are sufficient to compensate for initial ability differences between the two groups, the optimal threshold is the midpoint. Superior specialized resources lead to higher identification rates, while inferior resources result in lower identification rates.

Comparative Statics: Relationship between optimal threshold and exogeneous variables

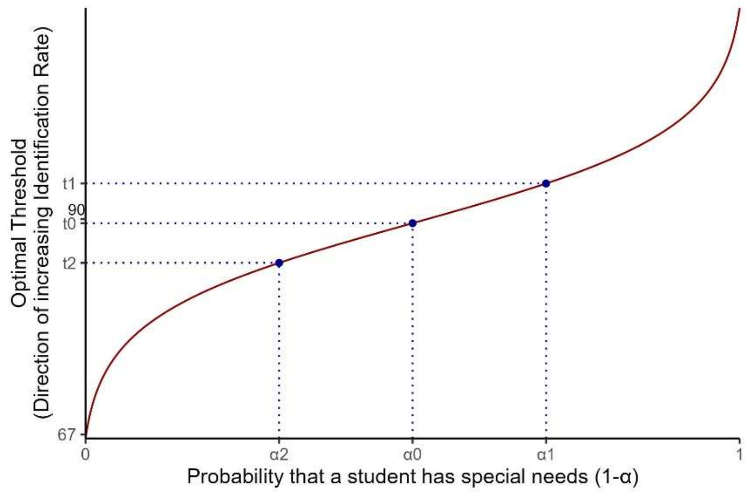
Table 1 describes a set of comparative statics noting how changes in model parameters affect the threshold location. Below, I interpret two exogeneous parameters of interest.

Probability that a student has specialized resource need $(\mathbf{1} - \boldsymbol{\alpha})$

All else equal, when α is low, schools prioritize identifying students with specialized needs (i.e., minimizing Type 1 errors), which increases the threshold leading more students to be identified. Conversely, when α is high, minimizing Type 2 errors becomes more important, which shifts the leads to a decrease in threshold. Figure 5 illustrates the relationship.

Figure 5

The relationship between value-maximizing optimal threshold and the a-priori probability that a student has specialized resources needs (or underlying prevalence rate).



Consistent with prior research on the relationship between demographic characteristics and identification rates, the model predicts that a higher prevalence of specialized needs in the student population is associated with a higher classification rate—that is, a larger share of students being identified for specialized resources, holding the measurement tool, penalties, cost structures, and resource effectiveness constant. This implies that an observable difference in need prevalence across schools may partly explain variation in the proportion of students identified for specialized resources.

Relative effectiveness of resources (R_S, R_G). The optimal classification threshold $t^*$is increasing in the relative effectiveness of specialized resources compared to generalized ones. That is, if specialized resources are more effective, $R_S > R_G$, then the marginal improvement in performance from correctly identifying students with specialized needs increases. Therefore, as $\frac{R_S}{R_G}$ increases, the optimal threshold increases leading to more students being classified.

A testable hypothesis is: holding other exogenous factors constant, schools that perceive—or have—more effective specialized resources relative to generalized resources will classify a larger share of students for specialized support. In other words, variation in identification rates across schools within the same state is partially explained by differences in the effectiveness or quality of specialized resources. Figure 6 shows the relationship.

Figure 6

The relationship between value-maximizing optimal threshold and effectiveness of specialized resources compared to general resources.

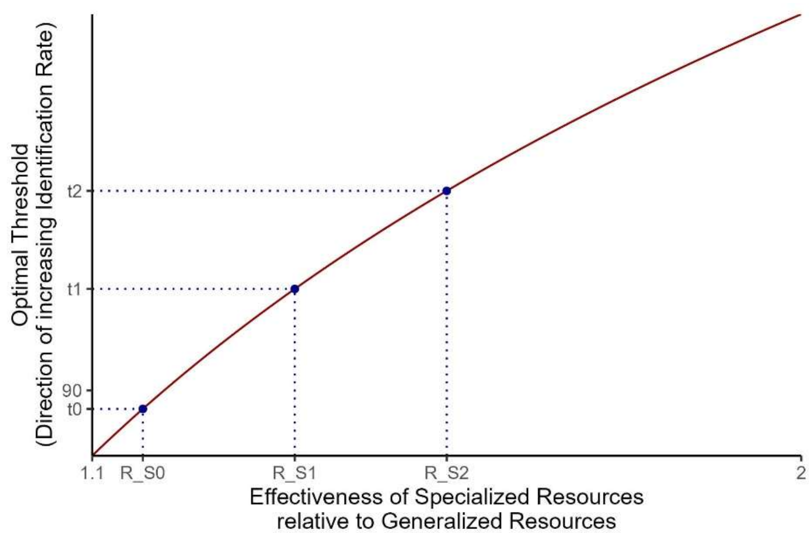


Table 1

Comparative statis describing the relationship between optima threshold (t^*) and key parameters.

Exogenous Parameter	Directional Relationship with Optimal Threshold
Probability that a student has specialized resource ne$ed(1-\alpha)$	Increasing
Average ability of students with specialized needs (A_S), holding the average ability of students with generalized needs (A_G) constant	Increasing
Penalties for misclassifying students with specialized needs (ρ_{SG}), holding the other group penalty constant (ρ_{GS})	Increasing
Effectiveness of specialized sources (R_S), holding constant the effectiveness of general resources (R_G)	Increasing

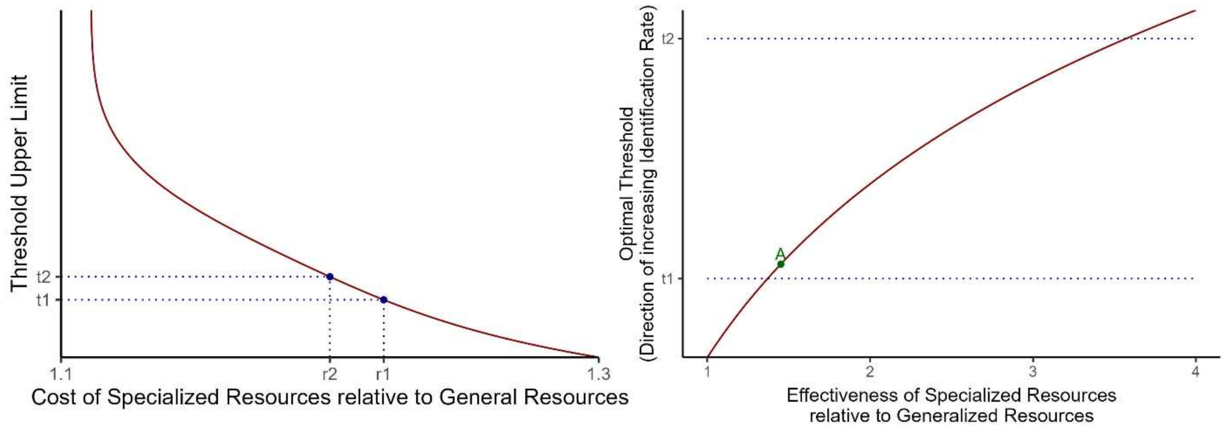
Solution to Constrained Optimization

The cost constraint is governed by the per-pupil base allocation and the relative costs of the two resource bundles. To analyze this relationship, consider the base revenue rate is fixed at 100 and the cost of the generalized resource bundle is 90. This budget constraint, shown in Figure 7, imposes an upper bound on the feasible classification threshold: schools can only set the threshold as high as their budget allows, ensuring they can afford to serve all students identified for specialized resources. For instance, if the cost ratio of specialized to generalized bundle is r_1, school can set a maximum threshold of t_1. When the relative costs of specialized and generalized resources are closer (i.e., specialized resources are not much more expensive), r_2, the school can afford special resources for more students, allowing for a higher feasible threshold, t_2. Conversely, as specialized resources become more costly relative to general ones, the maximum threshold declines. Note that increase in the base allocation or decrease in market prices for the general resource bundle shift the budget curve outward, expanding feasible thresholds; the reverse compresses it.

Jointly solving the budget constraint with the school's objective function (which depends on resource effectiveness), fiscal policy effectively introduces a ceiling on the optimal threshold. For example, in the absence of full reimbursement, schools that would ideally set a high threshold to identify more students (because they believe specialized resources are more effective) may be constrained by budget. Consider a school with optimal solution, A, in Figure 7. Under cost level r_1, its optimal threshold exceeds t_1, making it unaffordable. As a result, the school must adopt a second-best solution and set the threshold at t_1. However, if the relative cost of specialized resources compared to general resources were r_2, the school could afford to classify students at its preferred threshold, A, and implement its optimal allocation strategy.

Figure 7

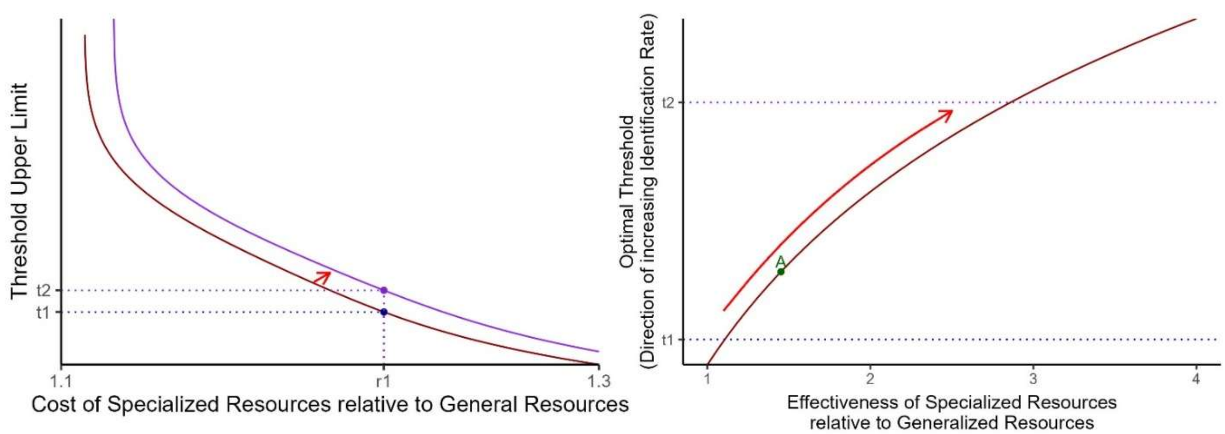
Left – Holding constant the base rate and cost of general resource bundle, the plot shows the relationship between the relative cost of resources and the upper limit of classification threshold that schools can set to ensure each student gets allocated a resource. The area under the curve shows the feasible range of thresholds for a non-negative budget. Right – For a school with optimal choice A, they will not be able to achieve their unconstrained optimal solution if relative costs were represented by r_1 *but can realize it if relative costs were* r_2.



In a more generous policies, such as differentiated rates instead of flat funding shifts the budget curve outward (see Figure 8), potentially enabling schools to approach their unconstrained optimum.

Figure 8

Holding the relative cost of special and general resources constant, under a less generous finance policy, school had to cap their classification threshold at t_1*. In the presence of a more generous policy regime, the budget curve shifts outward (Left panel) and schools can set a higher threshold. The right panel shows the movement along the resource-effectiveness curve a result of a generous funding policy.*



Testable hypotheses include: within the same policy regime, schools facing lower resource costs will identify a higher proportion of students for special needs, holding perceived effectiveness of the two resources constant. In a more generous funding environments, some schools—particularly for those schools near their upper threshold constraints—will identify more students for specialized support. However, schools that place low value on specialized resources are unlikely to adjust their identification rates. In other words, the model predicts that more generous funding will not lead to rent-seeking behavior by schools and will allow schools to approach their unconstrained optimal threshold. Additionally, states with higher per-student base revenue will enable schools to reach their optimal identification levels, resulting in higher average identification rates.

CHAPTER V

CONCLUDING REMARKS

The current paper develops a theoretical model linking special education identification rates with school funding policies, addressing a literature gap where these factors have been studied separately. By conceptualizing schools as decision-makers operating under incomplete information about student needs, the model formalizes how resource constraints and the relative effectiveness of specialized versus general education services influence identification rates. This framework integrates prior research on disproportionality and funding incentives using the signal extraction approach, advancing understanding of dynamic school-level factors shaping special education identification.

Despite its novelty, the model relies on several simplifying assumptions that warrant careful consideration. Most notably, peer effects and classroom heterogeneity are excluded, although these factors likely influence both student outcomes and identification decisions. Additionally, the model treats underlying needs and resource allocation as binary classification, whereas in practice, special education is highly customized. Moreover, I consider resource allocation as a one-time investment decision, whereas IDEA funding and service provision typically span multiple years, implying that schools may consider longer-term costs and benefits. Other potential modifications to the cost function (e.g., legal fees, administrative burdens) are also omitted. Further, the model assumes that schools solely optimize student performance, but school's objective likely operate under multiple competing objectives, including compliance, equity, and political pressures. Nevertheless, if these alternative goals correlate with student performance, the model's core insights remain relevant. Importantly, evolving accountability policies that increasingly emphasize student performance further supports the framework's applicability.

The theoretical model generates two key empirical predictions. First, identification rates will be higher in schools where the relative quality of specialized resources exceeds that of general resources, potentially explaining within-state variation in identification rates. Second, holding relative within-school resource quality constant, schools operating under more generous special education funding policies will, on average, identify more students, offering a potential explanation for between-state variation. Previous research on the effect of funding policies on identification rates has explored several mechanisms, one of the most important being changes in the workforce (Dhuey & Lipscomb, 2013). Although workforce size (e.g., number of teachers or support staff) does not directly indicate quality, it may nonetheless influence service quality, particularly in a personnel-intensive sector like education. In testing the theoretical model, I encourage future researchers to consider a broad set of operationalizations that capture within-school relative quality between specialized and generalized education services (e.g., value-added estimates, credentials, class ratings, instructional strategies).

It is also important to note that schools typically only observe students' assessment performance and not the underlying distribution of disability prevalence. As a result, schools' classification decisions are shaped by their perceptions of disability prevalence, student ability distributions and the relative effectiveness of general versus specialized resources. Therefore, tests of the models could include measures of perceived program effectiveness, such as past year average of teachers' students' scores and special education preference and advocacy among administrators.

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