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The impact of fiscal incentives on student disability rates

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Abstract

In this paper, I estimate the elasticity of student disability rates with respect to the generosity of state reimbursements. The classification response is identified from policy-induced variation in the amount of state aid generated by serving a disabled student across local school districts in Texas from 1991–1992 through 1996–1997. My central estimates imply that fiscal incentives can explain nearly 40% of the recent growth in student disability rates in Texas. The magnitude of the institutional response varies by district size and enrollment concentration, student race/ethnicity and the level of fiscal constraint.

Keywords: Disability; Financial incentives; Moral hazard; Special education

JEL classification: H30; H70; I22

1. Introduction

There is a substantial literature documenting the relationship between social insurance program generosity and caseloads.[1] The nature of this relationship is important to program design because changes in the size and characteristics of beneficiary populations not only affect the ultimate costs but may also undermine

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[1] See, for example, Anderson and Meyer (1997), Bound and Waidmann (1992), Moffitt (1992) and Krueger (1990) for reviews and analyses of this issue for various social insurance programs.

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stated policy objectives. Most analyses of the impact of financial incentives on program participation rates focus on individuals' decisions to participate, and little is known about how bureaucracies respond to similar incentives to expand caseloads. This paper explores an example of this type of institutional response by quantifying the relationship between the rate at which school districts classify students as disabled and the associated flow of state special education aid.

Programs that target resources according to disability status are becoming increasingly important in the USA. The number of adult Disability Insurance (DI) and Supplemental Security Income (SSI) recipients has increased from 6 million to nearly 10 million over the past two decades, driving the increase in the share of cash welfare expenditures dedicated to these programs. Childhood disability rolls and outlays have exhibited parallel growth following recent reforms to SSI (GAO, 1994). Growing fiscal claims are also made on behalf of disabled children through school-based disability programs as special education enrollments continue to rise. Since 1977, the fraction of elementary and secondary students classified as disabled has increased from 8% to over 12%. Over the same period, the fraction of school district spending that is dedicated to special education services has increased from 4% to 17% (Rothstein and Miles, 1995). In 1993–1994, 5.4 million students participated in special education at an estimated cost of over 32 billion dollars (Parrish, 1996).

There are several explanations for the rise in adult and childhood disability rates. First, the pool of eligible individuals has been expanding because of changes in cultural norms regarding what constitutes disability. Programs that were primarily intended for the severely physically disabled have been extended to include mental and emotional disabilities. Take-up of disability benefits among eligibles has increased with diminished stigma and the establishment of a legal support system. At the same time, socio-demographic factors that determine the at-risk population, such as the childhood poverty rate, have been worsening (Bassi, 1988). Finally, the financial incentives associated with the disability programs may influence disability rates. Empirical analyses of the DI and SSI programs (e.g. Kubik, 1999; Bound and Waidmann, 1992; Parsons, 1980) find evidence consistent with an important role for financial incentives in explaining the time trends in self-reported disability. The extent to which state school finance program parameters influence official student disability rates will depend on how school districts respond to similar incentives to classify more of their student population as disabled.

Fiscal incentives to classify marginal students as disabled arise because the claim that a locality can make on state elementary and secondary education funds typically increases with the number of students classified. The goal of the original 1975 special education legislation, the Education for All Handicapped Children Act (EHA),[2] was to guarantee disabled students access to an appropriate public

[2]Individuals with Disabilities Education Act (IDEA) is the current version of this legislation.

education. At the time, Congressional investigations revealed that two-thirds of children with disabilities were either totally excluded from or ignored within public schools (Verstegen, 1994). Following the passage of the federal mandate, states designed school finance policies to encourage school districts to locate and provide additional assistance to students with severe disabilities. Since then, special education has evolved into a program that primarily serves students with mild learning disabilities. Critics claim that vague definitions of disabling conditions coupled with financial incentives have pushed student disability rates to the current levels at which over one in eight students is classified as disabled. However, despite the popular perception that student disability rates are inflated, there has been no explicit analysis of the role of incentives embedded in state school finance policies.

In order to estimate the elasticity of official student disability rates with respect to such fiscal incentives, I rely on variation in the gain in state revenue from labeling an additional student as disabled across school districts in Texas over the academic years 1991–1992 to 1996–1997. In Texas, because of the structure of the school finance equalization policy, this revenue increase depends on a district's tax base wealth and other observable district characteristics. Changes in the parameters and the implementation of the policy led to sizeable changes in the revenue gain over time for all districts, and dramatic relative increases for higher wealth districts in the middle of the period. In a reduced-form specification that controls for district-specific trends, I relate student disability rates to these policy-induced movements in the incentive to classify students as disabled.

The results indicate that local responses to state incentives play an important role in determining the ultimate size of special education programs, and therefore, in determining the allocation of resources within and across schools. I find that a 10% increase in the supplemental revenue generated by a disabled student leads to approximately a 2% increase in the fraction of students classified as disabled. The magnitude of this elasticity implies that nearly 40% of the 6-year increase in student disability rates in Texas can be explained by the contemporaneous increase in fiscal incentives. As expected, the estimated elasticity is larger for the mildest and less well-defined disability categories, such as learning disability and speech impairment. The elasticity is smaller for larger districts and for districts in which student enrollment is less concentrated across schools where 'free-riding' may mute the strength of the incentive. While the welfare effects of the response are ambiguous, the fact that minority students and students in fiscally constrained districts are more likely to be classified in response to fiscal incentives suggests that school districts may be classifying students for financial gain.

The remainder of the paper is divided into four sections. Section 1 provides background on endogenous participation in the context of special education and relates this paper's approach to existing literature. Section 2 describes the empirical strategy and explains the source of identifying variation in fiscal incentives. Section 3 presents baseline estimates of the elasticity of student disability rates with respect to fiscal incentives and the results from a variety of sensitivity tests and extensions. Section 4 concludes.

2. Background

Special education encompasses a wide variety of disabilities and interventions. There are state and federal guidelines delineating which physical, emotional, and mental disabilities are eligible for special services provided in the school. Eligible students may be severely physically or mentally handicapped, or may be very difficult to distinguish from non-disabled slow-learning students. Nationally, the large majority of students currently served in special education have mild disabilities; learning disabled, speech impaired, and emotionally disturbed students comprise 80% of the special needs population served (U.S. Department of Education, 1998). Fig. 1 demonstrates that the same is true for Texas.

The types of services that special needs students receive may include additional support in the regular classroom, pull-out for part of the day in a resource room, or instruction in separate classes and schools. Students with relatively mild disabilities tend to be served in the less restrictive instructional settings. The excess costs associated with educating disabled students vary according to the intensity of

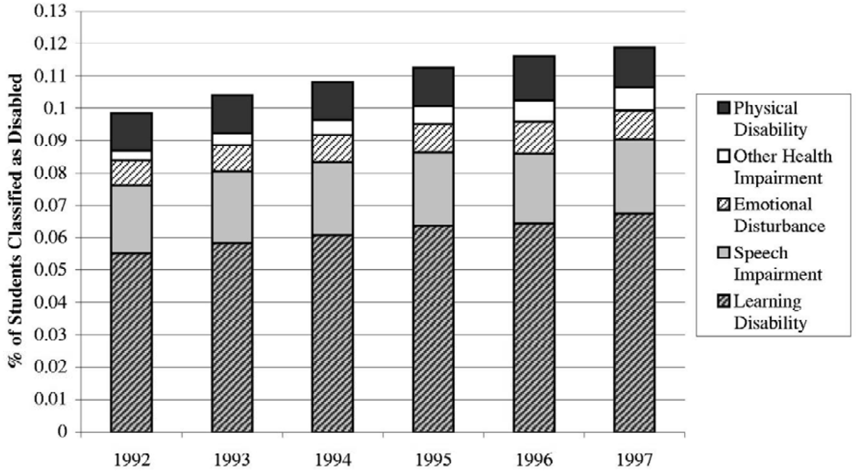

Fig. 1. Trend in student disability rates in Texas. The height of the bars shows the fraction of elementary and secondary students in Texas that is classified as disabled in each year (Source: PEIMS). The bar is divided into the share attributed to each disability category: learning disability, speech impairment, emotional disturbance, other health impairment (which includes ADHD), and 'physical' disability (which I define to include autism, deaf–blindness, hearing impairment, mental retardation, orthopedic impairment, traumatic brain injury, and visual impairment).

instruction provided.[3] In an analysis based on nationally representative data from the 1987 school year Moore et al. (1988) find that per-pupil spending on special education students is on average 2.3 times per-pupil spending on regular education students. Using Massachusetts expenditure data, Chambers (1998) finds a very similar average cost ratio, and disability and setting specific ratios that range from 1.24 for learning disabled students served within regular elementary schools to 31.4 for students with multiple disabilities served in external facilities.

States have implemented a variety of funding mechanisms to deliver resources to districts in a manner that accounts for these heterogeneous costs.[4] The dominant mechanism involves pupil weighting, in which special education students are weighted more heavily than general education students within the basic school finance formula. The weights are often specific to the type of disability, the type of instructional setting, and/or the grade-level. Pupil-weighting has the advantage of providing a relatively close link between districts' resource needs and the flow of state funds. However, because the financial rewards are directly tied to labeling and tend to be only loosely tied to additional costs incurred, school officials may have an incentive to over-classify or misclassify students as special needs while providing the minimum acceptable level of special services. This incentive is enhanced by state policies that put few restrictions on how funds generated by disabled students are spent.[5] To eliminate potential distortions, several states have recently implemented prospective reimbursement systems in which special education aid is based on predicted rather than actual special education enrollment.

The importance of fiscal incentives in determining the rate at which students are classified as disabled clearly depends on how much discretion local officials maintain in implementing special education programs. Federal and state mandates attempt to limit local discretion by explicitly prescribing the procedure for identifying and serving disabled students. The process begins with the referral of a student by either an appropriate school employee (e.g. a teacher, counselor, or psychologist) or a parent. Experts (e.g. psychologists, physicians, and educational diagnosticians) then administer a battery of tests to determine whether the student

[3] In 1993, the national average pupil–teacher ratio was 24:1 for learning disabled and speech impaired students, and as low as 6:1 for the more severely disabled (U.S. Department of Education, 1996).

[4] See Parrish et al. (1997) for a detailed analysis of the various state special education funding mechanisms. The federal government has traditionally provided a flat grant to states based on the total number of disabled students served in special education in each state. Since the IDEA Amendment of 1997, a new formula based on total student enrollment (85%) and school-age poverty rates (15%) is being phased in. The federal government's share of special education expenditures has never exceeded 10%.

[5] For example, in Massachusetts, revenue generated by disabled students can be allocated to any item within the local budget. In 35 states, districts are not required to expend funds generated by special education students on special education (Chambers et al., 1995). In Texas, the state requires that 85% of special education revenues be dedicated to educating disabled students. However, until recently, the method of accounting did not adequately distinguish regular and special education expenditures.

has a recognized disability. If the student is deemed disabled, school specialists must develop an individualized education plan (IEP) that describes the services that will be provided to address the student's needs. For the child to be served in special education, the child's parents have to approve both the disability classification and the IEP.

Despite the strict procedural regulations, there is evidence of substantial local leeway in practice (though the available evidence is somewhat outdated). First, though assessment tests are designed to provide rich information about students' abilities and deficiencies, the primary determinant of placement in special education is the initial referral (Thurlow and Ysseldyke, 1980). Mellard (1983) summarizes existing research on assessment as finding that special education placements are ''not consistently made on the basis of the data, and are frequently recommended in spite of the data''. In field work, Mellard (1985) also finds that the data are not necessarily objective. He discovers patterns of selective subtest administration that suggest examiners may 'shop' for tests to confirm their hypotheses. Finally, the clinician is supposed to consider student behaviors other than performance on test indicators, yet these other criteria are typically not well-defined or operationalized. Because of the scope for subjectivity in assessment, it is not surprising that the functional abilities of students classified as disabled and the services provided vary dramatically across school districts (Singer et al., 1989).

Given that localities can largely control special education program size, school districts would be expected to maximize the state payment per-student by classifying the entire student body as disabled—if labeling students as disabled were costless. However, in reality, the incentive to leverage state and federal funds will be tempered by both fiscal and non-fiscal costs. The financial costs begin with assessment costs, which can be large relative to average special education instructional costs.[6] Additional instructional costs also likely accompany a student's assignment to special education, though marginal costs may be minimal for slow-learning students who would otherwise be served in remedial education. Non-financial costs to aggressively classifying students as disabled include the possibility of attracting a state audit or censure. Also, parents may object to having their child labeled as disabled if special education does not involve more intensive resources, or even if it does because of the potential stigma associated with the label. Only those districts that face revenue incentives that outweigh the costs will engage in relabeling. The mechanism through which higher fiscal incentives are translated into higher disability rates in school districts will depend on the political process through which such decisions are made, and particularly on how the costs and benefits are distributed.

If classifying marginal students as disabled were to generate pre-determined

[6] Moore et al. (1988) estimate that 13% of total special education expenditures are dedicated to assessment.

excess costs, then the impact of special education finance policies on special education program size could be modeled in the same way as traditional categorical or matching grants. That is, these policies would alter the relative cost of expanding special education programs in a way that could be readily mapped into shifts in the budget constraint of the relevant local decision-maker. Empirical applications within the literature on intergovernmental grants commonly adopt a median voter model and consider decisions about the level of spending on a single public good. Analyses of local school spending demonstrate that localities are quite responsive to fiscal incentives within state education grants (Reschovsky and Schwartz, 1992).

The disability classification behavior of school districts does not fit directly into this framework. Official disability rates at the school district level will be influenced by a combination of practitioner, voter, and bureaucratic preferences, as well as state and federal regulations. Not only is the decision mechanism likely to be more complicated, the additional costs associated with classifying a student as disabled are not deterministic. State school finance formulas do not in general provide resources based on excess special education expenditures, but instead reward labeling by providing a given amount of revenue for each disabled student. Because the *net* financial gain from labeling an additional student will vary district to district and child to child, modeling explicit budgetary tradeoffs is not possible without more detailed information on the associated special education costs than is available. Therefore, I model the official rate of student disability as a function of the gross gain in state revenues. This gross gain can be thought of as the marginal financial benefit to expanding the student disability rate, which is then implicitly traded off against the unmeasured marginal costs. Rather than adopting a specific model of the decision-making process, I implement a reduced-form specification, assuming that increases in the gross revenue gain would be expected to increase disability rates regardless of the political process.

There are case studies that provide qualitative evidence that fiscal incentives affect special education caseloads. Montgomery (1995) describes interviews with special education directors who claim to have been asked by their superintendents to bring the disabled count up following an increase in state special education reimbursements in Oregon. Kane and Johnson (1993) document a fall in disability rates in Vermont 3 years following the shift to prospective reimbursement for special education. These case studies suggest that there is room for districts to respond to both increased and decreased incentives, despite the state and federal regulations. This paper attempts to quantify the relationship between changes in fiscal incentives and student disability rates. The estimate of the classification response will serve as a useful summary statistic for predicting district responses to specific school district reforms and for evaluating the role of fiscal incentives in determining trends in student disability rates. I am also able to explore factors that affect the institutional response. The next section describes in more detail the methodology.

3. Empirical strategy

In order to estimate the effect of the generosity of state special education reimbursements on student disability rates, I analyze the behavior of local school districts in Texas from 1992 to 1997.[7] In Texas, as in most states, disabled students generate more state revenue than non-disabled students. The incentive to expand the disability count is measured by the amount of additional state revenue raised by classifying a marginal student as disabled. The empirical specification relates the log of the fraction of the district student population classified as disabled (Disab)[8] to the log of this revenue gain (Gain):

$$\ln(\mathrm{Disab}_{it}) = \alpha + \beta \ln(\mathrm{Gain}_{it}) + \mathbf{X}_{it}\Omega + \delta_t + \varepsilon_{it}, \tag{1}$$

where i indicates district and t indicates year. The vector $\mathbf{X}$ contains district demographic characteristics, such as the student racial composition and poverty rate, that may affect either the underlying incidence of student disability or tastes for classifying mildly disabled students as disabled (Chaikind and Corman, 1991; Harry, 1992). $\mathbf{X}$ also includes district financial variables, such as the log of per-pupil wealth, to capture income effects that may be correlated with the 'price' incentive. β measures the elasticity of official student disability rates with respect to fiscal incentives. Before describing the steps that I take to ensure that β can be interpreted as the causal effect of fiscal incentives on student disability rates, I clarify the sources of variation in the revenue gain by reviewing the relevant aspects of Texas school finance policy.

3.1. Texas school finance policy

In Texas, districts that have less fiscal capacity (as measured by tax base wealth per-weighted pupil) and more student need (as measured by the weighted pupil count) receive more aid. Classifying a student as disabled inflates the pupil count because a special education student is weighted to count as a multiple of a regular education student. There is an associated revenue gain because a higher pupil count reduces measured fiscal capacity and increases measured need, and both effects lead to higher state aid.

Specifically, the magnitude of the revenue gain from reclassifying a student is

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[7] Here and in the rest of the paper I refer to school years by the year of the Spring term (e.g. 1992 corresponds to the 1991–1992 school year).

[8] I also estimated this relationship with the dependent variable expressed as the log of the disability rate over one minus the disability rate. Modeling the disability rate as following an exponential distribution in this way explicitly accounts for the fact that the rate is bounded between zero and one. This model produces results that are very similar to the above model, and I therefore chose to present the estimates that are most readily interpretable.

determined by the co-existing foundation grant (Tier 1) and matching grant (Tier 2) programs. Tier 1 guarantees a certain amount of revenue per-weighted pupil (f_{it}) for levying the required minimum tax rate (r_t):

$$\text{Tier 1 Revenue}_{it} = N_{it}(D_{it}) \times f_{it} - r_t \times W_{it}, \tag{2}$$

where $N_{it}(D_{it})$ is the weighted pupil count expressed as a function of the number classified as disabled and W_{it} is district tax base wealth. Tier 2 guarantees a certain amount per-pupil (g_{it}) for each 0.01% tax, or mill, the district chooses to levy above the required Tier 1 rate:

$$\begin{aligned}&\text{Tier 2 Revenue}_{it} = E_{it}(N_{it}(D_{it}) \times g_{it} - 0.0001 \times W_{it}),\\&E_{it} = \text{Min}[(t_{it} - r_t) \times 10{,}000, cap_t]\end{aligned} \tag{3}$$

where E_{it} is the number of mills matched by the state, t_{it} is the local tax rate, and cap_t is the maximum number of mills matched. The term in parentheses is simply the gap between the total Tier 2 guarantee per-mill and the local revenue raised per-mill.

For districts that qualify for positive aid under both formulas, the combined Tier 1 and 2 revenue gain from classifying a student as disabled can be found by calculating the change in both revenue amounts that would result from the associated increase in the weighted pupil count:

$$\text{Gain}_{it} = \frac{\partial N_{it}}{\partial D_{it}} \times (f_{it} + E_{it} \times g_{it}) \tag{4}$$

The gain is simply the increase in the weighted pupil count multiplied by the sum of the foundation program per-pupil allotment and the amount of per-pupil matching revenue. The increase in the pupil count depends on the instructional setting to which a student is assigned. Each setting, such as mainstream (additional support within the regular classroom) or resource room (intensive instruction in a separate class for part of the school day), carries its own multiplier. Therefore, in any given year, the incentive varies across these 'on formula' districts due to differences in instructional placement patterns and tax effort, as well as through adjustments to both base per-pupil guarantees that account for regional cost differences and economies of scale.[9] Across years, holding district behavior constant, the revenue gain changes because of legislative changes to the special education pupil weights, the statutory guarantee amounts, and the cap on the amount of mills matched.

[9] The Legislative Education Board (LEB) and Legislative Budget Board (LBB) developed these indices in 1990. The cost adjustment is based on the level of beginning teacher salaries in the counties contiguous to a district's county and is meant to capture regional variation in the labor market for teachers. See Ladd and Yinger (1994) for a discussion of methods of adjusting education finance formulas to account for cost differences across localities.

For districts that raise more than the total Tier 1 guarantee from the required levy or more than the guaranteed amount per-mill under Tier 2, the revenue gain depends on whether the state recaptures excess funds. In the first 2 years of the sample period, there was recapture under the foundation program and no recapture under the matching grant program. Under Tier 1, the state collected the required levy from each district and then redistributed the funds according to each district's total Tier 1 allotment. Therefore, even though wealthy districts transferred resources on net to the state, these districts faced similar Tier 1 incentives to other districts since increasing the pupil count increased their claims to the redistributed resources. However, classifying marginal students generated no financial benefit for wealthy districts under Tier 2 since these districts simply did not participate in the matching grant program.

The method of resource transfer through the foundation program was ruled unconstitutional, and starting in 1994 Tier 1 contributions could no longer exceed Tier 1 receipts. Under the current program, the local required contribution is not collected and is used only to calculate whether and how much Tier 1 aid a district receives. Marginal changes in the pupil count no longer generate additional Tier 1 revenues for wealthy districts that do not qualify for positive foundation aid. Yet, at the same time, Tier 2 was altered so that districts with more than \$280,000 in wealth per-weighted pupil (that raise more than \$28 per-mill) are required to return excess revenues raised from discretionary local taxes to the state. This recapture transforms Tier 2 into a 'matching tax' program for these districts. Just as the matching subsidy to low wealth districts increases with the weighted pupil count, the matching tax decreases for high wealth districts. High wealth districts therefore have no gain through Tier 1 but a similar Tier 2 gain to other districts in the second period.[10] These changes in the non-linearity of the gain formula provide the most striking variation in relative incentives to classify students as disabled.

3.2. Instrumental variables approach

As described, the school finance equalization scheme creates a nonlinear schedule of incentives that depends on district wealth and other observable district characteristics, as well as the year. Refinements to the specification in (1) are designed to isolate the exogenous sources of variation in incentives. Given the way that the incentive that a district faces is determined, an immediate concern with including the actual revenue gain is that many of the components depend either directly or indirectly on the disability rate. For example, a district that aggressively reclassifies students will boost its weighted pupil count and reduce its measured

[10]The magnitude of the marginal revenue gain from the reduced matching tax for high wealth districts is greater than the increased matching subsidy for low wealth districts. Not only is the Tier 2 per-pupil guarantee replaced by the \$28 limit on per-mill revenues per-weighted pupil, but the entire local tax rate including the Tier 1 required rate is used to determine the amount of recaptured revenue (i.e. $E_{it} = t_{it} \times 10{,}000$).

wealth per-pupil, which is a key determinant of the district's incentive regime (i.e. whether the district is on or off formula). In addition, any associated change in the flow of state funds may lead the district to change its property tax rate, which alters incentives through Tier 2.[11] Finally, any measure of the expected increase in the pupil count from newly identified students that is based on the district's actual pattern of instructional placement will partly reflect the severity of disability among special education students, which is clearly a function of classification behavior.

In order to eliminate these sources of endogeneity, I first predict the per-pupil Tier 1 and Tier 2 revenue components for each year based on districts' tax rates and special program shares in the initial year.[12] These amounts are then multiplied by the amount a disabled student is expected to add to the pupil count over what a regular education student would add. To capture broad differences in placement patterns due to district size, this scaling variable is a weighted average of the year-specific placement weights using the statewide pattern of placement of disabled students by enrollment decile.[13] Changes in predicted incentives over time, therefore, arise from changes in the state aid formula.[14] By including district fixed effects and using the predicted incentive as an instrument for the actual

[11] These feedback effects can be non-trivial. For example, a one standard deviation increase in the disability rate would generate enough additional state revenue to permit the median district to maintain the same level of spending while reducing its local tax rate by 7.5%. The reduction in the tax rate would, in turn, reduce the measured incentive for the median district by 5.3%. The moderate feedback effect for the median district masks very large effects for some districts: the district with the largest resulting reduction in the incentive is predicted to witness a fall of 67%, and the district with the maximum increase is predicted to witness a 71% increase. These extreme changes are generated by districts that are predicted to switch incentive regimes due to the change in district wealth per-weighted pupil.

[12] A detailed description of the method used to construct the actual and predicted incentives is available from the author on request. In an earlier version of this paper (Cullen, 1999), I implemented a strategy that is analogous to using the average incentive across broad tax base wealth categories as an instrument for a district's actual incentive. While that approach relies on only a subset of the available useful variation, it yields patterns of results that are qualitatively similar to the current approach.

[13] The scaling variable used in the actual incentive measure is calculated in the same way since a disproportionate share of severely disabled students could skew a district's incentive measure in a way that is unlikely to reflect the gain from classifying a marginal slow-learning student. Though I chose to use the average based on district size for this reason, empirically it makes very little difference which measure is used.

[14] Changes in a district's incentive over time are also technically partly due to changes in property values and overall enrollment. Both of these variables are included as control variables in the regressions. Also, the scaling factor is allowed to vary by year to reflect common changes in the relative use of various placements. Some of these changes can be attributed to changes in the weighting scheme (as demonstrated later), and incorporating these shifts more accurately captures the effective incentives within any given year. Using only the maximum placement weight relevant to mildly disabled students for each year for all districts yields very similar results to those shown. It should not be surprising that the results are not sensitive to scaling since the estimated effect is identified by movement in relative incentives and multiplying gains by a constant (or a near constant) does not affect relative gains nor the difference in the change in log gains across districts.

incentive, the effect of the fiscal gain is determined by changes in disability rates over time that are linked to policy-induced changes in the pattern of fiscal incentives.

There is a remaining channel through which policy-induced changes in incentives may be spuriously correlated with changes in disability rates. There may be secular differences in the rate of growth in classification rates across districts that are correlated with a district's treatment under the school finance formula. For example, if high wealth districts face increasing incentives over time and disability rates are otherwise growing more slowly than in other districts, the causal effect of fiscal incentives will be biased downward. To account for such confounding convergence or divergence in disability rates, I add controls for district-specific trends. I, therefore, estimate a system of equations of the following form:

$$\begin{aligned} \ln(\text{Gain}_{it}) &= \phi_{1i} + \phi_{2i}t + \beta_1 \ln(\text{Gain}^0_{it}) + \mathbf{X}_{it}\Pi + \gamma_t + \nu_{it}, \\ \ln(\text{Disab}_{it}) &= \alpha_{1i} + \alpha_{2i}t + \beta_2 \ln(\text{Gain}_{it}) + \mathbf{X}_{it}\Omega + \delta_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where the superscript '0' indicates the gain is predicted using base year district behavior. β_2 is now determined by marked changes in the pattern of fiscal incentives that lead to deviations in the disability rate around the district trend.[15]

3.3. Data and exploratory analysis

The analysis is based on district-level data collected by the Texas Public Education Information Management System (PEIMS). PEIMS collects annual information on a wide range of student characteristics, including the number of students in each district by disability type and instructional setting. The data also include district tax rates, property wealth, and the other variables necessary to calculate the revenue gain.

There are between 1043 and 1050 districts each year, for a total potential sample of 6276 observations for the years 1992 to 1997. I exclude the six special school districts that are not fiscally independent and for which the usual aid formulas do not apply. I also exclude districts that are not in the sample in the initial year. These two restrictions reduce the sample by 1.3%. I also limit the sample to

[15] A priori, it would seem important to include the level of per-pupil aid as a control variable to capture income effects that may be correlated with the incentive. However, per-pupil aid is endogenous since it too depends on the district's disability rate. Adding per-pupil aid to the model and using predicted aid (based on initial district behavior) as an instrument for actual aid has virtually no impact on the estimated elasticity of disability rates with respect to the fiscal incentive. This is because the marginal incentive is very weakly correlated with the level of per-pupil state aid (which is typically negative for high wealth districts). Because incorporating per-pupil aid does not affect the results in practice, I leave it out of the base specification to avoid complicating the presentation unnecessarily.

districts that always have non-zero disability rates[16] and non-zero simulated and actual revenue gains, which allows both variables to be specified in log form in the analysis. This eliminates an additional 0.9% of the observations. The analysis is based on the remaining 1023 districts and 6138 observations, which represent 97.8% of the original sample.

Table 1 presents summary statistics for the variables used in the analysis. All financial variables are converted into 1992 dollars using growth in statewide average beginning teacher salaries as a deflator.[17] The first column shows the mean and standard deviation for each variable for the full sample. The next two columns present the same statistics separately for low and high wealth districts. The high wealth category includes the 9.5% of districts that are predicted to have over $280,000 per-weighted pupil (based on 1992 program shares), which are those districts that experienced the most dramatic change in treatment over the sample period. All other districts are classified as low wealth.

The average actual revenue gain from classifying a marginal student as disabled across all districts and years is $2698, while the average predicted gain is $2542. The difference between the two is due to changes in district behavior such as increases in local tax rates or increases in the size of specialized programs that are not reflected in the second measure. Without information on the marginal excess costs of educating students classified as disabled, it is difficult to tell whether or not this represents a net gain to districts. The best information available on the marginal costs of educating disabled students, from Chambers (1998), suggests that the most mildly disabled students cost on average at most 24% more to educate than regular education students. In comparison, the median revenue gain is 118% of median per-pupil instructional expenditures for regular education students, suggesting that the majority of districts may in fact generate surplus revenue by classifying students within certain disability categories while still providing the typical set of services.[18]

The similarity in the mean predicted incentive for all years across low and high wealth districts masks significant differences over time. Fig. 2 depicts the time pattern in incentives for both groups (the underlying values are presented in Table 2). The parallel movements over time across low and high wealth districts reflect adjustments to the parameters in the school finance program, such as increases in per-pupil allotments and pupil weights. The figure also highlights the 37% increase in the average predicted gain for high wealth districts that occurred with the regime shift in 1994. This increase occurred at the same time that other districts' incentives fell by 4% on average. If school districts respond to fiscal incentives to

[16] The districts that have any years with no students classified as disabled tend to be very small districts. Median enrollment among these omitted districts is 29 students.

[17] The results are not sensitive to deflating by the national consumer price index for services instead.

[18] The gain is more likely to be a net gain when the additional contribution from the federal government per-disabled student is considered. This amount was $423 per-child in 1993.

Table 1
Summary statistics

District characteristics	Full sample	Low wealth districts	High wealth districts
Actual revenue gain	2698	2670	2960
	(586)	(475)	(1183)
Predicted revenue gain	2542	2539	2578
	(460)	(396)	(855)
Actual state aid per-pupil	2238	3014	−5163
	(3857)	(1141)	(9169)
Predicted state aid per-pupil	2130	2841	−4658
	(3357)	(1084)	(7538)
Tax base wealth per-pupil/1000	213	140	908
	(359)	(76)	(877)
% Tax base wealth residential	0.311	0.328	0.154
	(0.187)	(0.175)	(0.218)
Disability rate	0.135	0.136	0.125
	(0.044)	(0.044)	(0.043)
Non-physical disability rate	0.125	0.126	0.118
	(0.044)	(0.044)	(0.042)
% Students economically disadvantaged	0.447	0.456	0.362
	(0.186)	(0.185)	(0.175)
% Student White	0.658	0.655	0.689
	(0.262)	(0.266)	(0.223)
% Students Hispanic	0.252	0.252	0.255
	(0.265)	(0.268)	(0.230)
% Students Black	0.082	0.086	0.043
	(0.122)	(0.125)	(0.077)
% Students other race/ethnicity	0.008	0.008	0.012
	(0.017)	(0.015)	(0.027)
% Students in pre-K and kindergarten	0.096	0.097	0.095
	(0.034)	(0.032)	(0.044)
% Students in elementary grades (1–6)	0.477	0.474	0.504
	(0.072)	(0.064)	(0.122)
% Students in middle grades (7–8)	0.159	0.160	0.150
	(0.031)	(0.027)	(0.052)
% Students in secondary grades (9–12)	0.264	0.266	0.249
	(0.077)	(0.073)	(0.109)
District enrollment	3538	3663	2344
	(10786)	(11193)	(5423)
Number of schools	6.2	6.4	4.6
	(14.4)	(14.9)	(7.1)
Number of observations	6138	5556	582

Notes: The first column presents summary statistics for the full sample of Texas non-special school districts (with non-missing and non-zero data as described in the text) for the years 1992 through 1997. The next two columns break the sample down by district wealth. Districts that are predicted to have more than $280,000 per-weighted pupil (based on 1992 characteristics) are classified as high wealth. All other districts are classified as low wealth. Standard deviations are in parentheses.

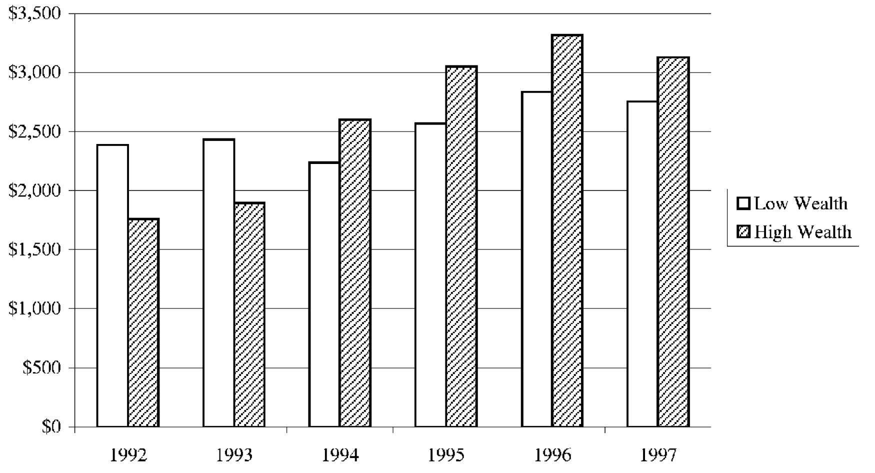

Fig. 2. Predicted revenue gain by year and district type. The height of each bar shows the mean predicted increase in state revenue that would result if a locality were to classify a marginal regular education student as disabled for the year and sample indicated. Districts that are predicted (based on 1992 program shares) to have tax base wealth of more than $280,000 per-weighted pupil are classified as high wealth. All other districts are classified as low wealth.

classify students as disabled, the response should be reflected in the classification behavior of the wealthiest 9.5% of districts over time relative to that of other districts.

The mean disability rate for the full sample is 13.5% including all disabilities, and 12.5% including only non-physical disabilities. The disabilities that I classify as non-physical are the disabilities that are arguably most subjective and therefore most likely to be affected by fiscal incentives: learning disability, speech impairment, emotional disturbance, and other health impairments (which includes Attention Deficit Hyperactivity Disorder (ADHD)). The average rate of non-physical disability is a percentage point higher in low wealth districts than in high wealth districts. The higher incidence of disability can be partly attributed to higher student poverty and minority rates in low wealth districts (Wagner, 1995).

Student enrollment in Texas increased each year of the sample period, rising 11% over the 6 years from 3.4 million to 3.8 million students. The number of students classified as disabled rose from 340,000 to 450,000, or by 32%, leading to rising disability rates. Fig. 1 shows that the rising rates are due mainly to increasing fractions of students classified within the non-physical disability categories; the fractions of students classified as learning disabled, speech impaired, emotionally disturbed, and other health impaired rose 34, 21, 31 and 158%, respectively. However, it would be premature to attribute this growth to the rising fiscal incentives depicted in Fig. 2 given that physical disability rates rose nearly as rapidly. The trend in both non-physical and physical disability rates may

Table 2
Average fiscal incentive by year and district type

	1992	1993	1994	1995	1996	1997
	Actual revenue gain					
Full sample	2319	2440	2375	2747	3187	3119
	(291)	(298)	(396)	(482)	(617)	(623)
Low wealth districts	2379	2496	2315	2666	3107	3046
	(240)	(256)	(296)	(358)	(471)	(466)
High wealth districts	1810	1961	2943	3576	3997	3898
	(161)	(175)	(680)	(743)	(1143)	(1250)
	Predicted revenue gain					
Full sample	2319	2377	2273	2613	2881	2788
	(291)	(289)	(340)	(417)	(513)	(469)
Low wealth districts	2379	2434	2239	2570	2838	2756
	(240)	(249)	(269)	(328)	(444)	(430)
High wealth districts	1810	1894	2600	3052	3318	3130
	(161)	(86)	(639)	(806)	(854)	(686)

Notes: Each cell presents the mean increase in state revenue that would result if a locality were to classify a marginal regular education student as disabled for the year and sample indicated. The top panel presents the fiscal incentive calculated using actual district behavior and characteristics in each year. The full sample includes 1023 districts in each year. In the top panel, districts that have more than $280,000 per-weighted pupil (9.5% of districts) are classified as high wealth. The bottom panel presents the fiscal incentive predicted from 1992 district behavior and characteristics as described in the text. In this panel, districts that are predicted to have more than $280,000 per-weighted pupil are classified as high wealth. Standard deviations are in parentheses.

be attributable to non-fiscal factors, such as worsening socio-demographic indicators (student poverty rates increased by 14% over the same period).

Comparing low and high wealth districts over time provides an initial sense of the role of fiscal incentives in explaining the trend in disability rates. In high wealth districts, the predicted revenue gain from classifying marginal students increased 12.1% annually on average, compared to an average increase of 3.2% in other districts.[19] The fraction of students classified as disabled also grew at a faster pace in high wealth districts, increasing at a rate of more than 1.5 times the rate in other districts (7.5% per-year versus 4.7%). Further, Fig. 3 reveals a close relationship over time between percent changes in disability rates and fiscal incentives both within and across these broad tax base wealth categories. This casual evidence suggests that there is a strong correlation between patterns in special education enrollments and revenue gains. The next section analyzes this relationship more carefully in a regression context.

[19]For this simple analysis, I exclude the 4.8% of districts that are predicted to switch tax base wealth categories over time (from below to above $280,000 per-weighted pupil, or vice versa) in order to avoid introducing confounding changes in the composition of the two samples.

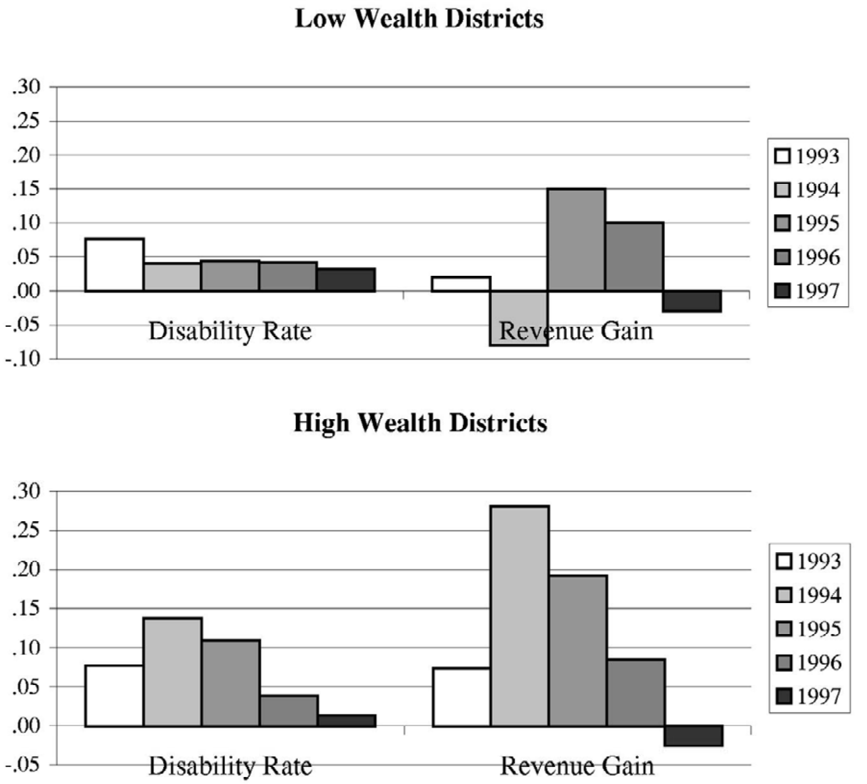

Fig. 3. Average percent change in disability rate and revenue gain. The sample in the top panel includes districts that are predicted (based on 1992 program shares) to have tax base wealth per-weighted pupil below $280,000 in all years. The bottom panel includes districts that are predicted to have more than $280,000 in all years. I exclude districts that are predicted to switch categories to avoid introducing confounding changes in the sample over time (4.8% of the sample). The height of the bar represents either the average percent change in the disability rate or the revenue gain between the indicated year and the prior year (e.g. '1993' represents the change between the school years 1991–1992 and 1992–1993).

4. Empirical analysis

4.1. Basic results

Table 3 presents instrumental variables estimates of the elasticity of student disability rates with respect to the revenue gain. The specification in each column is a variant of the system of equations in (5). The sample is based on the 6138 observations for non-special districts (with non-missing and non-zero observations) for the years 1992–1997. The dependent variable in the first three columns is the

Table 3
Instrumental variables estimates of the relationship between fiscal incentives and student disability rates

	Detailed district characteristics (1)	District fixed effects (2)	District-specific trends (3)	District-specific trends (4)	District-specific trends (5)
	Dependent variable: ln(student disability rate)				
	All disabilities			Non-physical disabilities	Physical disabilities
Ln(revenue gain)	**0.044**	**0.109**	**0.212**	**0.247**	**−0.049**
	(0.035)	**(0.023)**	**(0.040)**	**(0.045)**	**(0.082)**
Ln(per pupil tax base wealth)	−0.032	−0.008	0.023	0.023	−0.004
	(0.008)	(0.019)	(0.025)	(0.026)	(0.062)
High wealth	−0.006	−0.036	−0.080	−0.104	0.007
	(0.018)	(0.019)	(0.020)	(0.021)	(0.044)
% Tax base wealth residential	0.097	0.005	−0.040	−0.014	0.016
	(0.031)	(0.078)	(0.102)	(0.108)	(0.241)
% Economically disadvantaged	0.346	0.174	0.085	0.114	0.057
	(0.036)	(0.038)	(0.035)	(0.037)	(0.089)
% Hispanic	−0.568	0.233	0.018	−0.081	−0.384
	(0.025)	(0.099)	(0.119)	(0.126)	(0.489)
% Black	−0.279	0.448	0.475	0.306	1.441
	(0.039)	(0.167)	(0.234)	(0.247)	(0.646)
% Other non-White race/ethnicity	−0.546	−0.379	0.037	0.154	−1.426
	(0.242)	(0.514)	(0.536)	(0.567)	(1.818)
% Elementary (grades 1–6)	−0.562	0.646	0.486	0.493	0.021
	(0.152)	(0.107)	(0.104)	(0.111)	(0.366)
% Middle (grades 7–8)	0.131	0.706	0.662	0.637	0.278
	(0.160)	(0.130)	(0.129)	(0.137)	(0.441)
% High school (grades 9–12)	0.141	0.612	0.752	0.770	−0.512
	(0.128)	(0.113)	(0.127)	(0.134)	(0.429)
Ln(district enrollment)	−0.142	−0.183	−0.180	−0.149	−0.163
	(0.008)	(0.029)	(0.045)	(0.048)	(0.142)
Ln(number of schools)	0.140	0.040	−0.015	−0.017	0.001
	(0.012)	(0.016)	(0.018)	(0.019)	(0.049)
	Ordinary least squares estimates				
Ln(revenue gain)	**0.036**	**0.047**	**0.062**	**0.073**	**−0.011**
	(0.024)	**(0.015)**	**(0.017)**	**(0.019)**	**(0.038)**

Notes: The specifications are based on instrumental variables estimation where the actual revenue gain is treated as endogenous, and the instrument is the predicted revenue gain. The dependent variable in columns 1–3 is the natural logarithm of the overall student disability rate in the district and year. The dependent variable in column 4 is the non-physical disability rate and the dependent variable in column 5 is the physical disability rate. Column 1 includes observable district characteristics, column 2 includes district fixed effects, and columns 3–5 include district-specific trends. The high wealth indicator is set equal to one if the district is predicted to have wealth per-weighted pupil greater than $280,000 based on 1992 program shares. All columns include year indicators as well as the variables shown. The sample is based on the full sample of school districts for the years 1992–1997 with non-missing and non-zero observations as described in the text, except for the final column in which case the sample is restricted to the 80% of districts that always have non-zero physical disability rates.

log of the overall student disability rate. The first column includes observable district characteristics and year indicators as explanatory variables, the second column adds district fixed effects, and the third column adds district-specific trends. The observable student characteristics included in the control set are the fraction economically disadvantaged,[20] the race/ethnicity composition, and the grade distribution. I control for district size using district enrollment and the number of schools (both in log form). The district financial variables included are the fraction of the tax base that is residential and, to capture income and aid effects, the log of per-pupil district wealth and an indicator for whether or not the district is predicted to be high wealth.

The estimated elasticity with respect to the fiscal incentive is positive and steadily increases in magnitude across the three columns. The increase from 0.044 to 0.109 between the first two columns suggests that fixed district characteristics that are omitted from the first regression and are positively correlated with the predicted incentive are otherwise associated with lower disability rates, lending a downward bias to the estimate in the first column. The further increase to 0.212 in the third column suggests that districts that face increased incentives are those in which disability rates are expanding more slowly for other reasons, which would be a remaining source of downward bias in the fixed effects specification in the second column. The bottom row in Table 3 depicts the corresponding ordinary least squares estimates of the coefficient on the log of the revenue gain to emphasize the importance of using the predicted gain as an instrument for the actual gain. The OLS estimates are much smaller than the corresponding instrumental variables estimates, reflecting the potential for districts that aggressively classify students as disabled to shift to a reduced-incentive regime.

Other than the fiscal incentive, the variable that consistently has a strong positive impact on disability rates is the fraction of students that are economically disadvantaged. This link between disability and poverty has been well-documented elsewhere (e.g. Chaikind and Corman, 1991). The fraction Black is significantly positively related to the disability rate in the last two specifications that attempt to control for unobservable district characteristics. The fraction disabled decreases with district enrollment and with the fraction of students in the earlier grades. This last finding is consistent with the fact that one in 7.4 elementary education students is served in special education, while one in only 6.5 secondary education students is.

The preferred specification is based on the stringent identification strategy in column 3 that includes district-specific trends. The disability response is identified from deviations in the growth of disability rates around each district's trend that are caused by policy-induced deviations around trend in the growth of incentives. The interpretation of the estimated coefficient on the log of the revenue gain is that

[20] Students are considered economically disadvantaged if they are eligible for free or reduced-price lunch or for other public assistance.

a 10% increase in the revenue gain would lead to a 2.1% increase in the disability rate. From 1992 to 1997, disability rates grew annually by 3.8% on average in Texas. Actual revenue gains grew by 7.1% on average each year. Thus, the elasticity estimate implies that fiscal incentives can explain nearly 40% of the time trend in disability rates over the 6 years.[21]

The last two columns in Table 3 replicate the specification in column 3 using subsets of the overall disability rate as dependent variables.[22] The dependent variable in column 4 is the rate of non-physical disability. The non-physical disability categories are those in which the majority of students classified have mild disabilities and are often not easily distinguishable from poor academic performers in regular education (Reschly, 1996; Ysseldyke et al., 1982). The point estimate of the elasticity of non-physical disability rates with respect to fiscal incentives is larger than for all disabilities, as would be expected. A 10% increase in the fiscal gain is predicted to lead to a 2.5% increase in the rate of non-physical disability. Column 5 shows the regression results when the dependent variable is the rate of physical disability. Reassuringly, physical disability rates are found to be unresponsive to fiscal incentives.[23] The rest of the analysis focuses on the more responsive non-physical disability categories.

Table 4 tests the sensitivity of the estimated elasticity of non-physical disability rates in a variety of ways. Each row of the table displays the estimated coefficient on the log of the revenue gain from a separate regression. Each specification is identical to column 4 in Table 3, but is based on a different sample. The top row reproduces the estimate from Table 3. The following five rows each omit a segment of the full time period. Since the specification in (2) can be implemented by first expressing all variables in terms of first differences and then included fixed effects, it is straightforward to omit the first difference that corresponds to the change between any given pair of years. The estimated elasticity ranges from a

[21]There are several caveats to interpreting this as an estimate of the long-run impact of fiscal incentives. First, the measured response may reflect cross-district migration as well as reclassification, leading to an overestimate of the net impact on overall disability rates. However, migration is likely to respond more slowly than assessment practices. Second, the dependent variable is by necessity expressed as a stock variable rather than a flow variable so that the long-run impact on disability rates will be understated. Finally, understatement would also result if districts are slow to respond to changing incentives because of information lags or other rigidities. In this case, the estimated contemporaneous effect of the current year incentive will reflect correlation between current and past incentives and may be biased. Including a 1-year lag in the incentive increases the coefficient on the current measure slightly, since the partial correlation between the two measures is negative (-0.38) and both have positive effects. The coefficient on the lagged measure is 20% as large as the current measure, implying a modest lagged response, but the estimate is not statistically significant.

[22]Here and in all later cases, the expected increase in the pupil count is based on average placement patterns specific to the relevant disability type.

[23]The sample in column 5 is restricted to the 80% of districts that always have non-zero physical disability rates, which excludes the smallest districts. The estimated elasticity for non-physical disability rates in this restricted sample remains positive and significant.

Table 4
Sensitivity analysis

Specification	Estimated coefficient on ln(revenue gain)
Base specification (column 4 from Table 3)	0.247
	(0.045)
Excluding changes between pairs of years:	
1992–1993	0.218
	(0.048)
1993–1994	0.217
	(0.081)
1994–1995	0.244
	(0.042)
1995–1996	0.297
	(0.052)
1996–1997	0.238
	(0.046)
Excluding smallest 5% of districts	0.177
	(0.040)
Excluding largest 5% of districts	0.265
	(0.049)
Excluding smallest 10% of districts	0.142
	(0.038)
Excluding largest 10% of districts	0.282
	(0.052)

Notes: Each row corresponds to a separate instrumental variables regression. All specifications include district-specific trends and control variables as in column 4 in Table 3. In each case, the dependent variable is the natural logarithm of the fraction of students classified as having non-physical disabilities. The coefficients on the logarithm of the revenue gain and the associated standard errors are presented. The sub-samples are based on the full sample of 6138 district-year observations for the years 1992–1997.

low of 0.217 to a high of 0.297 depending on which change is excluded. What is notable is that when the change between 1993 and 1994 is excluded the standard error nearly doubles. These are the 2 years that span the key reform to the school finance policy. Given the striking relative movement in the predicted gain between those 2 years in Fig. 2, it is not surprising that excluding this change substantially reduces the useful variation in the predicted revenue gain. Despite differences in precision, the estimated elasticity is qualitatively similar to the base case regardless of which change is excluded. Therefore, the results are not sensitive to whether the elasticity is identified from the sharp change in the structure of the school finance policy in 1994 or from annual legislative changes to the underlying policy parameters.

The remaining rows conduct sensitivity tests with respect to district size. Excluding the smallest 5% of districts leads to a sizeable reduction in the estimated elasticity to 0.177. Given that small changes in the number disabled can generate large swings in the disability rate for very small districts, this could indicate that outliers drive the baseline estimate. However, excluding the smallest 10% of districts reduces the estimate further to 0.142, while the estimate increases to 0.265 and 0.282 when the largest 5 and 10% of districts are excluded, respectively. The magnitude of the elasticity appears to vary systematically with district size.

Table 5 examines the relationship between the estimated elasticity and district size more closely. Splitting the sample in half by district size reveals a response that is four times as great for the smaller districts, though still positive and significant for the larger districts. One possible explanation for the declining responsiveness by district size is that small districts are more able to respond to fiscal incentives because decision-making is more centralized. As district enrollment increases and is spread across more schools, the school-level incentive to classify students in response to fiscal incentives is weakened because the likelihood of receiving the full financial benefit is lower. To test whether the differential response may be due to differences in effective incentives, I further split the sample by enrollment concentration. Enrollment concentration is measured by a Herfindahl index calculated for each district i:

Table 5
Classification response by district size and enrollment concentration

	Enrollment concentration index	Coefficient on ln(revenue gain)
Bottom half in district size	0.670	0.389
	(0.005)	(0.074)
Below median concentration	0.434	0.126
	(0.002)	(0.069)
Above median concentration	0.904	0.608
	(0.004)	(0.136)
Top half in district size	0.226	0.095
	(0.002)	(0.043)
Below median concentration	0.140	0.083
	(0.002)	(0.047)
Above median concentration	0.311	0.161
	(0.002)	(0.091)

Notes: The rows divide the sample according to district size and whether the district is above or below median concentration within size categories. The first column presents the mean district enrollment concentration index for each sample. The concentration index is equal to the sum of the squared share of district enrollment across schools within districts. The coefficients on the logarithm of the revenue gain from separate instrumental variables regressions are shown in the second column. The dependent variable in each case is the natural logarithm of the fraction of students classified as having non-physical disabilities. All specifications include district-specific trends and control variables as in column 4 in Table 3. The sub-samples are based on the full sample of 6138 district-year observations for the years 1992 to 1997. Standard errors are in parentheses.

$$H_i = \sum_{si}(e_{si}/e_i)^2,$$

where s identifies schools and e is enrollment. Consistent with the hypothesis, Table 5 shows that the measured elasticity varies directly with the degree of concentration among districts in both size categories.

Table 6 explores how the responsiveness varies by grade level.[24] The representation of students within specific disability categories differs dramatically across grade levels. In both the elementary and secondary grades, over 90% of disabled students are classified as having disabilities that fall within the four categories I classify as non-physical disabilities: learning disability, speech impairment, emotional disturbance, and other health impairment. Within these, the dominant

Table 6
Classification response by disability type and by grade level

Dependent variable	Mean of the dependent variable expressed in levels	Estimated coefficient on ln(revenue gain)
	Elementary grades (ages 6–11)	
Non-physical disability rate	0.1148	0.242
	(0.0005)	(0.067)
Learning disability rate	0.0675	−0.023
	(0.0004)	(0.092)
Speech impairment rate	0.0392	0.286
	(0.0003)	(0.121)
	Secondary grades (ages 12+)	
Non-physical disability rate	0.1413	0.096
	(0.0007)	(0.048)
Learning disability rate	0.1219	0.127
	(0.0007)	(0.056)
Speech impairment rate	0.0035	–
	(0.0001)	

Notes: The first column presents the mean of the specified disability rates within elementary and secondary grades. The second column presents the coefficient on the log of the revenue gain from specifications that include district-specific trends and control variables as in column 4 in Table 3. The dependent variable is the log of the relevant disability rate. The sample in each row is derived from the full sample of 6138 district-year observations for the years 1992 to 1997, but excludes school districts that provide either only elementary or secondary education (6.7% of the full sample). Districts that ever classified no students within the specified disability category are also excluded. This potential sample selection is minor, with at most 2% of observations excluded. The specification with the speech impairment rate in secondary grades as the dependent variable was not estimated because nearly 75% of districts have a zero rate of speech impairment for students in that age range.

[24]The sample for this analysis excludes the 6.7% of districts that do not provide both elementary and secondary education in order to avoid confounding changes in the sample across grade levels.

categories are learning disability and speech impairment. The mean disability rates presented in the first column in Table 6 show that these two categories are distributed very unevenly across elementary and secondary grades. While learning disability comprises 59% and speech impairment 34% of elementary student disability, learning disability comprises 86% and speech impairment only 2% of secondary student disability.

The second column in Table 6 presents the estimated elasticity of student disability rates with respect to the fiscal gain by grade level and disability category. The estimates are based on the familiar instrumental variables specification that includes district-specific trends and time-varying controls. The non-physical disability rate is responsive to fiscal gains at both elementary and secondary grade levels, though the point estimate is over twice as large for the elementary grades. While increases in the fraction classified as speech impaired drive the response found for elementary grades, increases in the fraction classified as learning disabled drive the response for secondary grades. This pattern of student classification in response to fiscal incentives is consistent with average age patterns found by Hanushek et al. (1998). Using individual-level panel data from Texas, they find that there is significant movement in and out of special education for children classified as speech impaired at earlier ages, and that the same holds true for learning disabled at later ages.

It would be valuable to be able to more directly compare the response by disability type to test whether students are more likely to be classified with disabilities that are relatively better rewarded over time. However, given that districts are reimbursed based on the instructional setting and that the placement weights are uniform within any given year, the relative (gross) incentive for districts to classify students as one disability type relative to another is constant across districts. This means that the effect of financial incentives cannot be distinguished from secular changes in the relative incidence of differing disabilities (which can be important for cases like ADHD where diagnosis is relatively new).

A crude way to check whether relative incentives are compatible with changes across categories over time is to look explicitly at how statewide special education placement patterns have changed as placement weights have changed. The top three rows in Table 7 show the evolution of the statutory increase in the weighted pupil count associated with each of the three least-restrictive settings—pull-out speech therapy, mainstream placement with special support in the regular classroom, and resource room pull-out for part of the day. Most notable is that, in an effort to encourage more inclusive settings, the legislature dramatically increased the weight associated with mainstream placement in 1995. The next three rows show the mean share of all placements within each of these categories by year. These three settings represent over 80% of all instructional placements in every year. While the placement shares for speech therapy and resource room fall slightly over time, the mainstream share increases by 50% between 1994 and 1995 and continues to rise in the following 2 years. The final three rows in the table

Table 7
Relative placement incentives and shares over time

	Year					
	1992	1993	1994	1995	1996	1997
Student placement weight						
Speech therapy	0.243	0.243	0.243	0.159	0.159	0.159
Mainstream instruction	0.239	0.239	0.239	1.063	1.063	1.063
Resource room instruction	0.541	0.541	0.541	0.638	0.913	0.913
Share of placements						
Speech therapy	0.199	0.197	0.189	0.181	0.175	0.171
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Mainstream instruction	0.083	0.092	0.096	0.144	0.175	0.172
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
Resource room instruction	0.524	0.523	0.535	0.508	0.485	0.492
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Dep. var. = ln(placement share)						
Speech therapy	–	–	−0.022	−0.081	−0.129	−0.147
			(0.017)	(0.030)	(0.042)	(0.055)
Mainstream instruction	–	–	−0.048	0.294	0.418	0.342
			(0.033)	(0.058)	(0.082)	(0.106)
Resource room instruction	–	–	0.019	−0.044	−0.109	−0.097
			(0.014)	(0.025)	(0.035)	(0.045)

Notes: The top three rows show the marginal increase in the weighted pupil count associated with the three instructional settings indicated. The increase is equal to the statutory placement weight multiplied by the legislated FTE associated with each placement less the mechanical reduction in regular education FTE, multiplied by the statewide attendance rate. The shares of all special education students placed in these settings are shown in the next three rows. The final three rows present coefficients on year dummies from specifications relating the log of the placement share to district-specific trends and the full set of control variables as in column 3 in Table 4, except for the incentive measure. The summary statistics are based on the full sample of 6138 district-year observations for the years 1992−1997, but the regressions exclude school districts that ever have no placements in any category (31.3% of the full sample).

present regression results from ordinary least-squares specifications relating log placement share to the same set of control variables as in the other analyses, excluding the incentive measure.[25] The coefficient estimates associated with the year indicators are reported. Controlling for changes in observable district characteristics over time in this way reveals the same dramatic increase in the share of mainstream special education placements following 1995. The fact that placement shares mirror policy changes so closely supports a strong link between financial incentives and the decision of how to serve disabled students, in addition

[25] The regression analysis is based on the nearly 70% of districts that always have at least one student served in each of the three instructional settings.

to the already established tie to the decision of whether to classify students as disabled.

Taken together, the results in Tables 3–7 demonstrate that the qualitative finding that fiscal incentives play a significant role in determining disability rates is quite robust. Also, the relative magnitudes of the response across districts and grades conform to expectations. However, the finding that localities are sensitive to fiscal incentives when making decisions about student disability has ambiguous welfare implications. The following extensions provide indirect evidence on the possible welfare effects of the behavioral response by considering how student race/ethnicity and district fiscal constraints affect classification.

4.2. Response by student race/ethnicity

The first extension explores how the response of student disability rates to fiscal incentives differs according to students' minority status. Independent of considerations of the impact of school finance policies, there has been extensive public debate and legal concern about the potential over-classification of minority students as disabled.[26] National disability rates are higher among minorities, and this is true for Texas as well. Fig. 4 shows that while one in eight White students in Texas is classified as disabled, the rate is one in seven for Hispanic students and one in five for Black students. Several studies show that this 'over-representation' can be largely explained by differences in demographic characteristics that reflect real differences in the underlying prevalence of disability.[27] In order to measure the impact of fiscal incentives, I do not make any assumptions about whether the average rate of disability among minority groups relative to majority groups (controlling for observable characteristics) reflects true differences in the prevalence of disability or not. I simply observe whether or not districts that have incentives to expand special education populations draw disproportionately from minority groups relative to this baseline rate. An important caution in interpreting the results that follow is that, given the large standard errors, even large

[26]These concerns date from Hobsen v. Hansen (Washington, D.C.) in 1967 under which the tracking system that used standardized tests as a basis for special education placement was determined to be unconstitutional since it discriminates against Black and poor students. Concerns about minorities in special education persist: ''The Federal Government has warned that New York City could lose Federal aid if it continues to shunt disproportionate numbers of Black and Latino children into special education. [. . .] A 2-year investigation by the United States Department of Education's office of civil rights found that African–American children in schools where the principals, faculty, and student body are mainly White are most likely to end up in special-education classes. These children are often dumped into special ed even when diagnostic tests reveal no need for it.'' (*New York Times*, December 2, 1998).

[27]Wagner (1995) finds a higher incidence among minorities of deafness, blindness, and other objective physical disabilities; Shiono and Behrman (1995) calculate that Blacks are twice as likely as Whites to be born with low birth weight, which is an important factor determining the likelihood of childhood disability.

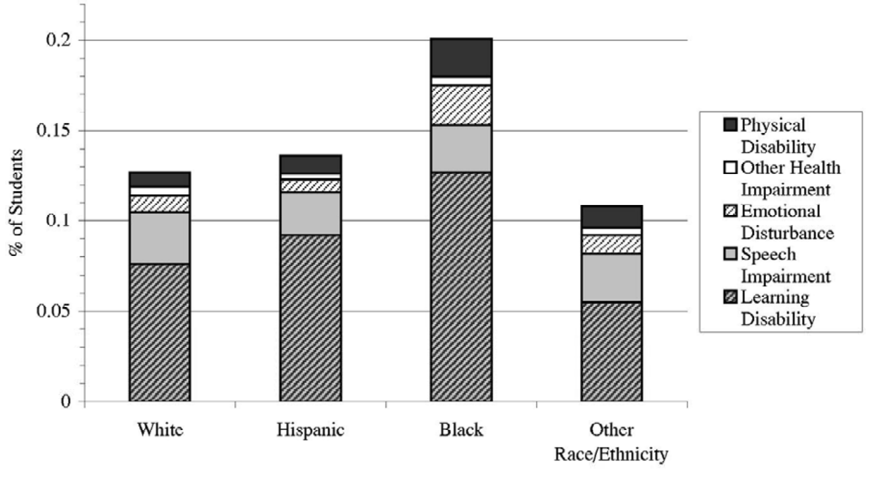

Fig. 4. Fraction of students classified as disabled by race/ethnicity in Texas. The height of the bars shows the average fraction of elementary and secondary students within each race/ethnicity category that is classified as disabled in Texas over the period 1992–1997. The bar is divided into the share attributed to each disability category, as in Fig. 1.

differences in point estimates across groups are not generally statistically significant.

The first and second rows in Table 8 present the mean enrollment share and disability rate (as a share of total enrollment) for White, Hispanic, and Black students separately. In order to exclude observations for which the relevant disability rate is zero, the sample in the left panel is restricted in each column to those districts in which student enrollment in the race/ethnicity category indicated comprises at least 5% of total enrollment. The number of observations in each case is shown at the bottom of the table. The third row presents results from the baseline instrumental variables specification that includes district-specific trends, where the dependent variable in each column is the log of the overall non-physical disability rate. The dependent variable in the following row is the rate for the relevant race/ethnicity group.

In the left panel, the estimated elasticity of disability rates with respect to fiscal incentives is of comparable magnitude for Whites and Blacks, and about half as large for Hispanics. This set of estimates is apparently not consistent with minority students being more likely to be classified in response to fiscal incentives. However, there may be important differences in the characteristics of the districts (e.g. district size) represented in each column that confound the interpretation of cross-column comparisons. Comparing the group-specific elasticity (row 4) to the overall elasticity (row 3) within each column reveals that Blacks are classified in response to fiscal incentives at much greater rates than other students in the same

Table 8
Classification response by student race/ethnicity

	Student race/ethnicity					
	White	Hispanic	Black	White	Hispanic	Black
Enrollment share	0.689	0.351	0.195	0.565	0.240	0.181
	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)
Non-physical disability rate	0.085	0.042	0.031	0.062	0.028	0.027
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
	Dep. var. = ln(overall non-physical disability rate)					
Full sample	0.250	0.162	0.155	0.138	0.138	0.138
	(0.045)	(0.042)	(0.081)	(0.066)	(0.066)	(0.066)
	Dep. var. = ln(group-specific non-physical disability rate)					
Full sample	0.281	0.123	0.254	0.143	−0.045	0.276
	(0.058)	(0.072)	(0.136)	(0.088)	(0.127)	(0.109)
Low minority teacher share	0.325	0.097	0.612	0.133	−0.052	0.590
	(0.070)	(0.098)	(0.190)	(0.144)	(0.216)	(0.179)
High minority teacher share	0.207	0.105	−0.200	0.283	−0.007	0.056
	(0.097)	(0.101)	(0.174)	(0.109)	(0.140)	(0.127)
At least 5% share for indicated race/ethnicity	Yes	Yes	Yes	Yes	Yes	Yes
At least 5% share for smallest race/ethnicity	No	No	No	Yes	Yes	Yes
Number of observations	5820	4152	2292	1416	1416	1416

Notes: The columns provide statistics for students in the race/ethnicity categories indicated. The sample in the left panel is restricted to districts in which the specific race/ethnicity category comprises at least 5% of total enrollment (in order to avoid sample selection due to zero disability rates). The right panel is based on a common sample for all three groups, restricted to districts in which the smallest category comprises at least 5% of total enrollment. The first and second rows show the mean enrollment share and non-physical disability rate, defined as the number disabled within the race/ethnicity category divided by overall enrollment. The next row presents the coefficient on the logarithm of the revenue gain from instrumental variables specifications with the overall non-physical disability rate as the dependent variable. The next three rows show the same coefficient from specifications where the dependent variable is specific to the race/ethnicity group. These results are shown first for the full sample, and then for halves based on district minority teacher share. Districts are assigned to the 'low' minority share sample if the teacher minority share is lower than expected given the student minority share (as described in more detail in the text). All specifications include district-specific trends and controls variable as in column 4 in Table 3. Standard errors are in parentheses.

districts. The somewhat lower than average rate for Hispanics compared to their peers could be consistent with those students being more likely to move in and out of bilingual education, which carries its own supplemental student weight.

The right panel controls more directly for sample composition by using a common sample of districts that have at least a 5% enrollment share within each category. In this select set of districts, the point estimate of the elasticity is twice as great for Black as Whites, and is negative and insignificant for Hispanics. To test whether the phenomenon that is observed for Black students could be explained by under-representation, I divide the sample into districts with higher and lower minority teacher shares. Several studies across a variety of disciplines suggest that minority students are more likely to be classified as disabled when the teaching staff is less minority.[28] To make sure the composition of districts in the two samples is otherwise similar, I divide the sample into districts with higher and lower than expected minority teacher shares given the minority composition of the student body.[29] What most stands out in the comparison of elasticities across these two samples is that the rate at which Blacks are classified in response to fiscal incentives is over five times as great when the teacher minority share is low.

The finding that Black students are more likely to be classified as disabled in response to fiscal incentives, particularly when teachers are more White, is consistent with two hypotheses with very different welfare implications. Districts could be 'dumping' children of less politically powerful parents and groups into special education to leverage state funds. Or, it may be that the implied reduction in the cost of serving special education students reduces barriers to minority children to securing the more intensive resources—though this seems unlikely given the concerns mentioned above.

4.3. Response by district fiscal constraint

The second extension tests whether or not students in districts that are fiscally constrained are more likely to be classified as disabled in response to increased incentives. Lacking a direct measure, I rely on changes in the level of net per-pupil state aid received by districts to proxy for changes in fiscal constraint. The equalization reform that altered classification incentives also greatly affected the level of per-pupil state aid flowing to districts. To identify whether changes in the net transfer affect the responsiveness to fiscal incentives, I add the level of per-pupil aid and an interaction term between per-pupil aid and the fiscal incentive to the regression. Per-pupil aid is specified in levels because it is negative for many districts, so that the log would be undefined. I also standardize per-pupil aid so that it has zero mean and a unit standard deviation in order to simplify the interpretation of the interaction term. Because per-pupil aid depends on endogen-

[28] See, for example, Serwatka et al. (1995), Oswald et al. (1999), and Pigott and Cowen (2000).

[29] To do this, I first rank districts by minority student share. I then assign the district with the higher minority teacher share from each successive pair of districts to the high minority share sample. Under the assumption that teachers and students are randomly matched within districts, the likelihood that a minority student has a minority teacher doubles in the high share sample (from 1 in 14 to 1 in 7). The other observable characteristics, including district size, are quite similar across the resulting sample halves.

ous district choice variables, the net per-pupil transfer is predicted using district tax rates and program shares from the initial year in a fashion parallel to the calculation of the predicted incentive. The predicted measure then serves as an instrument for the actual level of per-pupil aid.

Over the period, the median annual increase in the net per-pupil transfer from the state is 2.5% a year. The net transfer fell by 14.4% and increased by 18.5% between years at the bottom and top deciles. Some districts are predicted to witness extreme changes in the level of net transfers, falling by over 100% or rising by more than 100% between years.

Table 9 reports the key coefficients from the expanded version of the usual instrumental variables specification with the fraction of students classified with non-physical disabilities as the dependent variable. The estimated main effect of per-pupil aid is positive while the interaction term is negative, and both coefficients are significantly different from zero. Increases in the level of per-pupil aid lead to slightly higher fractions of students classified as disabled. Fixing the log of the revenue gain at the mean of the sample, a one standard deviation increase in the level of the net per-pupil transfer from the state ($4084) would increase the fraction classified as disabled by 1%. The coefficient on the fiscal incentive is very similar to the base case, 0.191 with a standard error of 0.049. This represents the elasticity at the average level of per-pupil aid, since the average of the standardized aid measure is zero. However, the response varies directly with the level of net per-pupil transfers. The implied elasticity of student disability rates with respect to fiscal incentives varies from 0.090 to 0.292 going from one standard deviation above to one standard deviation below the mean level of

Table 9
Classification response by net per-pupil transfer from the state

Independent variable	Coefficient (standard error)
Ln(revenue gain)	0.191 (0.049)
Standardized net per-pupil transfer from state	0.806 (0.256)
Ln(revenue gain) $\times$ std. net per-pupil transfer	-0.101 (0.031)

Notes: The coefficients shown are from on a single instrumental variables specification that includes district-specific trends and time-varying controls as in column 4 in Table 3. The dependent variable is the logarithm of the fraction of students with non-physical disabilities. The estimated coefficient on the logarithm of the revenue gain is presented in the first column, on the net per-pupil transfer in the second, and on the interaction between the two in the third. Net per-pupil transfers have been standardized to have mean zero and a standard deviation of one to simplify the interpretation of the interaction term. Since actual transfers are themselves a function of the actual disability rate, predicted net per-pupil transfers are included in the instrument set. The sample is the full sample of 6138 districts.

per-pupil aid. Greater responsiveness to fiscal incentives for reclassification when state aid per-pupil is particularly low suggests that districts may assess students to be disabled to increase an otherwise weak claim on state resources. While Hanushek et al. (1998) find that special education appears to improve students' performance on standardized exams, whether special education is equally beneficial for students classified in response to fiscal incentives remains an open question.

5. Conclusion

In this paper, I identify the response of official student disability rates to fiscal incentives by isolating policy-induced changes in the relative revenue gain from classifying students across school districts in Texas. The elasticity estimate suggests that a 10% increase in the revenue generated by a special education student in excess of that generated by a regular education student leads to a 2.1% increase in the student disability rate. The response is greater for students classified with non-physical disabilities, as expected. Students are most likely to be classified as speech impaired in response to incentives in elementary grades, while learning disability populations are most sensitive in secondary grades. The estimate of the average elasticity implies that changes in state revenue generosity can explain nearly 40% of the trend in disability rates in Texas from 1992 to 1997. These findings demonstrate that government entities, much like individuals, are responsive to fiscal incentives when making decisions about program participation.

The analysis also provides evidence that the local classification response is sensitive to district characteristics. Districts in which enrollment is more concentrated, and the effective incentive is likely to be stronger, are more responsive. Black students are more likely to be classified as disabled, and more so the fewer minority teachers. Also, districts are more likely to reclassify students in response to increases in fiscal incentives if the level of per-pupil state aid is simultaneously low. Localities appear to manipulate special education populations to increase leverage on state funds, which may or may not be dedicated to special services for these students. A priority for future research is to resolve the ambiguous welfare implications of this response.

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