Essays on Special Education Finance and Intergovernmental Relations

by

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Submitted to the Department of Economics
in Partial Fulfillment of the Requirements for the Degree of

DOCTOR OF PHILOSOPHY
in Economics
at the

Massachusetts Institute of Technology

May 1997

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Abstract

The three essays in this dissertation consider different aspects of the interaction between special education policies and local government decision-making. All three utilize current data from Texas and the differential treatment of school districts under the state's school finance program. Chapter 1, "The Incidence of Special Education Mandates: Does the Mainstream Pay," explores the incidence of under-funded mandates imposed on localities within the context of special education. The costs of satisfying state and federal special education mandates exert growing fiscal pressure on local governments. I investigate the extent to which the costs are shifted to students in other education programs through reduced resources. I compare spending on non-disabled students across school districts in Texas that incur differing special education costs. Because spending on special education may be correlated with unobservable variables that also determine regular education spending, I isolate plausible exogenous shifts in special education costs that are due to differing rates of severe physical disability (such as deaf-blindness) and the structure of Texas school finance policy. The results suggest that additional special education spending comes at the expense of spending on general education students.

Chapter 2, "New Evidence on the Impact of Differential Expenditures on Student Performance," utilizes this unique variation in spending to estimate the value of additional resources in producing student achievement. I relate per-district variation in spending on general education students resulting from exogenous differences in special education costs to variation in student outcomes. This strategy reveals that additional spending is productive.

Policy discussion has linked the trend in student disability rates to state funding formulas that reward local school districts for identifying students with special needs. However, there is little empirical evidence on the role of fiscal parameters in explaining student disability rates or on the responsiveness of localities to intergovernmental price incentives more generally. Chapter 3, "Local Fiscal Incentives and Student Disability Rates," estimates the elasticity of student disability rates with respect to the generosity of state special education reimbursements. I use variation in the state aid generated by serving a disabled student across local school districts in Texas to quantify the response.

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Acknowledgments

There are many people who were instrumental to the process and completion of this dissertation. First, I would like to thank my advisors, Jonathan Gruber and James Poterba, who were insightful and encouraging throughout the experience. Jon Gruber expertly guided the development of my research skills while I worked for him as a research assistant, worked with him as a co-author, and sought counsel as an advisee. Jim Poterba's vast knowledge and understanding of economics, approachability, and example were vital to what I have accomplished.

I would also like to thank other members of the MIT faculty who were particularly helpful. Josh Angrist, Peter Diamond, Jerry Hausman, Whitney Newey, and Steve Pischke all supported this research through informative discussions and excellent suggestions.

I would like to thank both current and past graduate students at MIT for providing an incredible intellectual environment and for their friendship. I benefited greatly from Steve Levitt's creativity, encouragement, and advice. My officemate, Matt Eichner, was particularly helpful to me as both a source of ideas and suggestions and as a source of emotional support. Jeff Kling always had time to answer questions and help to solve puzzles. I am also grateful to Kim Rueben, Todd Sinai, Catherine Wolfram, and Aaron Yelowitz for giving generously of their time.

Fellowship support from the National Institute on Aging and the Alfred P. Sloan Foundation is gratefully acknowledged.

People outside of MIT also provided invaluable support. John Kain and Kraig Singleton assisted me in acquiring and understanding the Texas data, as did numerous members of the Texas Education Agency. Finally, I would like to thank my husband Brian for keeping me sane. And, I would like to thank my parents, Sandra and William Berry, for being actively involved all along.

Contents

Introduction 9

1 The Incidence of Special Education Mandates: Does the Mainstream Pay

1.0 Introduction 13

1.1 Background on Special Education 16

1.2 Theoretical Framework 21

1.3 Empirical Framework 26

1.4 Texas School Finance Policy 30

1.5 Crowdout Analysis 43

1.6 Conclusion 47

Tables 50

Appendices 57

2 New Evidence on the Impact of Differential Expenditures on Student Performance

2.0 Introduction 61

2.1 Empirical Strategy 63

2.2 Data and Sample 70

2.3 Empirical Results 72

2.4 Conclusion 76

Tables 78

3 Local Fiscal Incentives and Student Disability Rates

3.0 Introduction 84

3.1 Related Empirical Literature 86

3.2 Empirical Strategy 87

3.3 Estimation Results 97

2.4 Conclusion 101

Tables 102

Bibliography 109

Introduction

The three chapters of this dissertation explore different aspects of the intersection between special education policies and local government decision-making. Special education has received a lot of media and policy attention lately due to the continuing growth in special education enrollment and costs. The fraction of the student body classified as disabled has grown from 8 to 12 percent over the past decade and special education expenditures have expanded to absorb nearly one-fifth of elementary and secondary school spending. The first chapter considers how localities finance the growing costs of partially-funded special education mandates. In particular, I estimate the impact of additional special education expenditures on regular education spending. The second chapter uses the budgetary link between special and regular education programs to identify the effectiveness of additional instructional spending on student achievement. The final chapter assesses the role of intergovernmental fiscal policies in explaining the trend in student disability rates. I measure the extent to which local school officials raise special education enrollments in response to price incentives in state school finance funding formulas. All three essays utilize current data from Texas and rely on the differential treatment of school districts under the state's school finance policy to provide identifying variation.

1. The Incidence of Special Education Mandates: Does the Mainstream Pay?

The use of state and federal mandates in a wide range of policy areas has escalated dramatically over the past two decades. However, there is little empirical evidence on how under-funded mandates impact localities. State and federal special education mandates are an example of mandates in an important area of local government finance. Localities are responsible for 30 percent of the growing costs of satisfying these mandates. This local burden will manifest itself in either higher local taxes or reduced resources allocated to other educational programs and other local services. In the first chapter, I investigate the extent to which the costs are shifted to students in other educational programs.

In order to estimate the magnitude of this "crowdout," I compare spending on non-disabled students across Texas school districts that spend differing amounts on special education. Because spending on special education may be correlated with unobservable variables that also determine regular education spending, I isolate plausibly exogenous shifts in special education costs that are due to differing rates of severe physical disability and the structure of Texas school finance policy. High rates of physical disability inflate total special education operating costs. The impact on the local special education budget depends on the amount of offsetting revenues generated. In Texas, the amount of state revenues generated by a physically disabled student and therefore the net cost varies by district tax base wealth and by year. In a regression explaining per pupil regular education spending, I instrument for special education spending using the fraction of the student population that is physically disabled interacted with the district's tax base wealth and the year. In some specifications, I include the physical disability rates as regressors to identify the effect on regular education spending only from the policy-induced variation in net costs across school districts with similar physical disability rates.

Though the cross-sectional correlation between regular and special education spending is positive, this strategy uncovers a negative causal relationship. I find that education budgets do not appear to adjust to accommodate additional special education costs so that crowdout is on the order of one-for-one. These estimates reject the standard median voter model under which special education costs can be treated as negative shocks to the public budget. Within this framework, the cost increases should not disproportionately reduce regular education spending relative to other private and public expenditures. The disproportionate effect on regular education spending may take place because the packaging of regular education and special education under the same budget affects voter behavior.

2. New Evidence on the Impact of Differential Expenditures on Student Performance

The second chapter utilizes unique variation in spending on elementary and secondary students to estimate the value of additional resources in producing student achievement. The literature that relates educational inputs to educational outputs has faced several empirical difficulties. The key difficulty is differentiating the effect of non-school resources from school

resources. There are two possible stories that one could tell. First, if parents who care a lot about education choose to locate in towns that dedicate high levels of resources to education, then comparing the performance of students across high and low resource schools will reflect both differences in family background and in resources. This will lead to an overstatement of the value of additional resources. On the other hand, state redistributive policies that target resources to schools with disadvantaged students may lead to the opposite bias-- students at high resource schools may be those students who are most likely to perform poorly.

I use campus-level data from Texas to solve this omitted variables problem. I relate the fraction of students who pass the end-of-year exams to per pupil spending over the course of that year. I include only spending on those students who are in the test-taking population, or general education students. Considering that the net costs of special education programs appear to come approximately one-for-one out of the resources budgeted to other educational programs, exogenous shifts in the costs of special education programs can be used to instrument for regular education spending. I relate the per-district variation on general education students resulting from this "crowdout" to variation in student outcomes.

While the raw correlation between achievement measures and spending is negative, ordinary least-squares regressions that control for student characteristics reveal a small positive relationship. Two stage least-squares estimation reveals an even stronger positive causal relationship. I find that a 10 percent increase in per pupil spending leads to a 2.7 percent increase in the fraction passing reading and math exams at all grade levels combined. I also find an important effect on dropout rates-- the same increase in spending would reduce dropout rates by almost one-third.

3. Local Fiscal Incentives and Student Disability Rates

The third and final chapter explores how localities respond to price incentives in state special education policies. Policy discussion has linked the rapid growth in student disability rates to state funding formulas that reward local school districts for identifying additional students with special needs. However, there is little empirical evidence on the role of these fiscal parameters in explaining student disability rates or on the responsiveness of localities to

intergovernmental price incentives more generally. In order to estimate the elasticity of student disability rates with respect to the generosity of state reimbursements, I use variation in the amount of state aid generated by serving a disabled student across local school districts in Texas. My central estimates imply that a 10 percent increase in this gain leads to a 1.5 to 2 percent increase in the fraction of students classified as disabled.

Chapter 1: The Incidence of Special Education Mandates: Does the Mainstream Pay?

The use of federal mandates in a wide range of policy areas has escalated dramatically over the past two decades. In the face of the growing budget deficit, the federal government commonly requires states and localities not only to conform to legislated provisions but also to provide the necessary funds. Since 1980, nearly 200 *unfunded* mandates have been passed by Congress. The Congressional Budget Office (1990) estimates that the annual cost of satisfying these mandates is $40 billion. As states come under increasing budgetary pressure, a growing share of this fiscal burden is passed through to local governments. In addition, local governments must also bear the costs of mandates that originate at the state level. One-fourth of local government expenditures are now dedicated to covering the costs of mandates from higher levels of government (House of Representatives, 1994). Local officials complain that mandated programs displace other essential priorities and are the primary reason for increasing tax burdens. However, there is little concrete evidence on how under-funded mandates affect either locally provided services or residents' tax burdens.

Special education mandates provide an opportunity to explore the incidence of under-funded public sector mandates that benefit a specific group. The Education for All Handicapped Children Act (EHA) was passed in 1975 on the heels of the Civil Rights Movement. This federal mandate guarantees students with disabilities the right to a "free appropriate education" "regardless of cost" and is the principal legislation affecting special education today. Though each state has its own legislation regarding the education of disabled students, those state laws essentially reproduce the federal provisions since compliance is a prerequisite for receiving federal education funds. The fraction of elementary and secondary public school students classified as "special needs" has increased from 8 to over 12 percent since EHA was instituted. Since the cost of educating a special needs student is on average 2.3 times that of a non-disabled student (Chaikind et al, 1993), expanding special education programs imply rising education costs. Though the federal government originally intended to cover 40 percent of these excess

costs, it has never covered more than 10 percent. Thus, the costs of assessing students with disabilities, planning individualized education plans (IEPs), and implementing those plans are borne largely by state and local governments.

In this paper, I focus on the degree to which the local fiscal burden of special education is borne by students who are in the mainstream, that is students who do not participate in special education. Though state governments fund the majority of special education costs, the average local share is 30 percent.[1] This local burden will manifest itself in either higher local taxes or reduced resources allocated to other educational programs and other local services. Time trends in spending on education have fueled concerns that it is other students who face resource cutbacks. Though there is controversy in the literature, recent studies suggest that a disproportionate share of new elementary and secondary education spending over the past quarter century has gone to special education.[2] This relative growth in special education spending may have come at the expense of regular education spending. To what extent has regular education experienced a "crowdout" effect? Throughout the paper, I use the term "crowdout" to mean the degree to which the incidence of mandated special education costs falls on regular education students.

Standard theory suggests that crowdout should be minimal. Empirical models of education spending are typically based on the median voter framework. According to the median voter theorem, local governments provide the level of services demanded by the pivotal voter in the community. If voters care "independently" about spending on regular and special education (the usual assumption of additive separability), then crowdout operates only through an income effect. An increase in per capita special education costs has the same effect on regular education spending as a comparable decrease in personal income, or a reduction on the order of two to four cents for every dollar. However, alternative assumptions on preferences or perspectives of the

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[1]Moore et al (1988) and Annual Reports to Congress on IDEA.

[2]Both Rothstein and Miles (1995) and Lankford and Wycoff (1996) examine district-level data and find that over a third of new education spending was dedicated to special education. Using a national cost decomposition, Hanushek and Rivkin (1994) attribute a much smaller 6 percent of the spending increase to special education. Rothstein and Miles analyze the period 1967-1991. The other two studies analyze the past decade only.

budgeting and political processes lead to deviations from this benchmark case of nearly zero crowdout. Thus, quantifying crowdout is an empirical question.

In order to estimate the degree of crowdout, I use district-level data from Texas. I focus on Texas for two reasons. First, the Texas Education Agency (TEA) has collected reliable spending data by educational program at a disaggregated level since 1990. Second, the structure of Texas school finance policy provides useful variation in the local cost of educating special needs students. The empirical analysis relates per-pupil spending on non-disabled students to the net local per-pupil cost of special education as well as community taste, cost, and price factors. Comparing spending on regular education students by observably similar districts that face differing special education costs will produce unreliable estimates of crowdout, since local spending on special education is likely correlated with unobservable factors that also determine regular education spending. For example, districts that are "pro-children" may choose to spend a lot on regular education and may also be more aggressive in classifying and providing services to mildly disabled students. To solve this problem, I use an instrumental variables approach to isolate the impact of shifts in special education costs that are outside the control of the community.

A valid instrument must affect special education costs and not otherwise be strongly correlated with regular education spending. The rate of severe physical disability is a potential candidate. Higher rates of physical disability inflate total special education operating costs. The impact on the local special education budget depends on the amount of offsetting revenues generated by disabled students. In Texas, school district special education costs are fully reimbursed on average through the school finance program, which is funded by a lump sum tax on each district. However, the relationship between expenditures and reimbursement differs by disability. For example, if a district's student body happens to include a deaf-blind student, the district can incur net costs over $25,000. Because Texas school districts are small (median enrollment is 800 students), this would mean an increase of one percent of operating expenditures to the median district or one-third of the typical annual increase in the operating budget. However, perversely, an orthopedically impaired student may actually generate net revenues for a school district. In either case, the resulting variation in special education costs is

not within the direct control of the school district.

Because the rate of physical disability alone does not provide enough variation to precisely identify crowdout, I take advantage of additional variation in special education costs that is generated by to the parameters of Texas school finance policy. A disabled student matters differentially to districts depending on the year and the district's tax base wealth. I expand the instrument set to include the physical disability rate times the year and times district tax base wealth. In addition to increasing precision, this additional variation allows me to test whether or not the physical disability rates are legitimately excluded from a regression explaining regular education expenditures since I can directly include the rates as regressors.

The principal results suggest that special education costs do crowd out spending on other educational programs. An additional dollar of special education spending is associated with between an 80 cent and a one dollar reduction in spending on other programs. The costs are borne specifically by regular education students, rather than students who participate in other supplementary programs such as gifted and bilingual education. Though the majority of students are educated in regular education classes alone, regular education appears to play the residual role in the education budget.

The format of the paper is as follows. Section 1 provides relevant background on the special education mandate and special education program costs and trends. Section 2 describes the incidence of the special education mandate from various theoretical perspectives. Section 3 describes the empirical framework for estimating crowdout. Section 4 introduces the aspects of Texas school finance policy that are relevant to the empirical analysis. I also introduce the data and summary statistics. In section 5, I conduct the crowdout analysis. Section 6 concludes.

1. Background on Special Education

Special education has recently been at the center of media and policy debate. The attention stems from the rapid and continuing growth in the percentage of students classified as disabled and the associated growing special education costs. Over the past two decades, the disability rate among the student population has increased by over 50 percent. While the average cost of educating a special needs student has been stable at slightly more than double that of a

regular education student, the share of elementary and secondary school budgets dedicated to special education may have as much as quadrupled since 1967.[3] Before situating physically disabled students in this overall picture, I will clarify the nature of the mandate that spurred this growth.

Mandates assure that special education programs are to a large degree protected from competition within education and local budgets. The Education for All Handicapped Children Act (EHA) was passed in 1975 and safeguards the right of disabled students to a "free appropriate education." The EHA and its successor, the Individuals with Disabilities Education Act (IDEA), very specifically outline the procedures that each public education agency must follow in order to identify, assess, and serve the needs of students with disabilities. The process begins either with systematic screening (for visual, speech, and hearing problems) or referral. Students can be referred by teachers, other appropriate school personnel, or by parents. Following referral, a team of qualified personnel must determine whether or not the student is eligible according to well-defined disability categories. If the student is deemed eligible, the team assesses the student's special needs and designs the individualized education plan (IEP). The IEP designates the services and the setting in which the services will be provided. Parents can refuse the IEP and have the right to due process with reimbursement for legal costs, and in recent cases damages, if their child is not being adequately served. The threat of expensive litigation has made school districts reluctant to challenge parents who want their children to have access to special education. Because the mandate stipulates that special education services be provided without regard to cost, expenditures are largely determined by the parents and specialists who play central roles in the process.

The mandated right to appropriate funds for disabled students is becoming problematic as the lines between disabled and non-disabled students are blurring. The nature of special education has clearly changed since the EHA was instituted. The mandate was originally intended to improve the access of severely disabled students to public education. The categories

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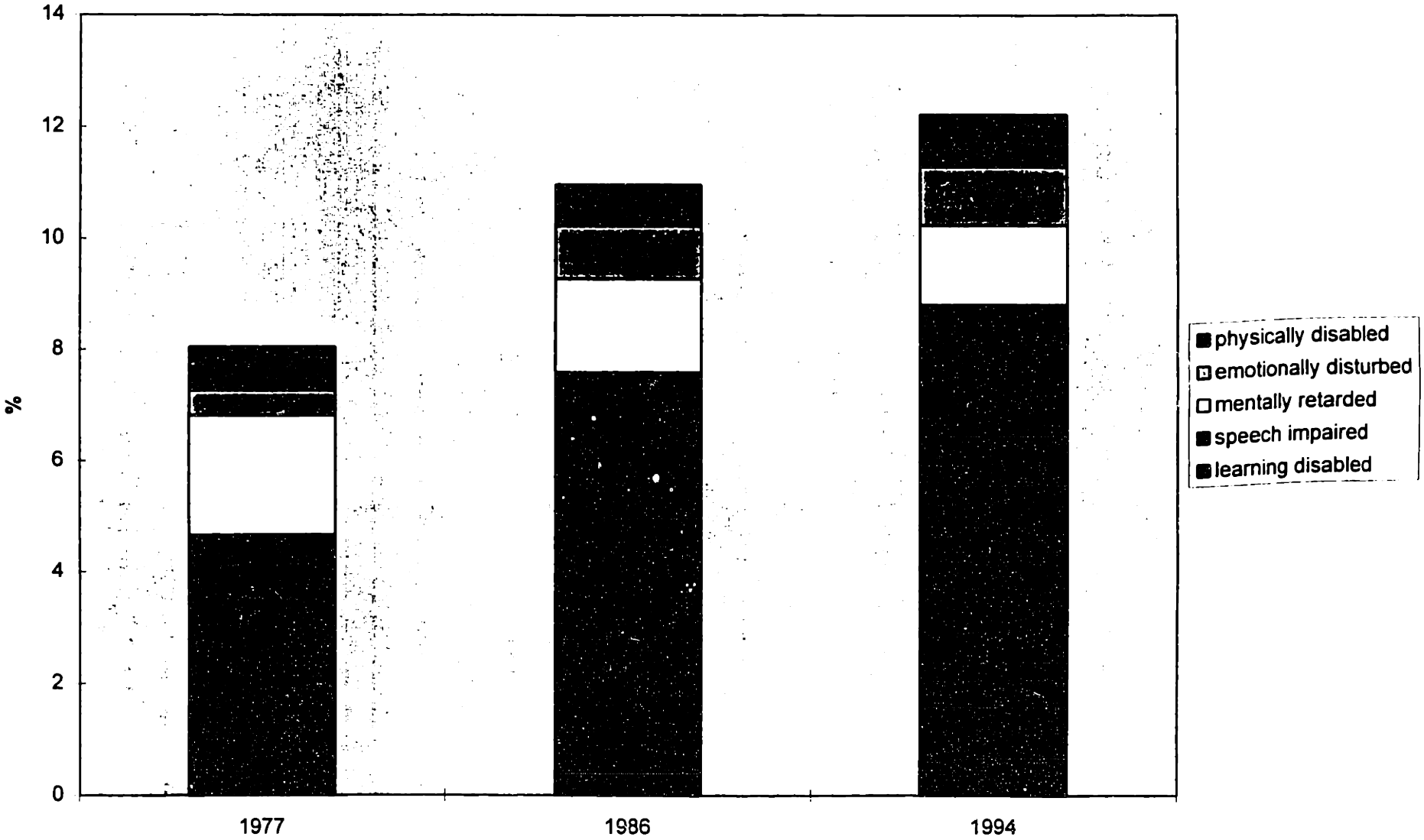
[3]Rothstein and Miles (1995) estimate that the fraction of the school budget dedicated to special education increased from 4 to 17 percent from 1967 to 1991.

Figure 1: Percentage of Students Classified as Disabled by Disability



Source: Annual Reports on IDEA, based on number disabled aged 0-21 over preK-12 enrollment
Note: In 1994, the total % of 0-5 year olds disabled is distributed according to the pattern for 6-21 year olds.

Table 1: Special Education Instructional Costs by Disability

Disability	Excess Per-Pupil Cost	Rate/100 Students	Implied Budget Share (%)
Speech Impairment	$ 861	2.29	5.8
Learning Disability	$ 2,404	5.54	39.2
Other Health Impairment	$ 3,532	0.19	2.0
Mental Retardation	$ 5,391	1.26	20.0
Orthopedic Impairment	$ 5,621	0.13	2.2
Emotional Disturbance	$ 6,191	0.94	17.1
Visual Impairment	$ 6,211	0.06	1.1
Multiple Disabilities	$ 8,448	0.25	6.2
Hearing Impairment/Deafness	$ 9,158	0.15	4.0
Autism	$20,133	0.04	2.4
Deaf-blindness	$36,397	0.003	0.3

Notes to Table 1: Chaikind et al (1993) estimate the average excess instructional cost per pupil (over and above any regular education costs incurred) by disability using national data. The values are in 1990 dollars and reproduced from Table 3 in their text. The rate of occurrence by disability is based on Tables AA4 and AF6 in the 17th Annual Report to Congress on the Implementation of IDEA (1995). The rate is calculated as the number of students aged 6-21 in each disability category in 1993-94 divided by pre-K through 12th-grade enrollment in the same year. The implied share of the special education budget is calculated from the relative cost and rate of occurrence of each disability.

of disabilities that qualify for special education are: mental retardation, serious emotional disturbance, autism, deaf-blindness, traumatic brain injury, speech, hearing, visual, orthopedic, and other health impairments and learning disabilities. At the time the mandate was instituted, students classified as having learning disabilities (difficulties with specific tasks) comprised only 7.5 percent of all disabled students. Currently, learning disabled students make up *over half* of special education enrollments. Figure 1 demonstrates that this category has largely driven the continued growth in special education enrollments. The rate of physical disability has been relatively constant.

Learning disabled students have come to dominate special education costs as well as special education enrollments. The cost of educating students varies greatly by disability and educational setting. The more expensive disabilities are the lower incidence disabilities, such as deaf-blindness and autism. The more expensive placements are the more restrictive placements, such as separate schools and residential centers. Using national data, Chaikind et al (1993) calculate that excess instructional costs range from around $900 for speech-impaired to over $36,000 for deaf-blind students (in 1990 dollars). Table 1 on the following page shows the average excess cost and rate of occurrence by disability, as well as the implied share of total special education expenditures dedicated to each. Though providing services to students with specific learning disabilities is less expensive, the relatively high rate of classification suggests that learning disabled students account for nearly 40 percent of special education spending. Also prominent in the overall budget are services for emotionally disturbed students.

The fact that much of the growth in special education is occurring in disability categories like learning disabled and emotionally disturbed makes estimating the fiscal impact of special education on other education programs particularly difficult. Singer et al (1989) find that the functional ability of disabled students, except for physically disabled students, varies considerably across districts. Because there is room for local judgement in classifying disabilities that are not evident, there may be a link between special education program costs and community tastes. In order to separate the effect of additional special education costs on regular education spending from the effect of these unobservable tastes, I rely on shifts in special education spending that can be attributed to students with five evident disabilities: deaf-

blindness, autism,[4] and orthopedic, visual and hearing impairments. Table 1 demonstrates that these disabilities constitute only a small share of disabled students and of the total special education budget. However, these disabilities account for a disproportionate share of the variation in costs across districts because of the associated high costs. Still, as the empirical section demonstrates, the additional variation in costs that arises from school finance policy is necessary to precisely identify the magnitude of crowdout. I turn next to presenting alternative frameworks relating regular and special education spending in the budgeting process. These alternatives demonstrate that the theoretical reduced-form relationship between the two is ambiguous.

2. Theoretical Framework

The difficulty with modeling crowdout is that there is no well-accepted framework for analyzing how resources are allocated across public programs. The median voter framework typically underlies empirical models of education expenditures.[5] According to the median voter theorem, the level of per pupil expenditures is determined by the preferences of the median voter, as well as community factors that affect the cost and price of providing educational services and state and federal aid. However, the theorem applies only to single-dimensional choices such as determining the overall level of spending on education and not choices between activities.

Because of the nature of the mandates, the applicability of the median voter model is preserved to some extent in the case of regular and special education. The services offered by the local special education program are outside the direct control of the typical voter. Parents, teachers, and specialists determine who qualifies for special education and what services are needed, which by law must be determined without regard to cost. So, the special education budget is largely predetermined from the perspective of other community members.[6] If voters

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[4]Autism is technically a mental disability but also appears to be relatively consistently diagnosed. I exclude this category from the instrument set in some specifications.

[5]See, for example, Gramlich and Rubinfeld (1982), Downes and Pogue (1994), and Hoxby (1996).

[6]Frank Sippy, Assistant Superintendent of a Connecticut high school, blames this year's 12 percent proposed

determine the total education budget taking special education costs as given, the median voter model can be extended to include special education costs as a constraint. I begin by considering incidence in this neoclassical model where regular and special education are the only public goods. The predictions serve as a benchmark for alternative perspectives of the budgeting and political processes.

Median Voter Model: Special Education Spending as a Constraint

Consider that the median voter's utility depends on local per-pupil regular education spending (r), per-pupil special education spending (s), and personal consumption (c). As usual, the median voter maximizes utility subject to an individual budget constraint. In the presence of the special education mandate, the voter maximizes utility subject to the additional constraint that special education spending is at least at the mandated level $\underline{s}$. The optimization problem is:

$$Max_{r,s,c}\ U(r,s,c) \quad st.\ c = y - \pi(n_r r + n_s s - g)$$

$$s \geq \underline{s} \qquad (1)$$

y = *income*
π = *median voter tax share*
n_i = *program enrollment, i=r,s*
g = *state and federal education grants*

It is reasonable to assume the pivotal voter does not have a special needs child because the ratio of disabled to non-disabled students is low. Such a voter may still demand some spending on special education since these programs provide benefits to other community members, such as reducing the future dependence of disabled persons on public aid (Conley 1973) and potentially reducing crime among a high-risk population. However, the direct benefits to the parents of disabled children and disabled children themselves likely outweigh these indirect benefits. The special education mandate effectively transfers the power of spending determination to these

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budget increase on special education cost growth that is beyond the school board's control: "That 5.75 percent [for special education] may be practically untouchable. We have to make some hard decisions. Some have already been made for us by the state." (*Easton Courier*, February 29, 1996)

parties with special interests. Therefore, I assume that the cost of special education exceeds what the median voter would choose to spend in the absence of a mandate. If the special education constraint is binding, the median voter determines total spending on education by choosing regular education spending given the level of special education spending:

$$Max_{r,c}\ U(r,s,c) \quad st.\ c = y - \pi(n_r r + n_s s - g) \tag{2}$$

The desired level of spending on regular education will be a function of the "price" of regular education spending (which includes the median voter's tax share and the number of regular education students) as well as income and the median voter's share of grants and special education costs. The predictions of this model depend on the nature of the median voter's utility.

The standard assumption, that utility is additively separable, generates the prediction that an increase in mandated special education costs will have a negligible effect on resources dedicated to regular education. The increase does not affect the marginal rate of substitution between regular education and consumption and desired regular education spending will change only because of the change in the budget. The increase in special education spending is analogous to a lump sum tax:[7]

$$\frac{\partial(n_r r^*)}{\partial(n_s s)} = -\frac{\partial(n_r r^*)}{\partial g} = -\pi\frac{\partial(n_r r^*)}{\partial y} \tag{3}$$

The effect is equal to the median voter's tax share times the income effect, an effect equivalent to a comparable decrease in personal income. Spending on both regular education and other goods is depressed because the voter is "poorer." Quantifying the degree of crowdout in this case requires information on the median voter tax share and the income effect. Using current Texas district-level data and typical estimated income elasticities (.2 to .4) to calculate the components of (3), an additional dollar of special education costs translates into a two to four cent reduction

[7]To simplify the analysis, I assume that the increase in special education costs comes from either a disabled student who is new to the district or more expensive treatment for an existing disabled student. I abstract from the case where a student who has been previously served in regular education class is diagnosed as disabled and begins receiving special education services. In that case, the increase in special education costs would also affect the number of students in regular education (i.e. $\partial n_r/\partial n_s \neq 0$).

in spending on regular education. This model, therefore, predicts essentially zero crowdout.

Within the median voter framework, significant crowdout can be explained by generalizing preferences. The incidence falls more heavily on regular education students if regular and special education enter as substitutes in the median voter's utility. Consider the extreme case in which the median voter cares only about average educational services provided and not the allocation across disabled and non-disabled students. In this case, regular and special education services are perfect substitutes. Increases in special education costs will merely shift the allocation of spending across programs:

$$\frac{\partial(n_r r^*)}{\partial(n_s s)} = -1 \qquad (4)$$

Each additional dollar of net local special education costs leads to a dollar reduction in regular education spending. These preferences may be consistent with a median voter who has no children or is elderly. This *voter demand* explanation for relatively fixed education budgets has the advantage of emanating from a simple model that directly informs the empirical relationship to be estimated. A drawback is that the median voter framework may be too simple, ignoring aspects of the budgetary and political process that affect community spending decisions.

Alternative Perspectives

An alternative perspective follows from the "flypaper effect" literature. This literature documents the empirical regularity that lump sum grants to local governments increase local spending more than predicted by the standard median voter model. If increases in special education costs are thought of as negative shocks to public income, then the empirical observation of significant crowdout is simply this same type of flypaper effect-- though in the reverse direction. Hines and Thaler (1995) review the empirical flypaper evidence and propose behavioral explanations related to the fungibility of funds. They note that voters may be willing to use grant money to fund projects for which tax increases would not have been approved, even though the implicit alternative to the project is a tax cut. The same type of argument holds in the reverse case. For example, if a school district's special education costs increase, the school board

may find it easier to shift the funds from other budgeted areas rather than to raise taxes. Voters who would not have traded a tax cut for lower regular education spending now essentially do just that in the face of the shock to public income. This division between public and private income through the budgeting process may explain why local education budgets are relatively fixed.

Finally, the political process may lead to something other than the implementation of the median voter's demands. Rather than each voter counting equally in the voting process, special interest groups may have varying degrees of bargaining power. The particulars of Texas education politics provide an example of how specific groups of voters can exert control over taxation decisions. In Texas, school officials are elected and have unilateral power to set property taxes for the school district. Voter's can discipline officials by voting them out of office in future elections. The median voter theorem relies on the effectiveness of this kind of political competition. However, in the period between elections, the Texas system empowers individual residents and special interest groups by providing complete access to district financial records. If the school board implements a budget and associated tax that displeases some residents, those residents can sift through the financial records and report any concerns to state regulatory agencies. The threat of costly audits, the demand for which is in fact higher just after districts have set tax rates, may make school boards reluctant to raise taxes to accommodate special education costs (even if the median voter would approve).

This discussion so far has considered only two alternative responses: special education costs either lead to higher taxes or reduced regular education spending. The third possibility is that spending on other local services may be reduced. Though it is difficult to consider an additional public good within the median voter context, the behavioral and political economy perspectives provide some insight into why the incidence may fall more heavily on regular education budgets than budgets for other local services. From the behavioral perspective, the location of funds matters. The fact that regular and special education are packaged under the same budget means that regular education funds are more "at hand" when programs need to be cut. The political mechanics also suggest that it may be difficult to dampen the impact of special education costs by absorbing funds budgeted for other local services. In Texas, the school board sets taxes for the school district. The city and other districts with taxing capabilities (i.e. county,

city, hospital, and community college districts) set separate property tax rates. Not only does each entity set a different rate, each covers a different geographic area. Therefore, the tie to funding for other local services is indirect. In the empirical work, I focus explicitly on the education budget. I will not be able to divide any residual effect between the effect on tax burdens and on other local goods.

In the empirical section, I take a reduced-form approach. The reduced-form relationship reveals that special education costs significantly crowd out spending on regular education. Though all three of the above perspectives can accommodate this result, the interpretation and policy implications of such crowdout differ. I return to this in the conclusion. Next, I introduce the empirical framework which is consistent with the assumptions underlying these perspectives.

3. Empirical Framework

There is a growing literature documenting the increase in elementary and secondary school spending on special education. However, little has been done to trace out the impact of growing special education budgets on overall education budgets. Lankford and Wycoff (1996) conduct the only previous study that directly analyzes the impact of special education on other services in the education budget. Using district-level data from New York school districts for the years 1979-1992, the authors estimate a fixed-effects specification relating changes in regular education spending per pupil to changes in regular and disabled student enrollment controlling for changes in total per pupil expenditures. Despite suggestive patterns, they do not find conclusive evidence that increasing special education enrollment is associated with falling regular education expenditure. But, their results are suspect if regular and special education spending are linked over time within districts through any channel other than the budget or predetermined student characteristics. I discuss potential channels below and directly address the problem of endogeneity in the empirical analysis.

In order to estimate crowdout, I postulate a linear relationship between regular education spending and factors that may affect the costs of providing and demand for educational services. I relate spending on non-disabled students (REGULAR) to net local special education costs (SPECIAL) and factors that capture voter tastes and control for community characteristics that

affect the cost and price of providing educational services (X):

$$REGULAR_{it} = \alpha + \beta SPECIAL_{it} + X_{it}\Omega + \epsilon_{it} \quad (5),$$

where I indexes district and t indexes time. The net local cost of special education is total special education operating costs less state and federal special education aid. Regular and net special spending are both normalized by regular education full-time equivalency (FTE). This denomination allows me to capture the effect of special education costs on resources *per* regular education student. X includes variables that determine state aid for regular education and the marginal tax price of spending on education.[8] The estimate of β from an ordinary least squares regression based on (5) would capture crowdout if the local cost of special education were determined solely by observable factors and factors outside of the locality's control. This specification would indicate whether localities that spend more on special education than observably similar localities spend less per pupil on regular education.

The most obvious problem with estimating the above cross-sectional model with ordinary least squares is that net local spending on special education is likely to be correlated with unobservable factors that also determine regular education spending (omitted variable bias). For example, despite the relative prescriptiveness of the EHA, the classification of borderline students as disabled varies with community characteristics. Consider the role that an observable variable such as income plays. Chaikind and Corman (1991) demonstrate that low birth weight and thus poverty is highly correlated with subsequent special education enrollment. In Texas, the relationship between the size of special education programs and median family income is actually an inverted-U, with middle incomes associated with the highest disability rates. Part of the relationship can presumably be attributed to tastes. If income were omitted as an explanatory variable in equation (5), the estimate of β would confound the true causal effect of an increase in special education spending and the underlying effect of income on regular education spending. Though income can be explicitly included in the regression, there may be other taste variables

[8]See Hoxby (1996) for a careful treatment of the impact of school finance equalization policies on the marginal tax price of spending on education and the role of the marginal tax price in education expenditure determination.

which cannot be.

Including a district fixed-effect will eliminate the omitted variable bias if unobservable variables which link the two types of spending are fixed over time. The coefficient estimate in this case answers, "When spending on special education increases in a district, does regular education spending fall (all else equal)?" This strategy will again fail to capture crowdout if omitted time-varying variables link regular and special education over time. One such variable could be changes in local labor market conditions that drive up the wages of educators and tie regular and special education wage bills over time. Another variable could be changes in community tastes for classifying marginal students as disabled that may also be related to preferences regarding other educational programs.

The more convincing solution is to identify variables that directly shift the local cost of special education programs but have no direct impact on regular education spending. An obvious consideration is variation in the number of students who are disabled in a school district. But, again, the classification rate of students with less evident disabilities may be influenced by unobserved tastes that also determine regular education spending. This is particularly true in the case of learning disabilities which are first discovered at school. Therefore, I use an instrumental variables strategy to isolate variation in special education spending that is due to differences in the rate of severe physical disability.[9]

Unfortunately, the variation in net costs that arises from physical disability rates alone does not allow precise estimation of crowdout. Therefore, I also use variation in the size of the budgetary shock associated with an additional physically disabled student that arises from the structure of Texas school finance policy. The level of state reimbursements for special needs students changes in the middle of the period I analyze. Also, the reimbursement rate varies depending on the wealth category into which a district falls. Therefore, the fiscal policy generates variation in net local special education costs over time and by district tax base wealth.

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[9]I rely on cross-district variation in the rate of physical disability. Ideally, I would like to include district-fixed effects in this instrumental variables context and rely only on changes within districts in the rate of physical disability. However, there is not enough variation within districts over the time period to permit this. I perform tests to check the validity of the instruments in the cross-section.

I instrument for special education costs using the physical disability rates interacted with time and tax base wealth.

An initial criticism with the above approach is that crowdout is identified from the excess costs of the most severely disabled students. Whereas there is public concern about the costs of expanding programs for the mildly disabled, there is less debate about spending to accommodate severe disabilities. However, the estimate of crowdout yielded by this strategy will be applicable for decisions affecting the size of learning disabled programs as long as districts respond in the same way to additional special education costs regardless of the source. This is likely given that all disabled groups are legally protected and parents of children with mild disabilities have turned increasingly to the courts to guarantee special services for their children. Further, this approach is currently more justifiable given the recent publicized cases of extravagant expenditures for severely disabled students.[10]

A second criticism with this approach is that variation in the rate of physical disability in a district may be contaminated. There are two potential sources of contamination. First, there is a link between poverty and physical disability through low birth weight, and a clear link between poverty and education demand. Second, parents with severely disabled students may move to school districts with well-developed special education programs. Both of these factors suggest that the rate of physical disability may not be randomly distributed across communities, even controlling for observable community characteristics. A second advantage to using the policy-induced variation in special education costs that this variation allows me to test the importance of these sources of contamination. I am able to instrument using higher-order interactions between the disability rate and the policy parameters and include the disability rates directly as regressors. The effect on regular education spending is then identified from the differential cost of educating physically disabled populations of similar sizes over time and across tax base wealth categories. The next section presents Texas school finance policy and this cost variation in more detail.

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[10]*New York Times*, Monday June 24, 1996.

4. Texas School Finance Policy

Though I am interested in the general proposition that high costs of special education mandate reduce resources available to other students, I focus on a single state in order to evaluate the extent of crowdout empirically. The main advantage to focusing on Texas is that the Texas Education Agency (TEA) has collected detailed data on spending and enrollment by educational program since 1990 through the Public Education Information Management System (PEIMS). Also, the education finance system is structured in such a way that the net local cost of special education varies across districts over time and by district wealth-- providing useful variation for identifying crowdout. Before making the nature of this variation explicit, I will provide some background on education in Texas more generally.

Texas has been at the forefront of recent reforms to improve the condition of education. Though Texas spent only slightly less per pupil ($5191) in 1990 than the national elementary and secondary school average ($5396), a recent study ranks Texas forty-first in terms of performance.[11] In order to improve the effectiveness of public education in the state, the Texas Education Agency has been managing a comprehensive testing and accountability program to ensure that all students attain basic skills in reading, math, writing, and science. In terms of special education, Texas classifies 13 percent of its 3.4 million students as special needs. Special education takes up the largest share of the operating budget after regular education:

1994-95 Operating Budget Shares	
Regular	68.9 %
Special	12.6 %
Compensatory	9.0 %
Vocational	4.0 %
Bilingual	3.7 %
Gifted	1.7 %

The state, local, and federal shares of special education spending are 45, 45, and 10 percent respectively, which is very similar to the breakdown for all education spending (47, 47, and 6 percent). State aid for special education is based on the number of special needs students and the

[11] Powell and Carr (1996) rank states according to SAT scores, adjusting for the fraction of the student population taking the exam.

educational settings in which those students are served. The Texas legislature and public have been concerned about the impact of state special education funding on the quality of services that special needs students receive. The issue of the potential crowding out of spending on other programs has not received much policy attention in Texas.

The first step in establishing the importance of crowdout is identifying under what circumstances and to what degree special education imposes net costs on localities. Calculating the net local cost is complicated by the fact that state funding for special education is embedded in the state school finance equalization plan. Public education in Texas is financed locally through property taxes. The state plays a very active role in distributing aid to school districts with the goal of equalizing expenditures and minimizing the disparities in spending that are related to district wealth. Picus (1993) analyzes the equity of the system in Texas that was instituted following the Edgewood Case (1989) and finds it to be "the most equitable in the nation." The two-tier system that was enacted in April 1991 under Senate Bill 351 applies throughout the period analyzed in this study.[12] This system combines a foundation grant program (Tier 1) and a guaranteed yield program (Tier 2).

The net local cost of special education programs is affected by both tiers. Tier 1 guarantees the same basic level of spending per pupil for levying the foundation tax rate (about 0.7%). The revenue formula for the first Tier 1 is:

$$REV1_{it} = (f_t \times N_{it}) - (r_t \times TAXBASE_{it}) \tag{6}$$

f_t = *per pupil foundation spending level*
N_{it} = *pupil count*
r_t = *foundation tax rate*

For tax rates above the Tier 1 required minimum, the second tier guarantees an equal per pupil yield for equal tax effort:

[12]Senate Bill 7 (1994) changed some aspects but not the basic structure of Senate Bill 351.

$$REV2_{it} = E_{it} \times (g_t \times N_{it} - .0001 \times TAXBASE_{it})$$
$$= Tax\ Effort_{it} \times Revenue\ Gap_{it}$$

$$E_{it} = (\tau_{it} - r_t) \times 1000 \qquad (7)$$
$$\tau_{it} = nominal\ tax\ rate$$
$$g_t = per\ pupil\ guarantee$$

In both cases, revenues vary inversely with ability to pay (tax base value) and directly with educational need (pupil count). The pupil count is adjusted for characteristics of the student population to reflect variation in the costs of providing educational services. Higher special education enrollment inflates the pupil count because special needs students count more than regular education students. Therefore, higher special education enrollment generates more state revenues.

I treat the difference between the Tier 1 and 2 revenues a district actually receives and the revenues it would receive with no special education program as special education aid. Therefore, net local special education costs (SPEDLOC) are equal to special education operating expenditures (SPEDEXP) minus this revenue gain (SPEDAID):

$$SPEDLOC_{it} = SPEDEXP_{it} - SPEDAID_{it}$$
$$SPEDAID_{it} = (REV1_{it} + REV2_{it}) - (REV1_{it} + REV2_{it})|_{(special\ ed\ enrollment\ =\ 0)} \qquad (8)$$

This measure, normalized by non-special education enrollment, is the key independent variable used in the empirical analysis. Here, I ignore federal special education aid which depends on the number of students in special education. When I actually construct the measure I subtract federal aid as well.

The instrumental variables strategy relies on variation in SPEDLOC that is due to differences in the fraction of district enrollment that is physically disabled. The number of physically disabled students affects SPEDLOC both by increasing operating expenditures and by increasing Tier 1 and 2 revenues generated by special education. Differentiating equation (8) gives the following expression for the change in local costs from an additional physically

disabled student:

$$\frac{\partial SPEDLOC_{it}}{\partial D_{it}} = \frac{\partial SPEDEXP_{it}}{\partial D_{it}} - \left(\frac{\partial (REV1_{it}+REV2_{it})}{\partial N_{it}} \times \frac{\partial N_{it}}{\partial D_{it}}\right) \qquad (9)$$

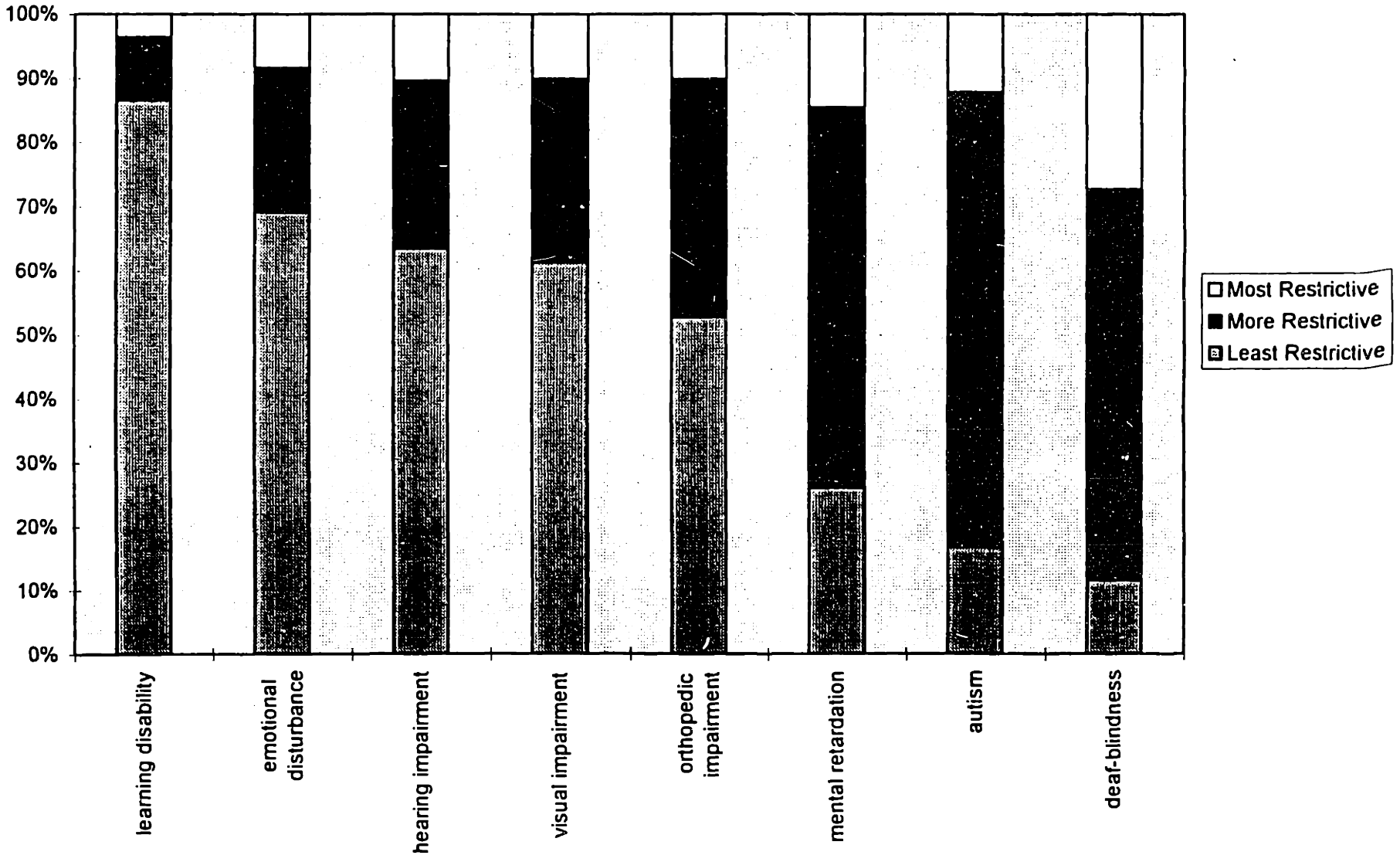
$$D_{it} = number\ of\ physically\ disabled\ students$$

This equation determines the signs and magnitudes of the coefficients from a first-stage regression of net local costs on the physical disability rates.

The first term is the marginal cost of educating a physically disabled student. Marginal costs are probably quite different from average costs in the case of special education. For example, the first deaf-blind student in a district may require not only special equipment and supplies but also a trained aide. If a second were to enter the school system, the aide could serve both students. Marginal costs would decline until a second aide is necessary. Because special education classes are small, the marginal cost schedule will be highly non-linear. However, in Texas, special education cooperatives are pervasive. Districts share itinerant specialists and regional programs and thus reduce these lump sum costs. Assuming that marginal costs are related to average costs, Table 1 (earlier in the text) provides some guidance to the marginal costs of educating students from the five most evident disability categories. Chaikind et al (1993) use national data to estimate these excess instructional costs. Deaf-blindness is the most rare and the most expensive disability with excess costs well above ten times the costs of educating a regular education student. Autism follows, and then hearing, visual, and orthopedic impairment.

The second term in equation (9) is the change in Tier 1 and 2 revenues from an increase in the pupil count multiplied by the change in the pupil count from an additional physically-disabled student. The relevant increment to the pupil count from a physically disabled student for calculating the overall revenue generated by special education is the increase beyond what the student would add as a regular education student. A disabled student adds more than one to the pupil count because special needs students are weighted-up. The weight is based on the student's placement, such as resource room or separate school, and not directly related to the type of disability. Figure 2 shows the distribution of placements for the different disabilities in Texas. Deaf-blind and autistic students are over-represented in the most restrictive settings. Students

Figure 2: Educational Setting by Disability in Texas



with orthopedic, visual, or hearing impairment tend to be placed in the least restrictive settings. The recent policy change in 1995 encourages districts to place students in less restrictive settings by reducing the weight for some of the more restrictive settings and increasing the weight for mainstream and resource room placement. The following table shows the average excess increment to the pupil count for each disability based on the distribution of placements for that disability:

Table 2: Excess Increment to the Pupil Count

Disability	1992-4	1995
Deaf-blindness	2.00	1.55
Autism	1.87	1.57
Hearing Impairment	1.09	1.08
Visual Impairment	1.02	1.11
Orthopedic Impairment	1. 15	1.15

These values represent $\partial N/\partial D$.

The last component needed to predict the first-stage relationship is the change in revenue from an additional student. The partial derivative of combined revenues with respect to the pupil count can be expressed:

$$\frac{\partial(REV1_{it}+REV2_{it})}{\partial N_{it}} = f_t + (E_{it} \times g_t) \qquad (10)$$

For each student (or each addition of one to the pupil count), the district gains the per pupil foundation allotment and the matching program per pupil guarantee multiplied by tax effort. The above formula only directly holds if the district levies a tax rate within the range that is matched under Tier 2. Also, equation (10) does not capture the treatment of districts that earn more than the Tier 2 guarantee ($REV2_{it} < 0$). Before 1994, such districts simply received no funds. However, beginning in 1995 the wealthiest districts actually had to give some of the excess tax revenue to the state. The technical version of equation (10) that accounts for all of the cases is relegated to the Appendix. The important result is that accounting for these complications

divides districts into three categories: property-poor (75%), property-neutral (9%), and property-rich (16%).

Figure 3 displays graphically the variation in the revenue effect of an additional student ($\partial REV_{it}/\partial N_{it}$) by both tax base group and time. I calculate these values at the median tax rate within each tax base group and year. All three district types gain the adjusted allotment through Tier 1 for an additional student. The U-shaped pattern is driven by Tier 2. An additional student raises Tier 2 matching revenue for the property-poor districts that earn less than the guaranteed yield. For property-rich districts, an additional student reduces the amount of locally-raised revenues that are recaptured by the state (because the revenues exceed the per-pupil maximum yield). The median revenue gain from an additional student is lowest for property-neutral districts in both periods since these districts receive neither the matching subsidy of poorer districts nor the reduced tax of wealthier districts through Tier 2. The time pattern in Figure 3 is driven by changes in the policy parameters, such as changes in the Tier 1 allotment and Tier 2 guarantee, and by the change in the treatment of property-rich districts after 1993 in Tier 2.

Combining all of this shows some surprising results. The median net revenue gain associated with an additional physically disabled student is simply the effects in Figure 3 scaled by the relevant change in the pupil count from Table 2. These values are presented in Table 3. Net local costs increase if the revenue gain is less than the increase in costs. Comparing the Texas revenue numbers with the Chaikind et al (1993) national cost estimates suggests that deaf-blind and autistic students impose large net costs on localities. For example, the average cost estimate for a deaf-blind student ($36,397) dwarfs typical marginal revenues which are under $8,000. In contrast, districts may actually make money on orthopedically-impaired students since marginal revenues are very close to estimated average costs.[13]

Net local costs vary not only by disability but also by tax base wealth category and time period through the revenue side. Consider hearing impairment. Hearing-impaired students impose excess costs in the neighborhood of $10,000. In the first period, 1992-94, the marginal

[13]Arnold et al (1989) note a similar "profit phenomenon" in Illinois school districts though they assume the results are due to poor data.

Figure 3: Marginal Revenue Effect of An Additional Student

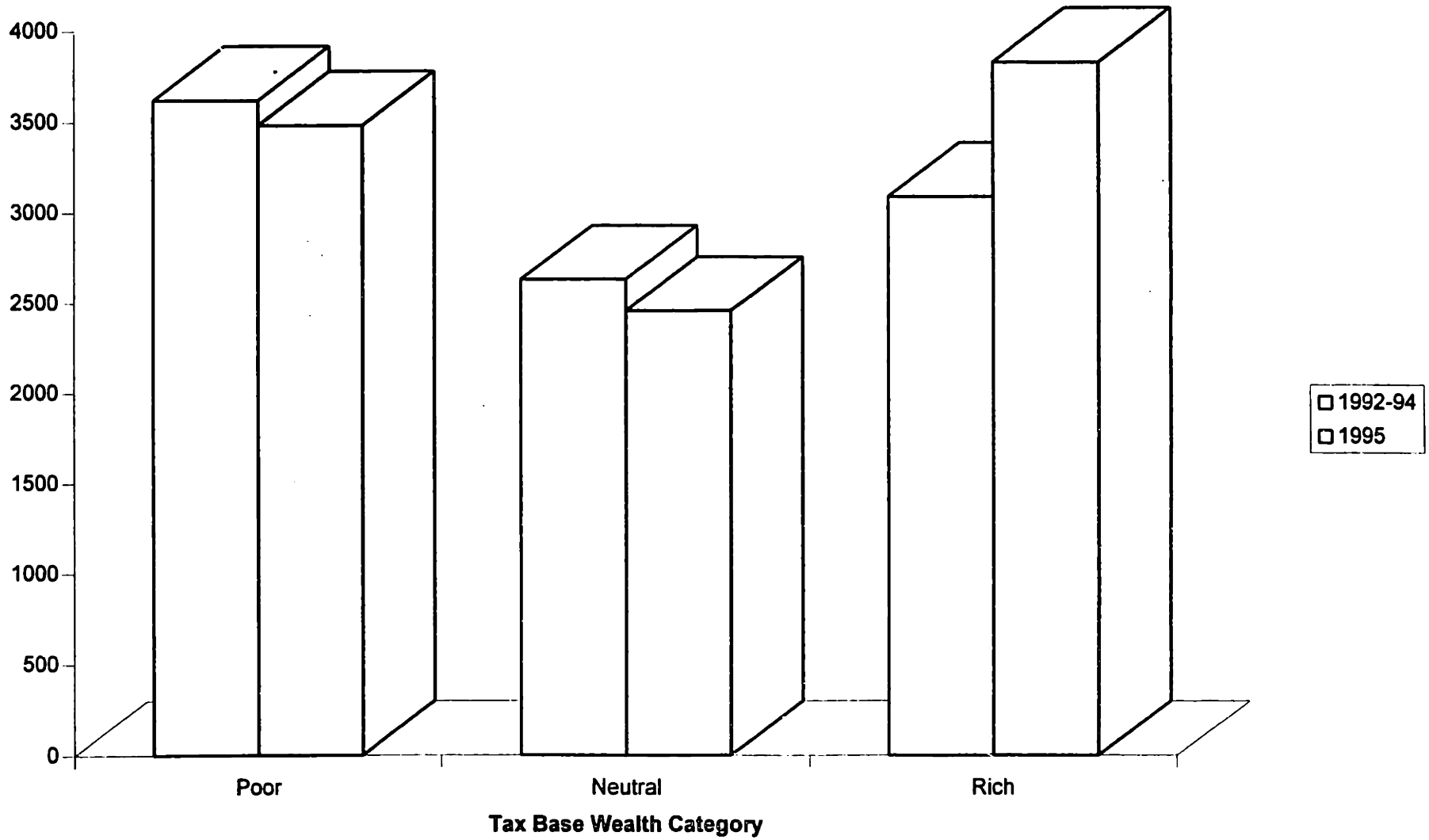


Table 3: Marginal Revenue Effect by Disability

Year and Tax Base Wealth Category	Disability				
	Deaf-Blindness	Autism	Hearing Impairment	Visual Impairment	Orthopedic Impairment
1992-1994:					
Property-Poor	7242	6771	3947	3693	4164
Property-Neutral	5278	4935	2877	2692	3035
Property-Rich	6174	5773	3365	3149	3550
1995:					
Property-Poor	5400	5470	3763	3867	4007
Property-Neutral	3807	3856	2652	2726	2824
Property-Rich	5933	6010	4134	4249	4402

Notes to Table 3: These values are calculated as the excess addition to the pupil count generated by a student in each disability (Table 2) multiplied by the marginal revenue of an additional student (Figure 3). The sample is all Texas school districts in each tax base wealth category for the years 1992 through 1995.

revenue from a hearing-impaired student for the typical property-neutral district is $2877-- about $500 below property-rich districts and $1,000 below property-poor districts. This implies that the net local cost of educating a hearing-impaired student in a property-neutral district would be 8 percent higher than in a property-rich district and 20 percent higher than in a property-poor district on average. And, in the second period, property-neutral districts would spend 30 percent more than property-rich and 21 percent more than property-poor districts. It is these differential shifts in special education costs that identify crowdout.

Two other important variables are also affected by state school finance policy. Both intergovernmental aid for non-special education programs and the marginal tax price of spending on education belong in a regression determining regular education expenditures. In Texas, all state aid to localities comes through the Tier 1 and 2 formulas, with 80 percent through Tier 1. Since all districts levy at least the minimum tax rate necessary to participate in Tier 1, the marginal tax price is determined by Tier 2. It would be problematic to interpret the coefficient on either aid or tax price in an OLS regression with regular education expenditures as the dependent variable. Both depend on tax effort and are thus jointly determined with spending on regular education. Because I do not have a separate identification strategy for these two variables, I do not explicitly attempt to measure these elasticities. Instead, I include determinants of aid and tax price in order to control for differences in these variables across districts.

Data and Summary Statistics

The data are compiled mainly from two sources. The detailed district-level data for 1992-95 are from Texas Public Education Information Management System (PEIMS). PEIMS collects extensive district-level data on actual and budgeted finances and detailed student and staff characteristics. PEIMS also keeps track of membership in educational cooperatives. Additional demographic and support variables that will be used in the analysis are from the School District Data Book (SDDB). The SDDB recompiles 1990 Census data by school districts, summarizing the data for all households as well as separately for households with children enrolled in public schools. A more detail description of the data sources is in the Appendix.

The information needed to construct the key independent variable determines the sample used in the empirical analysis. The variable is the net local cost of special education (SPEDLOC) normalized by non-special education enrollment.[14] This measure is equal to special education operating expenditures minus revenues generated by special education. Annual state school finance schedules and PEIMS data allow me to calculate the Tier 1 and 2 revenue gain due to a district's special education program. However, the existence of cooperatives complicates the calculation of special education operating expenditures and federal special education aid by district. When districts participate in cooperatives, typically the fiscal agent reports expenditures that are undertaken for the cooperative and federal revenues are distributed directly to the fiscal agent. There is currently no way to track the financial contributions of individual member districts. This is particularly problematic in the case of special education since half of all cooperatives are formed to provide special education services and 86 percent of districts participate in special education cooperatives.

For most districts in special education cooperatives, I can approximate district special education spending by using a simple rule to reallocate total cooperative spending. On average, 90 percent of special education expenditures from state and local funds are made at the district level for districts that participate in special education cooperatives. Since districts explicitly budget these expenditures, I use district-level budgeted instructional expenditures as an indicator for total district special education spending including cooperative spending. I aggregate actual program operating expenditures over the cooperative and then assign to each district a share equal to that district's share of budgeted instructional expenditures. Similarly, since federal aid for disabled students is distributed directly to the fiscal agent based on the number of special needs students, I redistribute these funds according to each district's share of cooperative special needs enrollment. Using the above procedure, I am able to approximate actual special education expenditures for the majority of the districts that are in cooperatives. This method certainly

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[14]Non-special education enrollment is total enrollment less special education FTE. A special education student spends on average 60 percent of the school day in regular education classes and, therefore, counts as .6 of a regular education student. I denominate special education costs in this way in order to capture the true resource costs for students in other programs.

smooths imputed spending relative to actual spending and reduces the power of physical disability rates in predicting spending.

The remaining member districts fall into two categories. In the first category, one or more districts within the cooperative does not budget any expenditures for special education at the district level. For members of these cooperatives, I calculate cooperative special education costs and construct cooperative-level observations for all other variables weighting each district by its share of total enrollment. In the second category, the cooperative fiscal agent is not a district but rather a regional Education Service Center (ESC). I exclude districts that belong to this type of cooperative from the analysis since the fiscal information for ESC's is not complete. These excluded districts do not differ along any observable dimensions from the districts included in the sample. Finally, the largest districts do not participate in special education cooperatives and all components of net local spending are available.

The sample, therefore, has three types of observations:

Sample Description

Type	Number of Observations	Percent of Sample
Not in Cooperative	203	29
Member District with Imputed Spending	473	68
Cooperative	24	3

The sample represents 86 percent of the 1044 districts (225 districts belong to the 24 cooperatives). Almost all of the remaining districts have missing data as described above. However, as a deliberate selection criterion, I exclude the few districts that have enrollment below 100 students in all years. This reduces the occurrence of extreme outliers in both per pupil spending and disability rates. Summary statistics for the 2800 observations that I use in the analysis (the above 700 observations in each of the four years 1991-92 through 1994-95) are presented in Tables 4A and 4B. All financial variables are deflated using the consumer price index for all services and are expressed in 1990 dollars.

For the median district in this sample, total special education expenditure per non-special

education enrollee is $282. After subtracting the Tier 1 and 2 revenue gain generated by special education and federal special education aid, the net local fiscal burden of special education is $21 per non-special education enrollee. This net cost ranges from -$129 at the 10th to $136 at the 90th percentile. The fact that median net special education costs are nearly zero does not imply that the state and federal governments fully fund the program. The local contribution (r_t x $TAXBASE_{it}$) under Tier 1 is a fixed cost. Each district contributes this lump sum amount and then receives back the foundation spending level (f_t) for each pupil. Therefore, some of the revenue gain generated by special needs students is from "recaptured" local funds rather than new state funds.

I use two dependent variables in the empirical analysis. First, I examine the response of spending on all non-special education programs. Then, I isolate the effect on regular education spending alone. Besides regular education, there are four supplementary educational programs that are not part of special education. These programs are vocational, compensatory, bilingual, and gifted education. Compensatory education programs target additional resources to classrooms with higher shares of economically-disadvantaged students. Over 70 percent of total operating expenditures are separately classified by the six educational programs. TEA accounts for shared resources, such as joint teachers, by reassigning these expenditures to each program based on that program's share of total FTE.

Table 4A presents operating expenditures by program. The top panel presents expenditures per pupil in each program (including any regular education expenditures based on the amount of time spent in regular education classes). The bottom panel shows program operating expenditures over program enrollment. Per pupil spending is a better indicator of student benefits, however program spending normalized by enrollment is useful in capturing the overall distribution of spending across programs. Mean operating expenditures per pupil are $2186 for all non-special education programs, and $1655 for regular education alone. Mean expenditures per special needs student are $3902. The average cost of educating a special needs student is about two and one-half times that of a regular student, which is consistent with the findings of Chaikind et al (1993).

Over the four-year period, the fraction of students classified as disabled increased from

12.1 to 13.6 percent. Special education operating expenditures expanded from 12.5 to 13.8 percent of the operating budget. This relative shift toward special education can be explained by higher special education enrollment and by a four percent rise in special education expenditure per special needs student. In contrast, all non-special education spending per student grew at less than half that pace. Per pupil expenditures on regular education alone remained stable. This time series evidence is suggestive of crowdout. I explore crowdout next in a regression framework.

5. Crowdout Analysis

I begin by documenting the correlation between non-special education spending and special education costs across districts in an OLS regression framework. I pool all four years of data from the 700 districts (and cooperatives) for which I can construct net local special education costs. Because of the panel nature of the data, it is important to account for correlation over time within districts. Also, the wide variation in district sizes and the different methods of constructing special education costs imply heteroskedasticity may also be an issue. Therefore, I adjust the standard errors to account for unspecified correlation over time within districts and heteroskedasticity across districts using White's generalized method. The results from an ordinary least squares regression based on equation (5) with per pupil spending on all other programs as the dependent variable are shown in the first column of Table 5. The regression includes the full set of price, cost, and demographic controls in Table 4B as well as year dummies and dummies indicating which of 20 regional Educational Service Centers (ESC) serves the district. The coefficient on special education costs per pupil is .272 with a standard error of .115. The estimated coefficient is positive and significant. Since the dependent and key independent variables are both denominated by non-special education enrollment, the coefficient has a direct dollar-for-dollar interpretation. The OLS estimate implies that an additional dollar of special education spending is associated with a 12 cent increase in regular education spending.

The OLS estimate will be a biased estimate of crowdout for at least three reasons. First, as mentioned above, there may be unobservable variables that jointly determine regular and special education spending. If tastes for the two programs are positively correlated as in the

example of "pro-children" communities, then this link will impart a positive bias to the estimate. This issue is the main motivation for employing an instrumental variables strategy. However, the other two potential sources of bias can also be solved using the same approach. The second source of bias is that local special education costs depend on revenues generated by special needs students under Texas school finance policy. The amount of revenues generated increases with a district's tax effort. This source of endogeneity probably pushes the estimate in the other direction since high spending districts face lower special education costs. Third, local special education costs are measured with error. In the univariate case, measurement error biases the estimate toward zero. However, the direction of the bias is uncertain in this multivariate analysis.

I attempt to solve these suspected omitted variables, simultaneity, and measurement error problems by instrumenting for special education costs using the rate of severe physical disability in a district. Again, it is important to account for the non-spherical error structure of the data in the estimation procedure. In order to account for this within the instrumental variables context, I apply an extension of White's generalized method in all of the subsequent regressions. The optimal instrumental variables (OIV) method that I use is described in detail in the Appendix. The OIV estimator is analogous to generalized least-squares and accounts for the presence of unspecified correlation over time within districts and unspecified heteroskedasticity across districts. Not only are the standard errors that are calculated from the OIV strategy appropriate for this type of panel data, the estimates are relatively more efficient than estimates based on ordinary instrumental variables if the system is over-identified.

In order to be valid instruments, the fraction of students in the physical disability categories must affect special education costs and not otherwise directly determine regular education expenditures. Column (2) in Table 5 presents the results from regression in which district special education costs are instrumented for by the rate of occurrence of the five most evident disabilities: orthopedic, hearing, and visual impairments, deaf-blindness, and autism. I include autism which is technically a mental disability. Unlike mental retardation which often overlaps with learning disabilities, autism should be consistently diagnosed across districts. I will test the robustness of the results to excluding any one of the five categories from the

instrument set.

Examining the first-stage relationship between local special education costs and the five disability rates reveals that the disability rates on their own are weak instruments. They are not jointly significant at the 5-percent level in the first stage. The p-value for this test is .166. Though the instruments are weak, the signs in the first-stage are as predicted by the last section. For example, deaf-blindness and autism are associated with positive net costs whereas orthopedic impairment is associated with negative costs. The fact that the severe disability rates do not significantly shift special education costs on average in my sample is largely due to the imputation of special education costs.[15] Allocating total expenditures for districts in cooperatives based on budgeted expenditures at the district level certainly smooths measured spending relative to true spending.

The poor first-stage fit in this specification is reflected in the large standard error in the second stage. The instrumental variables regression includes the full set of explanatory variables in Table 4B as well as year and ESC region dummies as before. The standard error on special education costs is nearly one. With this high degree of imprecision, I would not be able to distinguish full crowdout from no crowdout. It is surprising that the point estimate, -1.34, is larger than one in absolute magnitude. However, it cannot be distinguished from either negative one or zero. Tax base wealth has a strong positive effect on the level of per pupil spending. The elasticity of spending with respect to total district wealth is .05. It will be important to control for this secular effect of wealth when I instrument using the disability rate times the tax base wealth category of a district.

In order to improve the precision of the estimate, I expand the instrument set to use the non-linearities in net costs that arise through the revenue channel discussed in the last section. Columns (3) and (4) in Table 5 show the results from progressive instrumental variables regressions. Column (3) includes the disability rates interacted with dummies indicating into

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[15]The physical disability rates enter significantly in the first-stage regression when the sample includes only districts that are not in cooperatives-- the case where local special education costs are measured accurately. However, there are too few observations in this sample to obtain precise estimates in the second stage though the point estimates are similar.

which of the three tax base categories (poor, neutral, rich) a district falls. I control for the average effect on regular education spending of belonging to a certain tax base wealth category. So, the identifying variation comes from differences in the cost of educating physically disabled students across districts in the three wealth categories that is due to differential treatment under Texas school finance policy. The first-stage fit improves dramatically and the standard error in the second stage falls by a third. However, the point estimate of -1.05 is not significantly different from zero.

Column (4) adds higher-order interactions to the instrument set. I instrument using the physical disability rates times the tax base wealth category and times the time period. I control for secular effects of tax base wealth category by time period. In this case, the identifying variation comes from policy-induced differences in special education costs across not only tax base wealth categories but also over time. As expected, the first-stage fit improves and the standard error falls again. The estimate of -1.09 is highly significant. An additional dollar of special education spending appears to be fully offset by a reduction in non-special education spending.

The pattern of instrumental variables results in columns (2) through (4) is suggestive of full crowdout. However, I have yet to address whether or not the physical disability rates satisfy the second requirement of exogeneity. If physical disability rates cannot be treated as randomly distributed across communities controlling for the rich set of demographic covariates, then the results in columns (2) through (4) are suspect. Some evidence that the instruments are valid is that the instruments pass over-identification tests (shown in the bottom row of Table 5) in all specifications. However, these tests are weak given that the instruments are weak. A related test is to directly include the disability rates in the regression to see whether or not there are secular effects on non-special education spending. Column (5) in Table 5 is based on the same specification as column (4) except that the disability rates are included as regressors. The crowdout estimate of -0.96 is significant and very similar to the previous estimates. The results are robust to this test.

Table 6 addresses whether spending is diverted from the basic regular education program or from supplementary programs such as gifted and bilingual education. The dependent variable

is regular education spending per regular education FTE. Special education costs are also denominated by regular education FTE to preserve the dollar-for-dollar interpretation of the coefficient. The columns are based on the same series of instrumental variables specifications shown in Table 5. The results for regular education alone are very similar to the results for all non-special education spending. The preferred specifications (columns 4 and 5) produce highly significant coefficient estimates of -0.95 and -1.01 that are highly significant. It appears that it is the regular education budget that absorbs the shifts in special education spending.

Finally, I consider the robustness of the results to different instrument sets. The results in Table 7 are based on instrumental variables regressions where spending per pupil in regular education is the dependent variable. I present only the two preferred specifications from the previous tables. Each row corresponds to a different instrument set. The top row reproduces the results from Table 6 including all five disability rates as instruments. One of the disability categories is excluded in each of the following rows. The crowdout estimates all fall between -0.78 and -1.12. The results are not driven by a specific disability category and continue to support the finding of significant crowdout.

6. Conclusion

This paper examines the relationship between special education costs and spending on other educational programs. OLS estimates reveal a positive correlation between spending on special education and the other programs across Texas school districts. In order to identify a causal link between spending on special education and non-special education programs, I instrument for special education costs using the physical disability rate and parameters from Texas school finance policy. This strategy, which isolates the effect of plausibly exogenous shifts in special education costs across districts, uncovers a negative relationship. Increases in special education costs reduce spending on students in the mainstream. The magnitude of crowdout is on the order of one-for-one.

What are the implications of this financial crowdout for non-disabled students? An important question that remains is whether or not reduced spending has a real impact on students. There is a long-standing debate in the education production function literature about the value of

additional resources in education. The first strand of this literature relates educational inputs to academic performance and finds very mixed results. Hanushek (1981) concludes from a meta-analysis that there is no strong relationship between spending and performance. One issue these studies have struggled with is that spending on education is correlated with unobservable community characteristics that also affect student outcomes. The strategy I use to identify crowdout could also be employed to identify the performance effect of increased special education spending and is a priority for future work.

The second strand of this education production function literature relates school quality measures to labor market performance and has been more successful in establishing a link.[16] Card and Krueger (1994) review the literature on the United States and conclude that a one percent increase in annual education expenditures leads to a .16 percent gain in annual earnings. Districts in the top 75th percentile in costs in Texas face on average $326 more in special education costs per non-disabled student than districts in the bottom 25th percentile. Assuming one-for-one crowdout and taking this elasticity of earnings with respect to education spending seriously, students in the districts with high special education costs would earn 2.2 percent less annually than students in the schools with lower net special education costs. Students in the low-cost districts would receive benefits one-fourth as large as the increase in earnings associated with an additional year of schooling.

Finally, the finding of significant crowdout has implications for the incidence of public sector mandates more generally. My results reject the standard median voter framework which predicts that the incidence of the special education mandate operates through an income effect. Under this assumption, regular education students should not bear an extraordinary share of the costs of the special education mandate. However, the incidence of special education mandates is concentrated on regular education students. This concentration may arise because voters care only about aggregate education spending as in the generalized median voter framework. However, all communities would have to perceive spending on special and regular education as

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[16]See Burtless (1995) for a discussion of the relationship between and different problems facing these two literatures.

substitutes in order for there to be one-for-one crowdout on average.

Crowdout more likely arises because of aspects of the budgetary and political processes. If so, changing the packaging of activities may affect the incidence of mandates like the special education mandate. For example, imagine that special education had been incorporated under the umbrella of health services rather than education. The mandated costs may have been shifted to a very different group with different consequences. Though special education mandates intend to protect the rights of disabled students, an unintended outcome is the reduction in spending on other students. My estimates indicate that special education mandates redistribute funds from regular education students to special needs students.

Table 4A: Texas School District Program Expenditures 1992-1995

Variable: [2800 obs]	Mean	Std. Dev.	Minimum	Maximum
Operating expenditure per pupil (in the program) by program:				
Special education	3902	997	0	14178
All non-special education	2286	525	533	5945
Regular education	1799	474	475	5585
Vocational education	2145	650	0	8761
Compensatory education	2537	607	0	8581
Bilingual education	1697	1382	0	16038
Gifted education	2183	934	0	12163
Operating expenditures per enrollee:			0	
Special education	320	209		3200
All non-special education	2186	501	518	5698
Regular education	1655	432	432	5366
Vocational education	136	77	0	1087
Compensatory education	332	188	0	1410
Bilingual education	30	57	0	494
Gifted education	33	30	0	324
Net local cost of special ed/ Non-special education FTE	12	131	-908	1150

Notes to Table 4A: These values are based on data for 2800 district-year or cooperative-year observations. All values are expressed in 1990 dollars. Per-pupil spending is based in each case on the enrollment in the relevant program. Also, the per-pupil rates for non-regular education programs include the regular education costs associated with educating students in those programs. For special and vocational education, I add the share of the time students spend in regular education (based on the full-time equivalency reports) multiplied by regular education expenditures per pupil. For bilingual, gifted, and compensatory education, I assume students spend the full day in regular education classes and simply add regular education expenditures per pupil to the per-pupil program expenditures.

Table 4B: Texas School District Summary Statistics 1992-1995

Variable: [2800 obs]	Mean	Std. Dev.	Minimum	Maximum
Per pupil tax base wealth/ 1000	172	254	11	4593
% property value residential	.33	.18	<.01	.88
% property value business	.29	.16	.03	.99
% property value oil	.13	.20	<.01	.95
% property value land	.26	.18	<.01	.88
Nominal tax rate*	1.31	.18	.72	2.03
Student characteristics:				
% special needs*	.13	.04	0.00	.34
% vocational education*	.18	.07	0.00	.53
% economically disadvantaged	.44	.18	0.00	.98
% bilingual education*	.05	.09	0.00	.66
% gifted*	.08	.03	0.00	.25
% limited English proficient	.06	.11	0.00	.77
% white	.66	.26	0.00	1.00
% Hispanic	.24	.27	0.00	1.00
% black	.09	.13	0.00	.88
% other race/ethnicity	.01	.02	0.00	.24
% pre-school	.10	.03	0.00	.35
% elementary	.39	.04	0.00	.84
% middle school	.24	.02	0.00	.38
% high school	.27	.05	0.00	.48
% in public schools	.95	.04	.70	1.00
District enrollment	5149	15230	61	202149
Number of schools	8.9	23.3	1	272
Community characteristics:				
Population	20796	65805	202	1119062
% white	.84	.12	.12	1.00

Table 4B Continued

% black	.07	.10	0.00	.83
% Native American	.01	.01	0.00	.28
% asian	.01	.01	0.00	.08
% other race	.08	.09	0.00	.55
% aged 20-34	.21	.05	.08	.66
% aged 35-49	.19	.03	.07	.35
% aged 50-64	.14	.03	.04	.30
% over 65 years	.14	.06	.02	.38
% in central city	.10	.25	0.00	1.00
% in metropolitan/urban area	.12	.26	0.00	1.00
% in metropolitan/rural area	.49	.45	0.00	1.00
% in nonmetro/urban area	.12	.27	0.00	1.00
% in nonmetro/rural area	.17	.32	0.00	1.00
% w/o school-age children	.50	.08	.17	.83
% in poverty	.20	.10	.02	.69
Median family income	27547	8261	9181	90379
Family income >60,000	.11	.08	0.00	.68
Education:				
% no high school degree	.34	.11	.02	.79
% high school degree	.31	.06	.07	.61
% some college	.24	.07	.06	.52
% college or higher degree	.12	.07	0.00	.66
% blue collar	.31	.08	0.00	.62
% fathers unemployed	.04	.04	0.00	.56
% mothers working	.61	.12	0.00	1.00
% single-parent families	.15	.06	0.00	.39
% speak no English	.05	.08	0.00	.73
% same home past 5 yrs	.54	.11	0.00	1.00

Table 4B Continued

% work in county	.72	.20	0.00	1.00
% veterans	.15	.04	.01	.27
% adults mobility-limited (disabled)	.08	.03	0.00	.39

Notes to Table 4B: The summary statistics are for 2800 district-year and cooperative-year observations. The community demographic variables are from the School District Data Book (SDDB). The other variables are from PEIMS and AEIS files. *These variables are included for descriptive purposes only and are not included the regressions.

Table 5: Estimates of Non-Special Education Spending Per Pupil

	OLS	Optimal Instrumental Variables			
Independent Variable:	(1)	(2)	(3)	(4)	(5)
Local Special Education Expend/ Non-Special Education Enrollment	.272 (.115)	-1.34 (0.95)	-1.05 (0.69)	-1.09 (0.32)	-0.96 (0.40)
Tax Base Value Per Pupil	.0005	.0006 (.0002)	.0006 (.0002)	.0005 (.0001)	.0005 (.0001)
"Neutral" Tax Base Group	-	-	-5 (36)	24 (33)	16 (33)
"Rich" Tax Base Group	-	-	135 (60)	114 (36)	105 (37)
"Neutral" Group * (1992-94)	-	-	-	-23 (37)	-24 (36)
"Rich" Group * (1992-94)	-	-	-	31 (50)	32 (49)
p-value on instruments in first-stage	NA	.166	<.001	<.001	.006
p-value on over-identification test	NA	.788	.289	.534	.404

Notes to Table 5: Column (1) is based on an OLS regression of per-pupil spending on non-disabled students on net local special education costs. Columns (2) through (5) are based on optimal instrumental variables regressions using different instrument sets. In column (2), I instrument for special education costs using the five physical disability rates. Column (3) adds interactions between the disability rates and district tax base wealth category. Column (4) adds higher order interactions between the disability rates, tax base wealth category, and the time period. Column (5) is the same as column (4) except that the physical disability rates are included in the second stage. All regressions include the full set of explanatory variables in Table 4B as well as year and Education Service Center region dummies. The number of observations is 2800.

Table 6: Estimates of Regular Education Spending Per Pupil

	OLS	Optimal Instrumental Variables			
Independent Variable:	(1)	(2)	(3)	(4)	(5)
Local Special Ed Exp/ Non-Special Education Enrollment	.255 (.123)	-0.96 (0.92)	-1.27 (0.66)	-0.95 (0.32)	-1.01 (0.39)
Tax Base Value Per Pupil	.0005 (.0001)	.0005 (.0002)	.0006 (.0002)	.0005 (.0001)	.0005 (.0001)
"Neutral" Tax Base Group	-	-	-2 (35)	22 (32)	8 (33)
"Rich" Tax Base Group	-	-	121 (58)	95 (35)	96 (38)
"Neutral" Group * (1992-94)	-	-	-	-13 (36)	-13 (36)
"Rich" Group * (1992-94)	-	-	-	49 (50)	51 (49)
p-value on instruments in first-stage	NA	.180	<.001	<.001	.005
p-value on over-identification test	NA	.706	.284	.387	.354

Notes to Table 6: Column (1) is based on an OLS regression of per-pupil spending on non-disabled students (regular education program only) on net local special education costs. Columns (2) through (5) are based on optimal instrumental variables regressions using different instrument sets. In column (2), I instrument for special education costs using the five severe physical disability rates. Column (3) adds interactions between the disability rates and district tax base wealth category. Column (4) adds a higher order interactions between the disability rates, tax base wealth category, and time periods. Column (5) is the same as column (4) except that the physical disability rates are included in the second stage. All regressions include the full set of explanatory variables in Table 4B as well as year and Education Service Center region dummies. The number of observations is 2800.

Table 7: Optimal Instrumental Variables Estimates of Regular Education Spending Per Pupil

Instrument Set	(1)	(2)
All 5 Evident Disabilities	-0.95	-1.01
	(0.32)	(0.39)
Excluding:		
Autism	-0.96	-1.12
	(0.39)	(0.49)
Hearing Impairment	-0.79	-0.84
	(0.37)	(0.41)
Visually Impairment	-0.89	-1.01
	(0.38)	(0.46)
Orthopedic Impairment	-0.90	-0.86
	(0.38)	(0.44)
Deaf-Blindness	-0.78	-0.85
	(0.39)	(0.50)

Notes to Table 7: Each cell is based on a separate optimal IV regression. Columns (1) and (2) correspond to columns (4) and (5) in the two pervious tables. Column (1) includes the disability rates interacted with the tax base group and time period in the instrument set. Column (2) includes the disability rates in the second stage. All regressions include the full set of explanatory variables in Table 4B as well as year and Education Service Center region dummies. The number of observations is 2800.

Appendix 1: Data Sources

The following table makes explicit the source of the variables used in the analysis.

Source:	Variables:
Academic Excellence Indicator System (AEIS)	°student race, % in each grade, % in each program °local revenue by tax base source °appraised tax base value °nominal tax rate °budgeted instructional expenditures by program
Public Education Information Management System (PEIMS)	°number of students in each disability category °number disabled by grade and condition °placement of disabled students °actual operating expenditures by program °federal revenues by program °membership in non-special education cooperatives
Department of State Funding	°Tier 1 and Tier 2 revenues °adjusted allotment °equalized property valuation
School District Data Book	°median family income, poverty rate °community education, race, age, and geographic distribution °population °% in public school
Common Core of Data	°county indicators
Division of Special Education	°special education cooperatives

Appendix 2:
Formula for the Marginal Revenue Effect of an Additional Student

The following equations capture the true effect of an additional student on district revenues through Tiers 1 and 2 for the three different categories of district tax base wealth. The tax base category that a district falls into depends on how much revenue a district raises per weighted pupil for a .01 percent tax rate (per mil). If the amount of revenue raised is less than the per pupil guarantee under Tier 2, I classify the district as property-poor. An additional student increases the revenues of such districts by the Tier 1 per-pupil allotment and by the Tier 2 per-pupil guarantee multiplied by tax effort (if the district levies a tax in the range that is matched). If a district raises more than the Tier 2 guarantee per pupil but less than $28 per pupil per mil, the district is classified as property-neutral. Such districts receive only the Tier 1 revenue gain from an additional student. Finally, districts that raise more than $28 per pupil per mil are classified as property-rich. After 1993, the state recaptured revenues raised above the $28 per student limit per mil (for tax rates above the Tier 1 rate). Therefore, after 1993, these districts gain from a reduction in this "matching tax" when an additional student is enrolled. The calculations that underlie Figure 3 evaluate these equations at the median tax rate for each of the three district wealth groups.

Property-poor: $(.0001 * TAXBASE_{it}) < (g_t * N_{it})$

$$\frac{\delta REV_{it}}{\delta N_{it}} = \begin{cases} f_t + (E_{it} * g_t) & \text{if } \tau_{it} < \tau_{max} \\ 0 & \text{o/w} \end{cases}$$

Property-neutral: $(g_t * N_{it}) \leq (.0001 * TAXBASE_{it}) \leq (g_{max} * N_{it})$

$$\frac{\delta REV_{it}}{\delta N_{it}} = f_t$$

Property-rich: $(.0001 * TAXBASE_{it}) > (g_{max} * N_{it})$

$$\frac{\delta REV_{it}}{\delta N_{it}} = \begin{cases} f_t + E_{it} * g_{max} & \text{in 1994 and 1995} \\ f_t & \text{in 1992 and 1993} \end{cases}$$

f_t = *Tier 1 per-pupil allotment* , g_t = *Tier 2 per-pupil guarantee*
N_{it} = *weighted pupil count* , E_{it} = *matched tax effort* , τ_{it} = *nominal tax rate*
τ_{max} = *maximum rate matched* , g_{max} = $28

Appendix 3: Estimation Strategy

The regression analysis is based on the pooled sample of districts (and cooperatives) over the four years 1992-1995. The basic specification (in simplified notation) is:

$$y_{it} = X_{it}\beta + \epsilon_{it} \quad , \quad X_{it} = [S_{it};D_{it}] \ ,$$

where I indexes district and t indexes time. Y is non-special education spending normalized by non-special education enrollment. X includes net local special education costs (S) over the same denominator and detailed fiscal, student, and community characteristics (D). The set of instrumental variables (Z) includes all of the "pre-determined" variables D, as well as the various student physical disability rates (P). The ordinary instrumental variables estimator and the variance of the estimator can be expressed in matrix form as follows:

$$\beta_{IV} = (X'Z\ (Z'Z)^{-1}\ Z'X)^{-1}\ \ X'Z\ (Z'Z)^{-1}\ Z'y \quad , \quad Z = [P;D]$$

Ignoring the panel structure of the data when calculating the standard errors of the instrumental variables estimates will lead to misleading inferences for two reasons. First, there is likely to be heteroskedasticity across districts that is related to district size or the level of per pupil spending. Secondly, per pupil spending within a district is highly correlated over time. The structure of the data implies that the variance-covariance matrix will be block diagonal, with each block associated with the four years (i.e. t=4) for a specific district:

$$E[\epsilon\epsilon'] = \Omega_{nt\times nt} = \begin{pmatrix} \Sigma_1 & 0 & 0 & 0 & \dots & 0 \\ 0 & \Sigma_2 & 0 & 0 & \dots & 0 \\ 0 & 0 & \Sigma_3 & 0 & \dots & 0 \\ & & & \dots & & \\ 0 & \dots & 0 & 0 & 0 & \Sigma_n \end{pmatrix} \quad , \quad \Sigma_i = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \sigma_{24} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{44} \end{pmatrix}$$

White (1982) shows how to consistently estimate the standard errors in the case where Ω is *diagonal* (i.e. unspecified heteroskedasticity). A modified version applies to the case where there is also unspecified correlation over time within districts and omega is *block diagonal* as above.

The "optimal IV" (OIV) estimator and the variance of the estimator can be expressed:

$$\beta_{OIV} = (X'Z\ V^{-1}\ Z'X)^{-1}\ \ X'Z\ V^{-1}\ Z'y$$
$$Var(\beta_{OIV}) = (X'Z\ V^{-1}\ Z'X)^{-1}$$
$$V = Z'\Omega Z$$

There is a clear parallel to generalized least squares estimators. The point estimates will be identical to ordinary instrumental variables when the system is just identified (when there is only a single instrument for special education costs). Though the estimates are the same, the

calculated standard errors are robust to unspecified heteroskedasticity and serial correlation. However, when the system is over-identified, not only are the calculated standard errors appropriately adjusted, there is also an efficiency gain over ordinary instrumental variables.

In order to implement this strategy, an estimate of V is needed. I estimate V using a two-step procedure. First, I run three-staged least squares (3SLS). This involves running two-stage least squares and using the residuals to estimate the 4x4 matrix Σ assuming that matrix is constant across districts. The 3SLS procedure is equivalent to the optimal IV procedure using this restricted estimate of V. I then use the residuals from the 3SLS estimation to calculate a second more general estimate of V:

$$\overline{V} = Z'\epsilon\epsilon'Z = \sum_i Z_i'\epsilon_i\epsilon_i'Z_i ,$$

where i refers to all four observations for the same district. The extra 3SLS step increases the efficiency of the final step. In the final step, I use the general estimate of V to calculate the optimal IV estimates.

Chapter 2: New Evidence on the Impact of Differential Expenditures on Student Performance

Real spending on public secondary and elementary education has doubled over the past two decades while performance measures have not improved. These apparently conflicting time trends have fueled a long-running scholarly debate about the value of educational inputs in producing educational outcomes. One critical feature of the recent increase in education spending is the shift of this spending toward special education. Rothstein and Miles (1995) use district-level data to estimate that the share of spending dedicated to special education rose from 4 to 17 percent from 1967 to 1991. Regular education spending-- which is the type of spending expected to affect typical measures of outcomes such as test scores-- has not doubled, rather it has grown by only 28 percent. This paper uses the budgetary link between regular education spending and the more expensive special education programs in order inform the ongoing debate.

The problem of omitted variable bias is an empirical difficulty facing studies that relate student outcomes to educational inputs. In addition to educational inputs, non-educational inputs such as family background and student ability can affect achievement. These other factors may not be observable and may be correlated with school resources. For example, if families that are particularly supportive of education locate near high-resource schools, ignoring the role of family attitudes and comparing the achievement of students in high and low resource schools would exaggerate the value of additional spending. On the other hand, if the state targets resources to those schools that at-risk students attend, the cross-sectional relationship between spending and outcomes may understate the productivity of additional resources. What is needed to identify the true causal effect is variation in resources across students that is unrelated to unobservable determinants of student outcomes.

Federal special education mandates and state special education funding formulas may provide this type of variation. For example, if a district's student body happens to include a deaf-blind student, the district is federally required to provide appropriate services. In Texas, the amount of state reimbursement for such special education costs varies according to district tax

base wealth and the year through the structure of Texas school finance policy. If, as the findings presented in Chapter 1 suggest, higher special education spending comes at the expense of spending on other educational programs, then the net costs of educating the disabled student will be reflected in reduced regular education spending. In this paper, I first isolate variation in regular education spending across schools in Texas that can be explained by differences in physical disability rates and the state's special education funding policy parameters. I then relate this plausibly exogenous variation in resources over the year to student outcomes measured at the end of the school year.

This strategy has some disadvantages and advantages relative to previous studies that attempt to identify exogenous variation in school resources. For example, Angrist and Lavy's (1996) and Hoxby's (1996) strategies rely on variation in class size that comes about from the interaction between student enrollment and mandates regarding class size. The direct first-stage relationship between the level of resources applied to students and the mandates can be extremely useful for directing future policies. However, this strategy is not as useful in determining the effectiveness of additional resources that are expended with local discretion. How local education budgets are adjusted to accommodate shifts in mandated special education costs will reveal how localities allocate marginal dollars. If the question is whether or not schools use financial resources to effectively improve student performance, the strategy pursued in this paper will provide a better guide.

I conduct the empirical analysis for the over 5000 campuses in Texas that provide primarily regular education for the years 1993-95. I relate the fraction of students passing state-administered exams to per pupil expenditures dedicated to those students, controlling for an extensive set of demographic characteristics. Ordinary least-squares regression (OLS) analysis suggests that there is a moderate positive relationship between spending and student achievement. The magnitude of this relationship increases five-fold when I isolate the effect of variation in spending as described above. This more sophisticated two-stage least squares (2SLS) approach approximates the experiment of treating identical schools with differing levels of resources and observing the difference in achievement levels. In contrast, the OLS regression compares districts that are similar on observable dimensions but that may differ in unobservable

ways. Because the OLS estimates are biased downward relative to the 2SLS estimates, it appears that unobservable variables across campuses that affect achievement are actually negatively correlated with school resources. The state actively redistributes resources to schools with large populations of economically or otherwise disadvantaged students. It is important to compare schools with similar abilities and backgrounds to uncover the true highly productive relationship between spending and outcomes. The 2SLS estimates suggest that a 10 percent increase in spending leads to a 2.7 percent increase in the passing rate. I also finding a significant effect on campus dropout rates.

The paper proceeds as follows. Section 1 describes the empirical strategy and places it within the existing literature. In Section 2, I introduce the data and summary statistics. Section 3 presents the basic results and extensions. Section 4 concludes.

Section 1: Empirical Strategy

The approach that defines the education production function literature is relating student outcomes to educational inputs. Beyond this broad commonality, studies differ along numerous dimensions. An initial distinction is based on the type of dependent variable. One branch of the literature links school quality measures to future employment and earnings outcomes. The other links these measures to student achievement or school performance measures, and relies on the finding that achievement measures are strong predictors of future success to draw broader implications (Rivkin 1991 and Murnane, Willett, and Levy 1994). The debate between those who find that observable inputs, such as expenditure or class size, matter and those who find that they do not is very much alive in both branches.[17] The controversy persists because of the mixed success with which researchers have been able to deal with the empirical difficulties associated with measuring the productivity of school resources.

I will highlight two of these empirical difficulties as they pertain to the literature that examines student achievement. First, consider that the test score or other achievement measure

[17]See for example Card and Krueger (1996) and Betts (1995), and Hanushek (1996) and Hedges, Laine, and Greenwald (1994).

(A) for an individual student depends on the educational inputs (I) applied to that student, the non-educational inputs or family background (X) and the student's innate ability (a). This would suggest a cross-sectional specification that looks like the following:

$$A_i = \alpha + a_i + \sum_j \beta_j I_{ij} + \sum_k \gamma_k X_{ik} + \epsilon_i , \qquad (1)$$

where i indicates the student. Though ideally one would like to estimate this type of individual-level regression, very few data sets provide information on the resources applied to an individual student. The level at which inputs can be measured typically dictates that the analysis be implemented at the level of the campus, the school district, or even the county or state.

Estimating the aggregated production function by replacing the measures in (1) with the means for the campus or district may introduce some problems. The most obvious problem is that the unit of observation may not be comparable for the spending and achievement measures. For example, consider mean spending on students at a campus. A special education student typically costs two times as much to educate as a general education student. The 13 percent of students receiving special education services bring up the mean expenditure, so that the mean overestimates the amount expended for the typical general education student. Further, special education students are often not included in testing, so the increased intensity of resources is not relevant for test scores. Since there is significant heterogeneity across districts in the fraction of students in special education, a cross-sectional regression will attribute differences in test scores to these "spurious" differences in mean spending due to special education. Even if those students were included in test-taking, a district that has a higher incidence of disabled students and spends more than another district on special education would not necessarily witness increases in test scores. The goals of many special education programs are not closely tied to academic achievement. To uncover the true productivity of additional resources, the population where the resources should be expected to have an impact on the outcome in question and the resources applied to that population need to be appropriately matched.

Even with the spending and outcome measures defined for the same population, it is still difficult to establish the causal effect of those resources. The problem is one of omitted

variables. In the campus-level specification, controlling for observable indicators of student ability and family background, there may still be unobservable variables that determine both the level of school resources and student achievement. This argument is typically pitched as "good students go to good schools." This would suggest that the estimated coefficients on inputs would be biased upward in an OLS regression comparing achievement across observably similar districts that spend differing amounts per pupil. If this is the case, it is striking that the literature has had difficulty finding a strong positive relationship between spending and outcomes. On the other hand, compensatory education and school finance formulas that target resources to disadvantaged students lead to just the opposite bias: high resources may indicate a "hard-to-educate" student body. In either case, in order to identify the effect of more resources, what is needed is a methodology that effectively controls for the omitted variables or simulates the random assignment of students to more or less resources.

One method that has been implemented in the literature is to include past measures of achievement. Defined at the campus-level, specification (1) would be adjusted as follows:

$$A_{it} = \alpha + a_i + \delta A_{i\,t-1} + \sum_j \beta_j I_{ijt} + \sum_k \gamma_k X_{ikt} + \epsilon_{it} \qquad (2)$$

The past score ($A_{i\,t-1}$) presumably captures ability, the history of past inputs, and any other unobservable variables that are fixed over time that affect performance. If this is true, the term a_i no longer shows up in the error term in an ordinary least squares regression. However, if ability or other omitted variables are actually more closely correlated with the *trend* in achievement than with the *level* of achievement, then these unobserved variables remain in the error term and this semi-differencing strategy may instead exaggerate problems of omitted variable bias. Also, in the case of campus or district-level regressions, controlling for past outcomes is less relevant as the composition of the student population is less stable over time (i.e. there is more student mobility and higher retention and dropout rates).

A second solution also found in the literature is to use exogenous variation in schooling inputs that is uncorrelated with potential omitted variables. Class size is a common input considered in these studies. Hoxby (1996) and Angrist and Lavy (1996) separately use variation

in class size emanating from the interaction of state policies and student populations. If the state mandates (or suggests) a maximum class size of 35 and a student moves into a school that had been serving 70 students, the school is more likely to split two larger classes into three smaller classes. Though both studies use this same type of variation, Hoxby finds a precise zero effect of smaller class size on outcomes and Angrist finds an important and significant positive effect. Two other studies use strategies more similar to mine. Boozer and Rouse (1995) find that state policies mandating minimum class sizes for special education have the consequence of reducing regular education classes on average. Figlio (1994) finds that tax limitation policies following the recent tax revolt increase class sizes. Both of these studies use the interaction between the local assignment of resources to schooling and state policies and find that more school resources matter.

Finally, there has been a true experiment. In Tennessee, the STAR experiment randomly assigned elementary students to smaller and larger classes for a period of three years. Both the initial analysis of the results by Finn and Achilles (1990) and a more thorough analysis by Krueger (1997) find smaller classes had a significant effect on student performance. Interestingly, both analyses find that the effect is a level effect. Those students assigned to the early classes have an initial improvement in performance. Those students continue to perform better than students in the same cohort who attended larger classes, but the gap does not increase over time. It may be that the increased intensity of resources socializes students such that they learn how to learn. This finding suggests that specifications that attempt to find the effect of additional resources on achievement *gains* may not be successful.

In my analysis, I estimate the productivity of instructional expenditure for elementary and secondary student achievement in Texas. In Texas, school districts are evaluated based on their performance on three different measures: passing, attendance, and dropout rates. I will look at each of these three measures. I begin by relating the fraction of students passing achievement exams in a campus to student characteristics, community demographic characteristics, and (the logarithm of) per pupil spending on instruction:

$$PASS_{it} = \alpha + \beta EXPEND_{it} + S_{it}\Omega + X_{it}\Gamma + \delta_r + \tau_t + \epsilon_{it} \quad (3)$$

The student characteristics (S) include student poverty rates and the grade and race distribution of students at the school. These measures will help to capture differences in how expensive it is to educate students at different grade levels and with different backgrounds. S also includes controls for the number of students served at the campus and in the entire school district which capture potential returns to scale in educating larger populations if there are fixed costs. The community demographic controls, X, include family structure and parental level of income, education, and work status. I also control for the year (τ_t) and which of the 20 educational regional service centers in Texas serves the school (δ_r).

In constructing EXPEND, per pupil expenditure, an important point is that special education and bilingual education students are exempted from taking the academic tests administered in the Spring of each year in Texas. In order for the spending measure to match the test-taking population, I subtract from total instructional spending the amount spent on the instruction of special and bilingual education students (including expenditures during the part of the day those students are in regular education classes). However, though attendance and dropout rates are reported separately for special education students, bilingual education students are included in the campus-level calculated rates. Therefore, the spending measure that I use in regressions with those dependent variables includes spending on bilingual education students.

The strategy that I use to overcome omitted variable bias is to isolate variation in per pupil spending that can be treated as random using an instrumental variables strategy. In order to be a valid instrument, a variable must be correlated with per pupil spending and otherwise uncorrelated with regular education student outcomes. A plausible instrument is the fraction of students that are physically disabled in a school district. In Chapter 1, I find that the net costs of special education programs for these students come approximately one-for-one out of resources budgeted to non-special education programs. The way to think of this strategy is to imagine how a district responds when a deaf-blind student moves into the district. It is federally mandated for localities to provide disabled students with a "free appropriate education." While there is some local discretion over whether or not a mildly disabled student is classified as disabled, a deaf-

blind student will be classified as disabled and require special services no matter which school that student attends. The student will be relatively expensive to educate-- Chaikind et al (1993) use detailed data from a nationally-representative sample of schools to estimate that the excess annual costs associated with educating a deaf-blind student are over $35,000. In Texas, state and federal funds reimburse a share of these costs. If there is "crowdout" of regular education spending, spending on non-disabled students will be reduced in proportion to the net excess costs that the local school district bears. Comparing the achievement of students in an observably identical district that does not serve a deaf-blind student and does not reduce spending on other students to this district will reveal the value of additional resources.

The system of equations that approximates this type of experiment is of the following form:

$$\begin{aligned} EXPEND_{it} &= \alpha_1 + \pi DISAB_{it} + S_{it}\,\Omega_1 + X_{it}\,\Gamma_1 + \delta_{1r} + \tau_{1t} + \epsilon_{1it} \\ PASS_{it} &= \alpha_2 + \beta EXPEND_{it} + S_{it}\,\Omega_2 + X_{it}\,\Gamma_2 + \delta_{2r} + \tau_{2t} + \epsilon_{2it} \end{aligned} \qquad (4)$$

DISAB is the physical disability rate in the district. The first equation is the first-stage regression which relates spending on general education students to the physical disability rate. Though the spending and score measures are defined at the campus level, physical disability rates are only available at the district-level. Relating campus spending to the district disability rate will capture the effect of financial decisions made at the district level, though the relationship may be weaker than if the first-stage were defined at the level of the district. In the estimation, I will correct the standard errors for correlation across campuses within the same district so as not to understate the variability of the estimates.

I include four physical disability rates: deaf-blindness and hearing, visual, and orthopedic impairments. I would expect higher than average rates of deaf-blindness to reduce regular education spending because of the high net costs. The relationship will be just the opposite if a disability type generates higher marginal revenues than the marginal costs imposed so that the net cost is negative-- if a district makes money serving a disabled student the district may increase spending on other programs. In order to get at the probable net costs, the following

table compares the average state revenue generated and the average instructional costs that Chaikind et al (1993) calculate for each of these disability categories:

	Deaf-Blindness	Hearing Impairment	Visual Impairment	Orthopedic Impairment
Revenue Gain	$6174	$4302	$4182	$4580
Instructional cost	$36397	$6211	$9158	$5621

All values are in 1993 dollars. Remember that the cost is based on a national sample and given that the cost of education is lower than average the instructional costs may actually be lower in Texas. It appears districts bear net costs for educating deaf-blind and visually-impaired students, but are close to breaking-even or gaining on net when serving hearing and orthopedically impaired students.

The specification in (4) uses variation in per-pupil regular education spending across campuses that comes from the average net special education costs associated with a given sized physically disabled population. There are two reasons to expand the first stage to take advantage of additional variation in net costs due to the differential "reimbursement" from the state by tax base wealth category and by year. First, expanding the instrument set will reduce the variability of the 2SLS estimates. Second, one could argue that the physical disability rate has an independent effect on student outcomes and belongs in the second stage. Physically disabled students may be included in the regular education classroom which may either positively or negatively impact other students. Also, families with physically disabled children may choose to locate in school districts with well-developed special education programs. If such districts are different from other districts along unobservable dimensions that affect outcomes, then it is important to compare districts with similarly developed physically disabled programs. If the first stage is expanded to include the relevant interactions which are explained below, I can directly include the fraction physically disabled in the second stage and identify the performance effect only from the higher order interaction terms.

The expanded first stage recognizes that the net cost of educating a physically disabled student varies across school districts depending on whether the district is a poor, middle, or high

wealth district and on the year. The school finance program in Texas consists of both a foundation grant program (which guarantees a basic fixed per pupil allotment) and a matching grant program (which guarantees a certain amount of revenue per pupil for a given level of tax effort). For serving a physically disabled student, low wealth districts gain both (a scaled version of) the basic per pupil allotment through the foundation grant program plus additional matching revenues in all three years 1993-1995. In 1993, middle and high wealth districts do not participate in the matching grant program and gain only the foundation per pupil allotment. This changes for high wealth districts in 1994 and 1995. In those years, high wealth districts gain not only the per pupil allotment as before but also recapture funds that are taxed away through a negative matching revenue program. I break down the average marginal gain in state revenue from serving a disabled student (shown in the previous table) by tax base wealth category and year in Table 1. In all three years, middle wealth districts (85 percent of campuses) generate fewer revenues and bear higher net costs for serving a physically disabled student than either low (8 percent) or high wealth (7 percent) districts. Low wealth districts gain more than high wealth in the first year and high wealth districts gain more in the last two years.

These non-linearities in state revenue are transmitted to variation in net special education costs and, through the budget, to variation in regular education spending. In order to use this kind of variation, I expand the first-stage regression in (4) to include interactions between the four physical disability rates and indicators for the year and district tax base wealth category. I also control for separate year effects by tax base wealth category to control for any secular effects on achievement of falling into one or another of the three categories.

Section 3: Data and Sample

Schools in Texas are rated according to how students perform on three dimensions: passing rate on achievement tests, attendance rate, and dropout rate. Campuses receive a rating of excellent, good, satisfactory, or unacceptable. Low ratings can mean a reduction in state revenues and the system is intended to improve the accountability of school officials. The state collects campus-level student performance data through the Academic Excellence Indicator System (AEIS). The achievement tests administered by the state during the sample period (1993

to 1995) are known as Texas Assessment of Academic Skills (TAAS). TAAS was instituted in 1991. The goal of the new program was to shift the evaluation of school performance from achieving minimum skills to achieving academic skills. Tests are currently administered in the Spring of each year in reading and math for grades 3 through 8 and grade 10. Writing tests are given during eighth and tenth grades only. AEIS provides campus-level measures of the fraction of students taking the exams who performed at or above the appropriate grade level, meaning those who answered at least 70 percent of the items correctly. There are four test score statistics available: the fraction passing both the reading and math exams and the fraction passing the reading, math, and writing exams separately. The attendance rate (the fraction of school days students attend classes) and dropout rate (fraction of students ever enrolled during the year who quit school) are also included. I combine the AEIS campus-level performance data with district-level fiscal data from the Public Education Information Management System (PEIMS) and community demographic information from the 1990 Census School District Data Book (SDDB).

The sample that I use is based on all campuses that are primarily for general education. Campuses that serve only early education populations or primarily special, bilingual, or vocational education students are not rated by the Texas accountability system. Most of the students are exempted from taking the exams. Of a possible 19302 observations for the three years, these unrated schools account for 13 percent. I lose an additional 4 percent of observations because of missing data (including schools that are in districts that are not fiscally independent). Finally, I exclude campuses that are in districts with enrollment below 100 students and campuses with per pupil expenditures in the top and bottom one percent to avoid extreme outliers. The final sample includes 15351 observations: 5402 campuses from 989 districts for the years 1993-95.

The summary statistics for this sample are presented in Tables 2a and 2b. On average, 76 percent of students pass the grade-appropriate reading exam, 61 percent the math exam, and 83 percent the writing exam. The average attendance rate is 96 percent and the average fraction of students who drop out of school is 1.3 percent annually. Instructional spending on non-special and non-bilingual education averages $2016 per pupil. This spending value is adjusted for inflation using the average increase in teacher salaries across the state. It is also adjusted for

regional differences in the cost of education and for scale, both of which are indices developed by the Texas Legislative Education Board. The expenditure measure for the test-taking population includes regular, compensatory, gifted and vocational education spending. Regular education spending makes up 81 percent of instructional spending on these programs. Compensatory education, which targets resources to classes with large numbers of economically and otherwise disadvantaged students, comprises 13 percent. Vocational and gifted instructional expenditures make up the remainder. Vocational education spending would constitute a much larger share of instructional spending in the full sample of campuses because many schools that specialize in vocational education are not rated by the state and are excluded from the sample.

Over the school years 1993 to 1995, Texas students showed improvement based on the academic exams the state administers. The fraction of the student population passing both the reading and math exams increased from less than half in 1993 to more than 60 percent in 1995. Over the same three years, real per-pupil expenditures on the test-taking population increased by 4.3 percent annually on average. The next section addresses the role that dedicating more resources to education played in this improvement in academic performance.

Section 4: Empirical Results

Table 3 begins with ordinary least-squares (OLS) regressions relating the fraction of students in a school passing the reading and math achievement tests to the logarithm of per pupil spending on the students taking the exams. These are the only two exams administered to all grade levels. The first column includes the fraction of students in each grade level, 10-part splines in the logarithm of campus and district enrollment, region dummies, per pupil tax base wealth, and interactions between year dummies and indicators for the three tax base wealth categories, as well as the independent variable of interest. In all cases, the standard errors are adjusted to account for correlation across schools over time using White's generalized method. The estimated coefficient on expenditure is negative and highly significant. The point estimate of -.125 implies that a 10 percent increase in expenditures is correlated with a *decrease* in the fraction passing both exams of 1.25 percentage points. The next four columns help to explain

this initial counter-intuitive relationship.

In column 2, I add the full set of community demographic controls that are shown in Table 2B. These controls are based on the 1990 Census and are defined at the district level. The explanatory power of the regression increases and the signs on the coefficients other than per pupil spending are generally as expected. I show the coefficients and standard errors on a subset. Schools that serve students who are more likely to come from single parent families or live in households where English is not spoken have lower achievement. Median family income and parent education levels are positively correlated with student achievement. The coefficient on spending remains negative but the absolute magnitude decreases from -.125 to -.086.

Columns 3 and 4 add campus-level demographic descriptors of the student population. In column 3, I add the race distribution of students attending the school. These variables prove to be very important determinants of achievement. Schools with larger black and Hispanic student populations perform worse than schools with larger white (which is the excluded category) populations. A 10 percent increase in the fraction of students who are Hispanic {black} is associated with a 2.53 {3.15} percentage point reduction in the fraction passing. The coefficient on per pupil spending is insignificant but flips sign. The point estimate is .012 with a standard error of .008. Column 4 simply adds the student poverty rate. The point estimate increases to .032 and is significant at the 5 percent level.

This pattern of results suggests that resources are non-randomly distributed across schools with differing student abilities and backgrounds. One common presumption is that the distribution of resources is positively correlated with student ability. This is based on the notion that parents who care a lot about education sort to those schools that provide a lot of educational resources. State redistributive policies turn this argument on its head. In an attempt to equalize opportunity, states are actively targeting resources to schools with disadvantaged populations. This redistribution shows up in the raw correlations between student characteristics and per pupil expenditure and student achievement in the following table:

	Per Pupil Expenditure	Fraction Passing Reading/Math
% white	-.40	.59
% hispanic	.40	-.41
% black	.04	-.34
% other race	-.04	.20
% in poverty	.30	-.58

These correlations imply that excluding these student characteristics from the control set could lead to a wrong-signed relationship between spending and outcomes as in columns 1 and 2. The types of students to whom high levels of resources are targeted tend to perform poorly. If unobservable variables that are omitted from these specifications are similarly positively correlated with spending and negatively correlated with ability, the instrumental variables estimates should reveal an even stronger positive relationship.

Before moving on to the 2SLS regressions, there is one more important issue to address. Schools with larger bilingual and special education programs can exempt larger fractions of the student population from taking the exams. If one school is more aggressive in classifying students who are marginally learning disabled as disabled, for example, that school will change the distribution of ability in the test-taking population relative to a similar school that serves mildly disabled students in the general education program. In an attempt to correct for shifts in the distribution of student ability across schools, I add the fraction of students exempted from taking the exam as a control variable. As expected, the coefficient on this variable is positive and significant. School that exempt more students truncate the lower tail of student abilities in the test-taking population and perform better on the exams. However, including this measure has little effect on any of the other coefficients.

The "best" OLS estimates in column 5 may still be biased by unobservable variables that affect both spending and performance. The 2SLS strategy isolates variation in spending that is due to physical disability rates and Texas school finance policy parameters, variables which are plausibly unrelated to outcomes except through their impact on spending. Table 4 shows the

OLS coefficient in the first column followed by a progression of 2SLS estimates for several dependent variables. The dependent variable in the first row is the same as that in Table 3-- the fraction of students passing both the math and reading exams. Columns 2 to 4 correspond to different instrument sets. In column 2, I instrument for per pupil spending using a dummy for each of the four physical disability categories indicating when there are no students who fall into that category, and also a separate variable that is the logarithm of the fraction of students in that disability category when some are served at that campus. In this specification, and in the other 2SLS specifications, I correct the standard errors for correlation across campuses in the same district since the instruments are defined at the level of the district.[18] In column 3, I add interactions between the physical disability measures and the tax base wealth category and the year. Column 4 is the same as column 3 except that the physical disability rate is included in the second stage. The p-values from F-tests of whether the coefficients on the instruments are jointly equal to zero are shown in the bottom row of the top panel.

Focusing on the top row, the point estimate increases dramatically from column 1 to column 2. This results suggests that unobservables do follow observables in this case so that the OLS estimate *understates* the causal effect of spending on performance. A second reason why the 2SLS estimates are larger in magnitude than OLS may be due to measurement error in per pupil spending. The 2SLS estimates become much more precise in column 3 when the instrument set is expanded. The estimate of .190 is significant at the 5 percent level. The point estimate falls in column 4 when the disability rate controls are included in the second stage. However, at .145 it remains 5 times larger than the OLS estimate. The implied effect of a 10 percent increase in per pupil spending is a 1.45 percentage point increase in the fraction passing reading and math exams, for an implied elasticity of .27. A one standard deviation increase in resources would lead to a six percent increase in the passing rate.

The following three rows in the top panel of Table 4 corroborate the finding that additional instructional spending is highly productive in improving academic performance.

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[18]The median district is represented by 8 separate schools in the sample, though this ranges from one to 182 schools.

Rows 2 and 3 estimate achievement effects for reading and math exams considered separately and row 4 estimates the effect for writing exams. The estimates are significant at the 5 percent level in all three cases in the preferred specification in column 4 which includes the physical disability rates as regressors. A 10 percent increase in per pupil spending would lead to an increase of 2.9 percentage points in the fraction passing math, 3.7 for reading, and 1.5 for writing.

The final two rows presented in the bottom panel consider how expenditure affects attendance and dropout rates. In these rows, the dependent variable is non-special education instructional spending. The previous spending variable is expanded to include spending on bilingual education students, who are not included in the test-taking population but are included in attendance and dropout counts. Attendance and dropout rates are reported separately for special education students. I do not find a significant effect of additional spending on the fraction of school days students attend classes. The reduction in the number of observations is due to missing data. Though the point estimate increases moving from OLS to 2SLS, the standard error becomes too large to say anything conclusive. However, spending appears to be extremely effective in reducing dropout rates. In this case, the observations are fewer because dropout rates are only defined for campuses that serve student populations in grades 7 and above. The estimate of -.042 in column 4 implies that a 10 percent increase in per pupil spending would reduce the dropout rate by almost one-third on average.

Section 5: Conclusion

Because it is difficult to measure student ability and background, analyses of the productivity of school inputs on student outcomes must confront the problem of omitted variable bias. In a cross-sectional regression, it is likely that there are unobservable variables that are correlated with both spending and outcomes and confound the estimation of the true achievement effect of additional resources. I find that the bias from both omitted observable student characteristics and unobservable variables is negative. Because state redistributive policy targets resources to disadvantaged student populations, comparing schools that expend more and schools that expend fewer resources makes it appear as if more resources are counter-productive.

However, controlling for differences in student poverty rates and racial/ethnic backgrounds uncovers a positive relationship. The relationship becomes even stronger when I instrument for regular education spending using budgetary pressure from exogenous shifts in special education spending.

Table 1: Average Marginal State Revenue Generated by Serving a Disabled Student

	Deaf-Blindness	Hearing Impairment	Visual Impairment	Orthopedic Impairment
1993				
Low wealth districts	8076	4401	4119	4644
Middle wealth districts	6240	3401	3463	3588
High wealth districts	6546	3535	3633	3764
1994				
Low wealth districts	7958	4297	4417	4579
Middle wealth districts	5864	3196	3255	3372
High wealth districts	9478	5166	5260	5450
1995				
Low wealth districts	6267	4366	4488	4649
Middle wealth districts	4512	3144	3231	3348
High wealth districts	6935	4832	4966	5145

Table 2A: Summary Statistics

Variable		Variable	
tax base wealth/pupil	165874 (196449)	% 0-21 years enrolled in public school	.763 (.049)
% low wealth	.851	% no deaf-blind	.736
% middle wealth	.078	% no visually-impaired	.200
% high wealth	.070	% no hearing-impaired	.228
district enrollment	25933 (44099)	% no orthopedically-impaired	.175
campus enrollment	620 (443)	% deaf-blind if >0	.00014 (.00035)
total instructional spending/pupil	2722 (612)	% visually-imp if >0	.0009 (.0008)
"regular" education spending/pupil	2016 (457)	% hearing-imp if >0	.0016 (.0013)
% pass math	.613 (.176)	% orthopedic-imp if >0	.0017 (.0011)
% pass reading	.756 (.143)	% in poverty	.449 (.249)
% pass writing	.825 (.129)	% Hispanic	.294 (.285)
% pass reading and math	.562 (.177)	% black	.140 (.202)
% exempt from test-taking	.133 (.089)	% other race (non-white)	.019 (.034)
attendance rate	.957 (.016)	% special education	.118 (.044)
dropout rate	.013 (.018)	% bilingual	.064 (.093)

Notes to Table 2A: The means (standard deviations in parentheses) are based on the sample of 5402 campuses (in 989 school districts) for the years 1993-95. The student achievement and demographic variables are from AEIS. The district financial and disability information are from PEIMS.

Table 2B: Summary Statistics for 1990 Census Variables (Table 2A Sample)

Variable:		Variable:	
% adults graduated high school	.297 (.082)	% mother less than 15 years old when born	.146 (.044)
% attended some college	.278 (.075)	% single mother	.189 (.078)
% graduated college +	.162 (.102)	% parents never married	.027 (.025)
median family income	26840 (8611)	% divorced	.071 (.025)
% fathers unemployed	.043 (.030)	% speak no English	.061 (.074)
% mothers working	.623 (.096)	% foreign-born	.120 (.114)
% professionals	.521 (.129)	% recently arrived in US	.039 (.041)
% work in manufacturing	.309 (.092)	% lived in same county in 1985 and 1990	.799 (.097)
# persons in household	2.76 (.30)	% lived in same home in 1985 and 1990	.500 (.091)
# workers in household	1.57 (.15)	% work in county where live	.792 (.204)
# children under 18 in household	1.73 (.39)	% veterans	.127 (.038)
% aged 25-34	.586 (.060)	% adults mobility limited (disabled)	.088 (.036)
% aged 35-49	.360 (.060)	% living in a central city	.336 (.420)
% aged 50-64	.029 (.019)	% in nonmetro-rural area	.220 (.371)
% aged 65 +	.002 (.003)	% in nonmetro-urban area	.100 (.246)

Table 3: Ordinary Least Squares Regression of Fraction Passing Reading and Math Exams

Independent variable	(1)	(2)	(3)	(4)	(5)
log(per pupil expenditure)	-.125	-.086	.012	.032	.031
	(.009)	(.009)	(.008)	(.007)	(.007)
log(tax base wealth per pupil)	.071	.006	.005	-.003	-.003
	(.005)	(.004)	(.004)	(.004)	(.004)
% black	-	-	-.468	-.315	-.312
			(.012)	(.014)	(.014)
% Hispanic	-	-	-.435	-.253	-.259
			(.011)	(.015)	(.015)
% other race	-	-	.067	.057	.056
			(.059)	(.051)	(.051)
% students in poverty	-	-	-	-.240	-.246
				(.014)	(.014)
% exempt from exam	-	-	-	-	.051
					(.021)
% single mother families	-	-.257	-.111	-.097	-.097
		(.049)	(.049)	(.047)	(.047)
% parents have high school degree	-	.161	-.001	.001	-.004
		(.040)	(.034)	(.033)	(.033)
% parents attended some college	-	.159	.046	.039	.036
		(.041)	(.037)	(.036)	(.036)
% parents attended 4 years of college	-	.227	.216	.177	.176
		(.053)	(.043)	(.042)	(.042)
% parents speak no English	-	-.182	-.153	-.132	-.131
		(.077)	(.070)	(.068)	(.068)
log(median family income)	-	.077	.044	.028	.028
		(.015)	(.016)	(.015)	(.015)
% family income>$60,000	-	.211	.021	.008	.007
		(.048)	(.044)	(.042)	(.042)
R-squared	.365	.463	.601	.620	.621

Notes to Table 3: All specifications are based on the sample of 15351 school-level observations (5402 campuses over the years 1993-1995). The dependent variable in each case is the fraction of test-taking students in the school who passed both the reading and mathematics exams. All columns include the fraction of students in each grade level, 20 regional service center dummies, 10-piece splines in the logarithm of both campus and district enrollment, tax base wealth per pupil, and tax base wealth category dummies interacted with year dummies. Column 2 adds the rich set of community controls shown in Table 2B. Column 3 adds student race/ethnicity variables and Column 4 adds the student poverty rate. Column 5 adds the fraction of the student population exempted from taking the exams. The standard errors are adjusted for correlation within schools over time using White's generalized method.

Table 4: Instrumental Variables Estimates of the Effectiveness of Instructional Expenditure

Dependent Variable	Obs	(1)	(2)	(3)	(4)
% passing reading and math	15351	.031	.239	.190	.145
		(.007)	(.120)	(.070)	(.083)
% passing math	15351	.031	.270	.221	.177
		(.008)	(.123)	(.074)	(.086)
% passing reading	15351	.014	.176	.232	.283
		(.006)	(.096)	(.061)	(.074)
% passing writing	14658	.008	.213	.162	.120
		(.007)	(.104)	(.061)	(.053)
p-value from 1st-stage		.091	.001	<.001	<.001
attendance rate	15705	.005	.008	.011	.012
		(.001)	(.014)	(.008)	(.009)
dropout rate	6634	-.003	-.081	-.050	-.042
		(.002)	(.041)	(.015)	(.011)

Notes to Table 4: Each row corresponds to the designated dependent variable. The coefficient shown is the estimated coefficient on the log of pupil spending. The first column is based on ordinary least-squares. The following four present 2SLS estimates. All specifications include the full set of controls included in the previous table. The standard errors in column 1 are corrected for correlation within campuses over time, and the standard errors in the other columns are corrected for correlation within districts over time. Columns 2-4 correspond to different instrument sets. Column 2 includes 0/1 dummies and the log of the fraction physically disabled in four disability categories (8 variables). Column 3 adds interactions between these variables and the tax base wealth category and year. Column 4 is the same as column 3 except the physical disability rates are included in the second stage. The last two rows add bilingual education spending to the dependent variable since bilingual education students are included in the campus-level calculation.

Chapter 3: Local Fiscal Incentives and Student Disability Rates

Disability status is increasingly used as a means for targeting resources in the United States. Disability Insurance (DI) and Supplemental Security Income (SSI) make up a growing share of cash welfare programs. The number of adult disability benefit recipients has increased from to 5.1 to 9.1 million over the past two decades, driving the increase in the expenditure share. This growth in adult disability programs and populations is mirrored by the trends for children. Recent reforms in the SSI program have led to an expansion in childhood disability rolls and outlays (Kubik 1997, GAO 1995). Also, growing fiscal claims are made on governments for disabled children in the realm of education as special education enrollment and costs continue to rise. Since 1977, the fraction of elementary and secondary students classified as disabled has increased from 8 to over 12 percent. Over the same period, the fraction of the education budget dedicated to special education has increased from 4 to 17 percent (Rothstein and Miles 1995). In 1994, 5.3 million students participated in special education, costing a total of 32 billion dollars.

There are several explanations for the rise in disability rates. The pool of individuals eligible for disability 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. At the same time, socio-demographic indicators that determine the at-risk population have been worsening. And, take-up of disability benefits among eligibles has increased with diminished stigma and the establishment of a legal support system. Finally, the financial incentives embedded in the disability programs themselves may influence disability rates. How large a role financial incentives play in explaining the time trends is a subject of both popular and academic debate. There is particularly little known about how program take-up responds to program generosity when the decision-making body is the local government.

In the case of special education, a nationwide reform effort is currently underway to

reduce the incentives in state school finance policies for localities to inflate student disability rates. The goal of the Education for All Handicapped Children Act (EHA 1975) was to guarantee that all disabled students receive an appropriate public education. Federal and state policies were designed to encourage school districts to locate and serve students with severe disabilities. Under these policy regimes, local special education costs are typically reimbursed according to the number of special needs students served. Because the claim that a locality can make on state funds varies with the number of students eligible for special education, school officials have an incentive to manipulate the size of special education programs. Critics claim that vague definitions, such as learning disabled, coupled with these types of financial incentives have pushed student disability rates to the current levels of over 1 in 8 students classified.

The purpose of this paper is to quantify the relationship between student disability rates and the generosity of state special education reimbursements. The empirical analysis will help to clarify both how important the parameters of state special education finance policies are in determining student disability rates and also how responsive localities are to the price incentives embedded in these policies. In order to estimate the elasticity of student disability rates with respect to fiscal incentives, I rely on variation in the gain in state revenue from labeling an additional student as disabled across school districts in Texas from 1992 to 1995. In Texas, this revenue increase depends on a district's tax base wealth through the structure of the school finance equalization policy. In the middle of the period, there was a dramatic change in the relative gain across poor, middle, and high wealth districts. The empirical strategy that I use isolates the impact of this change on the growth in student disability rates across the three types of districts. I relate the fraction disabled in a school district to the district-specific revenue gain, and instrument for that gain using these broad policy changes. I find that a 10 percent increase in the supplemental revenue generated by a disabled student leads to approximately a 1.5 to 2 percent increase in the fraction classified as disabled. This large response is robust to a variety of specification checks.

The paper is divided into 4 sections. In Section 1, I review previous studies that are related to this question. Section 2 describes the empirical strategy and data. Section 3 presents the basic results and extensions. Section 4 concludes.

1. Related Empirical Literature

The empirical literature relating student disability rates to the fiscal incentives facing local school districts is nearly nonexistent. However, there is a substantial literature examining the response of both adult and childhood disability rates to the incentives that individuals face in the context of DI and SSI. In these cases, the individual or individual's family trades off the costs and benefits of qualifying for the disability program. The case I consider involves a different mechanism. Because the provision of special education is mandated by state and federal governments, localities pay residual costs above state and federal aid for special education.[19] The disabled individual is therefore only the indirect beneficiary of any increase in the generosity of state funding for special education. By linking student disability rates to state special education finance policies, I will gauge the response of local governments' take-up of these disability programs to the price incentives embedded in the policies.

Studies of factors that affect childhood disability rates have typically overlooked program generosity. The focus has been in identifying the role of various cultural and demographic factors (Chaikind et al 1993, Harry 1992). In a recent attempt to link childhood disability rates to financial incentives, Kubik (1997) measures how much more willing an AFDC mother is to designate her child as disabled as the net cash gain from switching that child onto the SSI program increases. He finds that a 10 percent increase in the net benefit level increases the rate of disability by 0.9 percentage points and that the effects are concentrated among boys with ADHD. It will be interesting to compare the response of student disability rates to local government incentives to this response to individual incentives.

There is a more closely related literature that directly analyzes the impact of special education policy incentives. However, this literature has not produced any summary statistics that would be useful in predicting the responsiveness of student disability rates. Until recently, the focus has been on another margin. Researchers have speculated about how different state special education reimbursement policies translate into the quality of services offered to special

[19]On average, localities pay 30 percent of total special education costs, states 60 percent, and the federal government 10 percent.

needs students *once classified.* Several studies do suggest that the type of services that are provided is affected by patterns of reimbursement rates (O'Reilly 1995, Dempsey and Fuchs 1993). The few studies that consider the effect of fiscal incentives on whether or not a student is labeled as disabled are case studies that follow isolated state reforms. These provide some qualitative evidence that fiscal policies have substantial effects on student disability rates. Montgomery (1995) discusses the impact of recent special education financial reform in Oregon. The system was changed so that all disabled students are reimbursed in the same way (two times the regular education reimbursement) up to a cap of 11 percent of enrollment. This new system created an incentive to label students up to the cap. Montgomery describes interviews with special education directors who claim to have been asked by their superintendents to bring the count up to 11 percent. She also reports:

> "One director admitted to changing district policy on identification of children for special education in kindergarten. Previously this district had tended not to identify children in kindergarten []. Now, to increase their count, they were starting to identify these children, although they were not very comfortable pushing [teachers] to label."[20]

Clearly, despite the prescriptiveness of EHA there is room for districts to respond to such incentives. In a separate study, Kane and Johnson (1993) document the outcome of a different type of reform in Vermont. When Vermont changed to a census-based regime, under which the reimbursement for special education is unrelated to number of students classified as disabled, the number of students receiving special education over the following three years declined by over 17 percent. Most of the students who were returned to general education had minor learning disabilities or speech impairments.

Previous empirical work suggests that student disability rates do respond to fiscal incentives. However, a more direct methodology is needed to quantify the response.

2. Empirical Strategy

I analyze the behavior of local school districts in Texas in order to estimate the effect of

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[20]Montgomery (1995), p.18.

the generosity of state special education reimbursements on the rate of classification of marginal students as disabled. In Texas, disabled students generate more state revenue than non-disabled students. Therefore, school districts can secure supplementary revenue by classifying additional students as disabled. I take a reduced-form approach, relating the fraction of the student population classified as disabled (DISAB) to the log of the amount of state revenue raised (GAIN) by serving a disabled student:

$$DISAB_{it} = \alpha_i + \beta \ln(GAIN_{it}) + X_{it}\Gamma + \gamma_r + \delta_t + \epsilon_{it}, \quad (1)$$

where i indexes the individual district and t indexes the year. X includes community and student characteristics such as racial composition and poverty rate that may affect either the underlying prevalence of student disability or tastes for classifying mildly disabled students as disabled. I also include indicators for which of the twenty state education centers services a district to capture regional differences and year dummies to capture time trends. I include district-fixed effects in order to capture any omitted factors that are constant over time within districts that determine student disability rates. β measures the change in the disability rate from a percent change in the revenue gain.

Identifying variation

The identifying variation in the revenue gain comes from the structure of Texas school finance policy and changes in the policy parameters over time. The additional revenue generated by a special needs student is determined by the complicated revenue equalization scheme and varies by district and year. Some components of the revenue gain depend on district choice variables that may in turn depend on the student disability rate, such as the property tax rate. Therefore, I isolate variation in the revenue gain that can be attributed to components that are outside the control of the district by constructing a simulated gain measure (SIMGAIN) for each district and instrumenting for the actual gain using this measure. This strategy allows me to link changes in the reimbursement rate that arise from the differential treatment of low, middle, and high wealth districts over time to changes in the disability rate. I will therefore be estimating a system of equations of the form:

$$\ln(GAIN_{it}) = \alpha_{1i} + \pi\ln(SIMGAIN_{it}) + X_{it}\Gamma_1 + \gamma_{1r} + \delta_{1t} + \eta_{it}$$
$$DISAB_{it} = \alpha_{2i} + \beta\ln(GAIN_{it}) + X_{it}\Gamma_2 + \gamma_{2r} + \delta_{2t} + \epsilon_{it} \quad (2)$$

This two-stage least-squares approach simulates the experiment of changing the reimbursement rate for special education students for a district and measuring the resulting change in the fraction of students classified as disabled.

I will review the basics of Texas school finance policy in order to clarify the nature of the variation. In Texas, districts that have less fiscal capacity (as measured by tax base wealth) and more student need (as measured by the pupil count) receive more aid. There is a revenue gain associated with classifying a student as disabled because such a student counts as more than one regular education student and this weighting inflates the pupil count. The magnitude of the revenue gain is determined by the foundation grant program of Tier 1 and the matching grant program of Tier 2. Tier 1 guarantees a certain amount of revenue per pupil for levying the foundation tax rate (about 0.7 percent). Tier 2 guarantees a certain amount per pupil for each .01 percent the district chooses to levy above that. The combined Tier 1 and 2 revenue gain from classifying a student as disabled can be expressed as follows:

$$GAIN_{it} = \frac{\partial N_{it}}{\partial D_{it}} \times (Tier\ 1\ allotment_{it} + (E_{it} \times Tier\ 2\ guarantee_{it}))$$
$$(a) \qquad (b) \qquad (c) \quad (3)$$

$$\frac{\partial N_{it}}{\partial D_{it}} = change\ in\ the\ pupil\ count$$

$$E_{it} = tax\ effort\ matched$$

The gain consists of three components: the increase in the pupil count multiplied by the foundation per pupil allotment and by the amount of per pupil matching revenue. I will describe each of the three components and how the actual and simulated gain measures that will be used in the analysis are constructed. The most useful variation comes through (c), with the additional Tier 2 matching funds. In response to challenges to the constitutionality of the

formula in effect in 1992 and 1993, the structure of the matching program was changed in 1994 and 1995 in a way that differentially affected districts of differing tax base wealth. Tier 1 provides some "low-level" variation but is most important for correctly measuring the level of the revenue gain.

a) Marginal increase in the pupil count

The first term is the marginal increase in the pupil count (N) from classifying a student as disabled (D). The measure of student need used in Texas is not a strict pupil count but a weighted pupil count that more heavily weights students that are more expensive to educate. The amount that a disabled student adds to the pupil count relative to a regular education student depends on the type of instruction that student receives. Each instructional setting, such as separate class or residential school, carries its own multiplier in the funding formula.[21] In order to study disability rates rather than placement rates, I need to construct a measure that captures the expected change in the pupil count from classifying a student as learning disabled, for example, rather than for placing a student in a certain setting. To do this I use the district's pattern of placement within each disability category and construct a weighted average of the additions to the pupil count for the various settings. The placement weights are constant across districts but do change over time. In 1995, the weights were increased on less restrictive and decreased on more restrictive placements in order to encourage mainstreaming. Because of this change, the milder disabilities which tend to be served in the less restrictive settings increased the pupil count more than in the previous years.

An important thing to stress is that this is the only component of the revenue gain that varies by disability. What this means is that the relative gain is constant across disability categories for all districts within any year (actually for 1992-94 and for 1995). This limits the type of analysis that is possible because I will not be able to control for changes in the revenue

[21] This funding weight is then multiplied by the district's attendance rate to get a measure of weighted average daily attendance. For example, in a district with a 95 percent attendance rate, a student served in a resource room (educated in a more intensive setting for a few classes a day) would add 3 (the setting funding weight in the first period) times .95 to the district's pupil count. The relevant change ($\partial N/\partial D$) for my analysis in this case would be 1.9, the amount over what a regular education student would add (.95).

gain in related categories and time effects at the same time. Rather than analyzing individual disability categories, I focus on broad groups, such as non-physical and physical disability categories. I will not be able to convincingly compare the response of specific disabilities to fiscal incentives.

I construct the actual gain measure using the increase in the pupil count derived from the district's actual pattern of instructional placement by disability.[22] However, how disabled students are served may reflect characteristics of the community that also affect disability rates. The simulated revenue gain measure is therefore calculated using the expected increase in the pupil count given the average statewide pattern in how disabled students are served. The following table summarizes the simulated version of the marginal increase in the pupil count by broad disability categories:

Table A: Simulated Marginal Increase in the Pupil Count

	1992-94	1995
Non-physical disabilities	0.65	0.74
Physical disabilities	1.05	1.05

The increase in the pupil count was 14 percent higher for the non-physical disabilities in the last year but flat over time for the physical disabilities. This provides some variation in the revenue gain over time and this change in scaling enhances the variation that comes through the matching grant program in Tier 2.

b) Tier 1 allotment

The level of the per student allotment under Tier 1 varies over time and by district. The nominal basic allotment was $2200 in 1992, $2400 in 1993, and $2300 in 1994 and 1995. The real value fell over time as the state faced difficulties in meeting all of it funding commitments under the school finance program. The basic allotment is adjusted in two ways to account for

[22]The actual measure also includes the district attendance rate (for FTE). Because the district attendance rate may reflect decisions the school district has made about the size of special education programs and may be endogenous, the simulated measure uses statewide rates.

differences in the cost of providing education across districts. The first is a *price* component that adjusts for variation in prices of educational inputs that are outside the control of the district.[23] The second is an economies of *scale* component (which is rare in state aid formulas) that adjusts for higher per-pupil costs in smaller and more sparsely populated districts.

For the analysis, it is important that the financial gain be in real terms-- accounting for both inflation and cost differences across districts. I use the CPI index for all services to convert values to 1995 dollars and the Texas-developed education price index to convert district-specific values all to the same base. All financial variables in the analysis are converted in this same way. The variation across districts within years that remains in the basic allotment is generated by the scale adjustment. Most (80 percent) of this cross-district variation in the Tier 1 allotment can be explained by district enrollment. Table B presents the average real allotment by year.

Table B: Mean Tier 1 Allotment

	1992	1993	1994	1995
Tier 1 allotment	2818	3072	2940	2936
	(380)	(416)	(401)	(401)

Note: Standard errors in parentheses. Based on 1035 observations each year.

The mean allotment rose in 1993 and fell afterward. Though there is some variation in this component over time and across districts, most of this will be absorbed by the controls.

c) Tier 2 matching revenue

Tier 2 is the key to the analysis. Tier 2 matching revenue depends on the tax rate that a district chooses to set and district tax base wealth, as well as the per pupil state guarantee which is set each year.[24] Property-poor districts raise less than the guarantee per pupil (about $22) for each .01 percent tax (i.e. tax base wealth is less than $220,000 per pupil). These districts receive

[23]The Legislative Education Board (LEB) and Legislative Budget Board (LBB) were required to develop this index in 1990. The price 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.

[24]The guarantee varies by district since it incorporates one-half of the Tier 1 cost and price adjustments. I abstract from this in the discussion but account for this when calculating the gain measures used in the analysis.

a matching subsidy to meet the guarantee. In 1992 and 1993, districts that raise in revenues more than the guarantee simply did not participate in this program. In 1994 and 1995, districts that raised more than the guarantee fell into two categories. Those that did not raise "too much" more continue not to be affected at all by this tier. However, the wealthiest districts (those that raise more than $28 per pupil for each .01 percent levied) actually had to return the excess to the state. This recapture transforms Tier 2 into a "matching tax" program for these high wealth districts after 1993.

Because Tier 2 revenue depends on the amount of revenue raised per weighted pupil, classifying a student as special needs affects the size of the matching grant or tax. For low wealth districts, an increase in the pupil count increases the gap between revenue raised per pupil and the guarantee and increases the subsidy. For high wealth districts, an increase in the pupil count reduces the excess revenue raised and therefore reduces the tax. Thus, low wealth districts gain in all years and high wealth districts gain in the second period, whereas middle wealth districts are unaffected by Tier 2 in all four years.

In calculating the Tier 2 component of the actual gain from classifying a student as disabled, I use the tax rate each district chooses to set. However, this tax rate may be directly affected by the size of the disability program. Therefore, the simulated measure is based on the average tax rate by tax base wealth category and year across the state. The simulated Tier 2 Gain is presented in the following table:

Table C: Tier 2 Gain

	1992	1993	1994	1995
Low wealth	1099	1148	1077	1140
	(80)	(84)	(79)	(84)
Middle wealth	0	0	0	0
High wealth	0	0	1593	1679
			(134)	(149)

Note: The values are based on a total of 1035 observations in each year.

The jump in the gain for the high wealth districts after 1993 provides much of the identifying variation for the analysis. 83 percent of districts fall into the low wealth, five percent into the

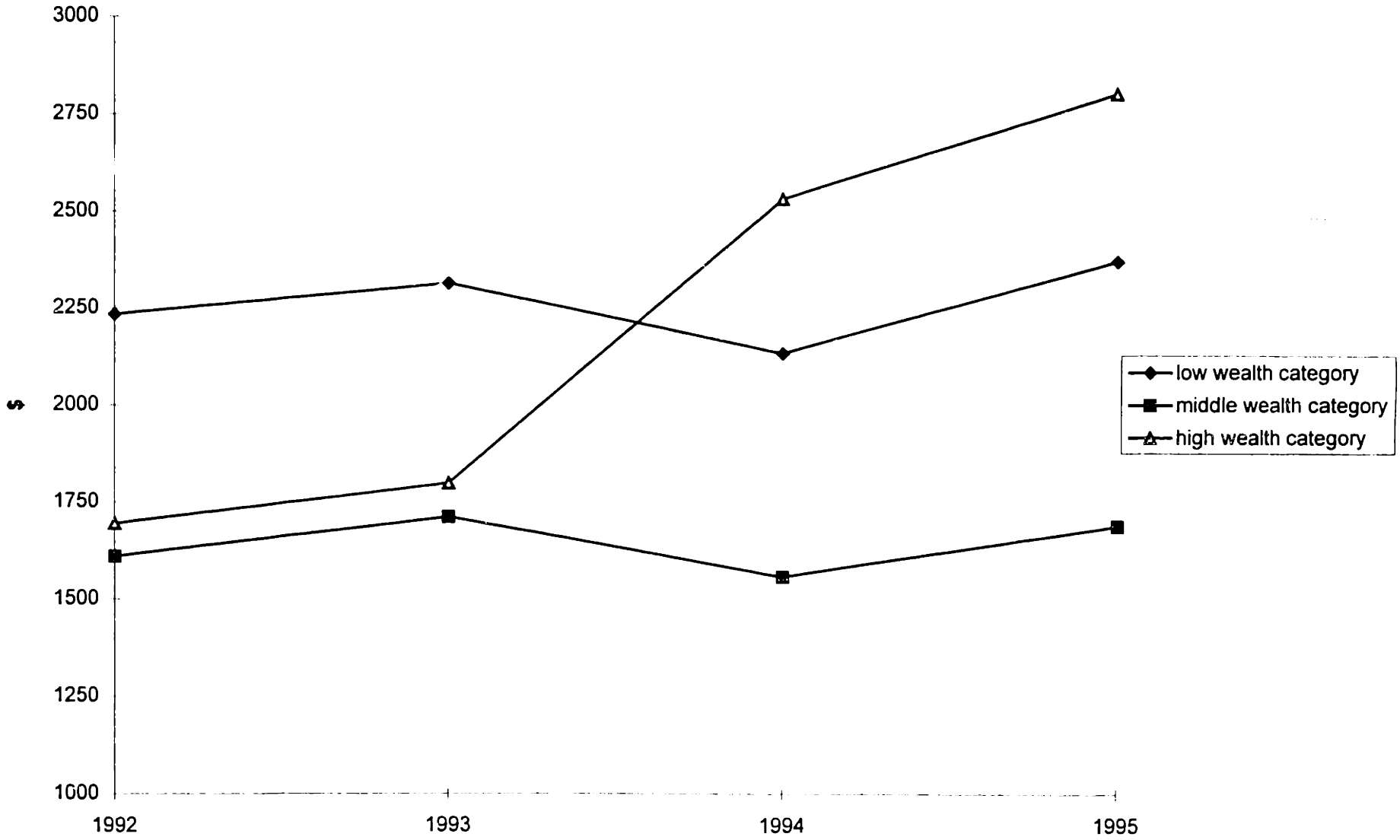
middle, and twelve percent into the high wealth category. If school districts respond to fiscal incentives to classify more students as disabled, the response should show up in the behavior of the wealthiest twelve percent of districts over time relative to the other two categories.

Putting all three of these components together (a x {b+c}) yields actual and simulated measures by tax base wealth category and year. To reiterate, the actual measure calculates the marginal increase in the pupil count, component (a), from classifying an additional student as disabled using the district's own probabilities for determining how that student would most likely be served. Component (c), the additional matching funds, are determined based on the district's actual tax rate. These two components in the simulated measure are based on statewide patterns of service for disabled students and statewide tax rates. Component (b), the foundation grant per pupil, is calculated in the same way for both the actual and simulated gain.

In addition to simulating components (a) and (c), I take one more step to insure that the variation in the simulated revenue gain is not correlated with other factors that may independently affect disability rates. I assign districts to tax base wealth groups based on the financial and program variables in the initial year. Most districts (93 percent) remain within the same classification for the following three years. However, there are some districts that do shift across categories. A shift might occur if a district is on the margin between two categories or if a district's property value changes substantially. Also, a district that aggressively expands programs other than general education may be able to do so enough to move into a more favorable category and actually affect the gain it receives from classifying an additional student as disabled. In order to avoid this type of endogeneity, I freeze the district where it is in the initial year to define the *simulated* tax base wealth measure. Tax base wealth controls included in the regression will also be defined based on the initial category.

The means of the actual and simulated revenue gain for all disabilities combined are presented in Table 1. The average revenue gain over all years is about $2200 over and above the revenue generated by a general education student. Figure 1 shows the variation in the simulated measure visually and highlights the 40 percent increase in the gain for high wealth districts that occurred in 1994.

Figure 1: Simulated Marginal Revenue Gain
All Disabilities



Note: The gain is the mean amount of state revenue generated by a disabled student above that generated by a non-disabled student by tax base category. The calculation for each district is based on statewide placement, attendance, and tax rates.

An important aspect of this study is that I focus on the gross measure of the revenue effect. Without information on the costs of educating disabled students it is difficult to tell whether or not there is a gain on net to a district. Using detailed expenditure data from a nationally representative sample of school districts, Chaikind et al (1993) estimate that the excess costs associated with educating a speech-impaired student are $861 and $2404 for a learning disabled student. Comparing this to the average gain of $2200 (and recognizing that the cost of education in Texas is less than average across the states) implies that districts may in fact be able to generate surplus revenue by classifying students within certain disability categories while still providing the typical set of services.

Data

I use district-level data collected by the Public Education Information Management System (PEIMS) on a wide range of financial variables. PEIMS also collects information on student characteristics, including the number of students in each district in Texas by disability type and instructional setting. I include in my sample all districts except for the six districts that are not fiscally independent and those few districts which appear or disappear over the sample period. There are 1035 districts in the sample in all 4 years for a total of 4140 observations.

The summary statistics for the variables used in the analysis for the full sample are presented in the first column of Table 2. For those variables that change over time within districts, I include not only the overall standard deviation but also the standard deviation within districts over time since most of the analysis includes district-fixed effects. The overall mean disability rate is 12.9 percent for all disabilities. The mean rate excluding physical disabilities is 12.7 percent, and 12.0 percent also excluding mental retardation. The narrowest categorization of disabilities that I use includes only the two largest categories: learning disabilities and speech impairments. These two alone account for 85 percent of student disability. I will use this succession of disability rates, from all-inclusive to just these two most prevalent, as dependent variables in the empirical analysis.

The last three columns in Table 2 break the summary statistics down by tax base wealth category. There are some important differences in the demographic characteristics across the

columns. The low wealth districts tend to have higher childhood poverty rates, more students who are not proficient in English, and more blacks. The differences in some of these characteristics suggest that low wealth districts have larger at-risk student populations and can help to explain the initial higher incidence of disability in these districts. Changes in these variables may also be important in explaining the trend in disability rates. I will compare the importance of some of these demographic variables to that of fiscal incentives.

3. Empirical Results

Exploratory Analysis

To get an initial sense for how the changes in revenue gain across districts map into trends in disability rates, I compare mean changes across districts in the three tax base wealth categories. The first three columns in Table 3 presents the mean annual percent changes in the simulated revenue gains and the mean annual changes in the student disability rates. The means are presented for all disabilities combined and for the broad categories of non-physical and physical disabilities. Non-physical disabilities include learning or speech disabilities, emotional disturbance, mental retardation, and other health impairments (e.g. ADHD). The physical disabilities are deaf-blindness, autism, and visual, hearing, and orthopedic impairments. The simulated revenue measure is adjusted in each case to reflect the average pattern of instructional placement across the state for the relevant disabilities.

For all disabilities, the increase in the revenue gain averaged 20 percent annually in high wealth districts, compared to an average increase of 2.9 percent in low wealth districts and an average 3.8 percent fall in middle wealth districts. The relative growth in disability rates parallels the relative changes in the fiscal gain across groups. Disability rates increased annually by .0051 in low wealth, .0034 in middle wealth, and .0076 percentage points in high wealth districts. The last three columns show the p-values from t-tests of the hypothesis that the mean changes in disability rates across the tax base wealth categories are different from one another. The difference between low and high districts is significant at the five percent level and the difference between middle and high wealth districts, in which case the number of observations

and precision fall, is significant at the ten percent level. These results are slightly strengthened when physical disabilities are excluded in the second row of Table 3. I would expect physical disability rates to be immutable with respect to financial incentives because these disabilities are severe and evident. In fact, the differences in changes in physical disability rates are not significant in any of the comparisons. However, physical disabilities account for only three percent of all disabilities and the standard deviations are extremely high. This initial evidence shows that there is a strong correlation between price incentive patterns and trends in local special education enrollments. Next, I turn to regression analysis to establish a causal link between the two.

Regression Analysis

Table 4 presents the results from regressions based on the two-stage least squares (2SLS) specification in equation (2). Each column pertains to a different dependent variable. All regressions include, as well as the variables reported, district-fixed effects, year and region effects, and a 20-piece spline in the log of district enrollment.[25] The dependent variable in the first column is the student disability rate in a district including all disabilities. The log of the actual district-specific gain for classifying an additional student is instrumented using the simulated measure. The coefficient on the revenue gain, .017, is positive and significant at the five-percent level. The coefficient can be interpreted as the change in the fraction of students disabled for a given percent increase in the reimbursement rate. A ten percent increase in the revenue gain leads to an increase of .0017 percentage points, or 1.3 percent, in the disability rate. The implied elasticity is .13. From 1992-1995, both disability rates and benefit generosity increased by 10 percent on average across districts. This means that increases in benefit generosity can explain almost one-eighth of the time trend in disability rates in Texas over the four years.

Another control variable that has a significant effect on disability rates even after

[25]Note that the tax base wealth category is excluded from the regression since it is defined in the first period and does not change over time.

controlling for district-fixed effects is the fraction of students in poverty, defined as receiving a free lunch through the federal program at school. This variable is strongly positively correlated with the fraction disabled. The link between disability and economic disadvantage has been well-documented elsewhere (Chaikind and Corman 1991). The implied elasticity of student disability rates with respect to childhood poverty rates evaluated at the means of both variables is 0.1. Fiscal incentives have effects that are on the same order as or even larger than changes in childhood poverty rates.

Columns 2 through 4 in Table 4 reestimate the 2SLS specification using different dependent variables. Column 2 excludes physical disability rates from the disability rate measure. Little changes from column 1 since physical disability rates make up such a small share of the fraction disabled. Column 3 excludes mental retardation which makes up about 5 percent of the disabled population. Of the non-physical disability rates (mental retardation, emotional disturbance, other health impairment, speech impairment, and learning disability), mental retardation is the most evident and least likely to be affected by fiscal incentives. This redefinition of the dependent variable does increase the point estimate slightly. Column 4 isolates the two most prevalent disabilities: speech and learning disabilities. These two disability categories are also those in which the majority of students classified have mild disabilities and are in many cases not distinguishable from poor academic performers in regular education (Reschly 1996). Here, as expected, the point estimate increases slightly again from .018 to .019.

Table 5 tests the robustness of the 2SLS results in Table 4 in a variety of ways. The first row excludes districts with enrollment in the top and bottom 1 percent. Very large districts with small special education programs or very small districts with a few disabled students may generate outliers in the dependent variable. However, the results do not change and it does not appear that outliers are driving the strong findings. The second column changes the dependent variable to the log of the fraction disabled. The coefficients are directly interpretable as elasticities and are close to 0.2, slightly larger than the log-level regression. These higher estimates probably arise because the high tax base wealth districts experience the most growth yet started with the smallest share of students classified as disabled, or the smallest base. Rows 3 through 7 drop the observations from each of the four years in turn with little effect on the

estimates. For just learning and speech disabilities (column 4), the estimated coefficients lie between .014 and .022. The implied elasticities lie between .13 and .2. The results appear to be quite robust.

Response by Student Race/Ethnicity

The estimated elasticities in the previous section reveal that local officials are sensitive to pricing in state funding formulas when making decisions about student disability. It is ambiguous whether this response is beneficial to students or not and difficult to think of an experiment that would answer that question. I consider one aspect of the local response that has received extensive legal attention. There is a long-standing contention that localities tend to over-classify minority students and may do so particularly for fiscal gain. A recent New York Times articles describes this presumption:

> "In New York City, for example, most special education students are not deaf, blind, or classified with any other readily defined disability. Rather, 70 percent are labeled "learning disabled" or "emotionally handicapped," terms that many experts say are so loosely applied that they provide cover for teachers who want to get rid of troublesome students. Critics say that a disproportionate number of the students classified in this way are black and Hispanic male students."[26]

It is true that student disability rates are higher among blacks and Hispanics. However, several studies show that this "over-representation" can be explained to a large degree by differences in demographic characteristics that reflect real differences in the underlying prevalence across these groups. Wagnes (1994) finds a higher incidence among minorities of deafness, blindness, and other objective disabilities; Shiono et al (1995) claim blacks are twice as likely as whites to be born low birth weight. Despite studies that attest to these differences, the perception persists that there are some factors that are not legitimate. Secretary Richard W. Wiley recently stated in testimony (1995), "current law tends to encourage over-identification of children, particularly minority children, as disabled" (Testimony June 20, 1995).

Table 6 explores whether or not districts that have fiscal incentives to expand special

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[26]*New York Times*, Monday March 4, 1996, "Critics Attack Pataki Formula for Helping Disabled Students."

education populations draw disproportionately from minority groups. To define "disproportionate," I use the average relative incidence of disability by race/ethnicity across the state as the baseline. I then compare the estimated elasticities of the disability with respect to the fiscal gain measure for the different race/ethnicity groups to this baseline. The pattern of point estimates suggest that Hispanics are drawn on more frequently than would be anticipated given the current racial/ethnic shares of disability. However, the estimates are too imprecise to reject that the pattern of classification response to fiscal incentives is the same as the average pattern.

4. Conclusion

In this paper, I use variation in the amount of state aid generated by disabled students across school districts in Texas to identify the response of disability rates to the generosity of state reimbursement for special education. The central results suggest that the elasticity lies between 0.15 and 0.2. A ten percent increase in the state reimbursement rate for disabled students would lead to a 2 percent increase in the fraction disabled. This elasticity implies that changes in state revenue generosity can explain 15 percent of the trend in disability rates in Texas from 1992-95. Local decision-making is fairly responsive to these intergovernmental price incentives. An important priority for future work is expanding this analysis to consider national trends in reimbursement and disability rates and the applicability to other state-local relationships.

Table 1: Revenue Gain from Classifying an Additional Student (All Disabilities)

	1992	1993	1994	1995
		Actuai gain		
Low wealth	2216	2278	2110	2361
	(615)	(663)	(690)	(511)
Middle wealth	1640	1851	1724	2071
	(420)	(547)	(602)	(517)
High wealth	1541	1558	1826	2258
	(513)	(542)	(554)	(622)
		Simulated gain		
Low wealth	2234	2318	2133	2368
	(277)	(289)	(268)	(296)
Middle wealth	1609	1685	1562	1707
	(247)	(260)	(241)	(265)
High wealth	1694	1780	2506	2774
	(266)	(282)	(343)	(379)

Note to Table 1: The values are based on a total of 1035 observations in each year: 83 percent low wealth, 5 percent middle, and 12 percent high (based on initial tax base wealth category in 1992). Standard deviations are in parentheses. The revenue gain is the average amount of state revenue generated by labeling a student as disabled across all categories over that generated by a general education student. The actual gain is based on the district's own tax, attendance, and placement rates. The simulated gain is based on the average tax rate within each tax base wealth category and statewide placement and attendance rates.

Table 2: Summary Statistics

Variable:	Full Sample	Tax Base Wealth Category Low	Middle	High
Tax base wealth category				
% low wealth	.84	1	0	0
% middle wealth	.05	0	1	0
% high wealth	.11	0	0	1
Dependent variables				
% disabled, all disabilities	.129 (.044) [.016]	.132 (.044) [.015]	.117 (.042) [.016]	.117 (.045) [.020]
% disabled, all non-physical categories	.127 (.044) [.016]	.129 (.044) [.015]	.115 (.043) [.016]	.115 (.045) [.020]
% disabled, all non-physical categories excluding mental retardation	.120 (.043) [.016]	.122 (.043) [.015]	.109 (.043) [.016]	.110 (.044) [.020]
% learning/speech disabled	.109 (.040) [.014]	.111 (.039) [.014]	.100 (.042) [.015]	.103 (.043) [.019]
% physically disabled	.003 (.003) [.002]	.003 (.003) [.002]	.003 (.003) [.001]	.003 (.004) [.003]
Independent variables				
tax base wealth/pupil (divided by 1000)	194 (334) [54]	112 (542) [14]	284 (68) [36]	826 (776) [163]
% of tax base residential	.30 (.19) [.02]	.33 (.17) [.02]	.23 (.21) [.02]	.13 (.20) [.01]
district enrollment	3432 (10535) [256]	3432 (10320) [245]	6167 (18461) [443]	2028 (4937) [218]

Table 2 Continued

Variable:	Full Sample	Tax Base Wealth Category Low	Middle	High
% daily attendance	.957	.956	.959	.960
	(.012)	(.012)	(.010)	(.011)
	[.008]	[.008]	[.003]	[.005]
% in poverty	.439	.452	.397	.360
	(.187)	(.185)	(.175)	(.189)
	[.047]	[.046]	[.035]	[.058]
% not English proficient.	.058	.059	.056	.054
	(.108)	(.112)	(.080)	(.082)
	[.018]	[.017]	[.016]	[.027]
% white	.660	.657	.646	.692
	(.263)	(.267)	(.241)	(.234)
	[.017]	[.016]	[.017]	[.025]
% Hispanic	.252	.250	.269	.255
	(.267)	(.271)	(.241)	(.244)
	[.016]	[.014]	[.016]	[.024]
% black	.081	.086	.072	.042
	(.121)	(.125)	(.112)	(.077)
	[.008]	[.008]	[.006]	[.005]
% early education	.098	.098	.096	.099
	(.033)	(.032)	(.031)	(.044)
	[.016]	[.014]	[.015]	[.024]
% elementary	.402	.396	.419	.437
	(.068)	(.055)	(.094)	(.120)
	[.022]	[.020]	[.024]	[.036]
% middle	.242	.243	.240	.235
	(.034)	(.029)	(.049)	(.057)
	[.018]	[.017]	[.021]	[.026]
Number of Observations	4140	3496	219	425

Notes to Table 2:These summary statistics are based on district-level PEIMS data for the years 1992-1995 (4140 observations). Both the overall standard deviations () and those removing district-fixed effects [] are shown. Column 1 is based on the entire sample; columns 2-4 break the sample down by tax base wealth category. Omitted categories are: % property base other, % students other race, % students in high school, % adults with 4 years college or more, and % living in central cities.

Table 3: Mean changes in Disability Rate and Revenue Gain by Tax Base Wealth Groups

	Mean Changes by Tax Base Wealth Category			P-values from t-tests of Differences in Means		
	Low	Middle	High	Low-Mid	Low-High	Mid-High
All disabilities						
Change in disability rate	.0051 (.0004)	.0034 (.0018)	.0076 (.0076)	.278	.040	.087
% change in revenue gain	.029 (.002)	-.038 (.010)	.195 (.010)	<.001	<.001	<.001
Non-physical disabilities						
Change in disability rate	.0048 (.0004)	.0030 (.0018)	.0073 (.0015)	.253	.041	.080
% change in revenue gain	.031 (.002)	-.037 (.011)	.197 (.010)	<.001	<.001	<.001
Physical disabilities						
Change in disability Rate * 100	.017 (.005)	.033 (.016)	.016 (.023)	.409	.975	.627
% Change in revenue gain	-.012 (.001)	-.077 (.010)	.154 (.011)	<.001	<.001	<.001
Number of Observations	2632	166	307			

Note to Table 3: The first three columns present the means of district-level annual changes in disability rates and in the revenue gain from classifying a student as disabled by tax base wealth category. Standard errors are in parentheses. The means are presented both for all disabilities and separately for non-physical (mental retardation and speech, learning, and emotional disabilities) and physical disabilities. The p-values presented in the last three columns are based on t-tests of the hypothesis that the two means from the row and tax base categories indicated are different from one another.

Table 4: Two-Stage Least Squares Estimates of the Response of Student Disability Rates

	Disability Category			
Variable	(1)	(2)	(3)	(4)
log(actual revenue gain)	.017	.017	.018	.019
	(.007)	(.007)	(.006)	(.006)
% students in poverty	.024	.028	.026	.023
	(.006)	(.006)	(.006)	(.006)
% students black	.006	-.009	-.025	-.040
	(.034)	(.034)	(.033)	(.032)
Hispanic	-.003	-.005	-.013	-.015
	(.018)	(.018)	(.018)	(.017)
other race	.029	.028	.023	-.026
	(.092)	(.091)	(.090)	(.085)
% students early education	-.049	-.050	-.057	-.047
	(.022)	(.022)	(.021)	(.020)
elementary	-.010	-.011	-.007	-.012
	(.018)	(.018)	(.018)	(.017)
middle school	.019	.015	.015	.004
	(.020)	(.020)	(.020)	(.018)
log(per pupil tax base wealth)	-.005	-.005	-.005	-.005
	(.005)	(.005)	(.005)	(.004)

Note to Table 4: The coefficients are based on two-stage least-squares estimates using all districts in all four years 1992-95 (4140 obs). All regressions include district-fixed effects, year dummies, and a 20-piece spline in the log of district enrollment. The dependent variable changes across columns (and the key independent variable and instrument change accordingly to match). In column 1, the dependent variable is the fraction of the student body that has any disability. The dependent variable in column 2 is the fraction with any non-physical disability. Column 3 looks at any non-physical disability except for mental retardation, and column 4 is based on the fraction either learning or speech disabled.

Table 5: Testing the Sensitivity of the 2SLS Estimates

Independent Variable	Disability Category			
log(simulated revenue gain)	(1)	(2)	(3)	(4)
Excluding largest and smallest districts (top and bottom 1%)	.017 (.006)	.017 (.006)	.017 (.006)	.018 (.006)
Dependent variable in log form	.182 (.056)	.195 (.057)	.209 (.056)	.226 (.185)
Excluding Years from Analysis				
1992	.013 (.007)	.013 (.007)	.014 (.007)	.014 (.007)
1993	.019 (.009)	.019 (.009)	.020 (.009)	.022 (.008)
1994	.018 (.008)	.018 (.008)	.018 (.008)	.019 (.007)
1995	.016 (.009)	.017 (.009)	.017 (.008)	.019 (.007)

Note to Table 5: The coefficients are based on two-stage least-squares estimates using the full or specified sub-sample of the 4140 observations. Each cell is the coefficient on the revenue gain from a separate regression. The specifications include all of the regressors in Table 4. The dependent variable changes across columns (and the key independent variable and instrument change accordingly to match). In column 1, the dependent variable is the fraction of the student body that has any disability. The dependent variable in column 2 is the fraction with any non-physical disability. Column 3 looks at any non-physical disability except for mental retardation, and column 4 is based on the fraction either learning or speech disabled.

Table 6: Two-Stage Least Squares Estimates by Race/Ethnicity

	Disability Category				
Race/Ethnicity	(1)	(2)	(3)	(4)	(5)
White	.066	.070	.618	.0117	.0115
	(.263)	(.044)	(.279)	[.0037]	[.0049]
Hispanic	.252	.027	.267	.0051	.0061
	(.267)	(.029)	(.288)	[.0016]	[.0026]
Black	.081	.012	.110	.0021	.0006
	(.121)	(.018)	(.157)	[.0007]	[.0013]
Other race/ethnicity	.008	.001	.005	.0001	.0004
	(.017)	(.002)	(.018)	[.0001]	[.0003]

Note to Table 6: Each row corresponds to the indicated race/ethnicity group. The first column presents the mean share of total enrollment represented by that group. The second column shows the mean of the dependent variable used in the regressions, which is the number of disabled students (speech or learning) in the respective race/ethnicity group over total enrollment. Column 3 is the average fraction of speech and learning disabled students represented by that group and Column 4 is this fraction multiplied by the coefficient from the previous table (.019). This provides the baseline or predicted coefficient for each group. The standard error is derived using the delta method. Finally, Column 5 is the coefficient from individual regressions of the number of students speech or learning disabled in each category over total enrollment on the log of the revenue gain. T-tests of the hypothesis that the predicted responses (column 4) and the estimated responses (column 5) are the same cannot be rejected. Standard deviation are in () and standard errors in [].

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